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Artificial Intelligence for detection and prevention of mold contamination in tomato processing

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Abstract

This study investigates the use of computer vision couples with artificial intelligence to detect mold in tomatoes during the drying process.

Mold presence in tomatoes poses threats to human health and the food industry as it leads to several issues beyond appearance. It is primarily caused by fungi that spread rapidly over the tomato surface, compromising their quality, and potentially producing toxins that can harm human health.

The experimental aim of this work focused on the issue of wastage and loss within the food industry. When tomatoes succumb to mold, they become unsuitable for consumption, resulting in a loss of food and resources. Considering that tomato production requires resources such as land, water, energy, and time, wasting tomatoes due to mold also represents a waste of these valuable resources.

The goal was to evaluate the mold detection capabilities of an object detection algorithm, particularly in its early stages, to facilitate preventative measures. This experimental analysis entailed training the algorithm with an extensive array of images, encompassing a variety of healthy and spoiled tomatoes of different shapes, types, textures and drying stages. The chosen object detection algorithm, YOLOv7, is convolutional neural network-based and was utilized for image labeling and training epochs. Evaluation metrics, including precision and recall, were utilized to assess the algorithm's performance.

The implementation of artificial intelligence in the future has significant potential for enhancing food production processes by streamlining mold identification. Prompt mold detection would expedite segregation of contaminated products, thus reducing the risk of toxin dissemination and preserving the quality of uncontaminated food. This approach could minimize food waste and resource inefficiencies linked to discarding significant product amounts. Furthermore, integrating computer vision in the HACCP (Hazard Analysis Critical Control Points) context could enhance food safety protocols via accurate and prompt detection. By prioritizing prevention, this technology offers a promising chance to optimize quality, efficiency, and sustainability of future food production processes.

Riassunto

Il presente elaborato si propone di analizzare l'uso dell'intelligenza artificiale attraverso il riconoscimento di immagini per rilevare la presenza di muffa nei pomodori durante il processo di essiccazione. La muffa nei pomodori rappresenta un rischio sia per la salute umana sia per l'industria alimentare, comportando, anche, una serie di problemi che vanno oltre l'aspetto estetico. Essa è causata principalmente da funghi che si diffondono rapidamente sulla superficie dei pomodori. Tale processo compromette così la qualità con la conseguente produzione di tossine che possono influire sulla salute umana.

L'obiettivo sperimentale di questo lavoro è il problema dello spreco e della perdita di prodotto nell'industria alimentare. Quando i pomodori sono colpiti da muffe, infatti, diventano inadatti al consumo, con conseguente perdita di cibo. Lo spreco di pomodori a causa delle muffe rappresenta anche la perdita di preziose risorse, utili alla produzione, come terra, acqua, energia e tempo. Il proposito è testare, anche nella fase iniziale, la capacità di un algoritmo di rilevamento degli oggetti per identificare la muffa, e adottare misure preventive. L'analisi sperimentale ha previsto l'addestramento dell'algoritmo con un'ampia serie di foto, tra cui pomodori sani e rovinati di diversi tipi, forme e consistenze. Per etichettare le immagini e creare le epoche di addestramento è stato quindi utilizzato YOLOv7, l'algoritmo di rilevamento degli oggetti scelto, basato su reti neurali. Per valutare le prestazioni sono state utilizzate metriche di valutazione, tra cui "Precision" e "Recall".

L'ipotesi di applicazione dell'intelligenza artificiale in futuro sarà un grande potenziale per migliorare i processi di produzione alimentare, facilitando, così, l'identificazione delle muffe. Il rilevamento rapido delle muffe faciliterebbe la separazione tempestiva dei prodotti contaminati, riducendo così il rischio di diffusione delle tossine e preservando la qualità degli alimenti non contaminati. Questo approccio contribuirebbe a ridurre al minimo gli sprechi alimentari e le inefficienze delle risorse associate allo scarto di grandi quantità di prodotto. Inoltre, l'integrazione della computer vision nel contesto dell'HACCP (Hazard Analysis Critical Control Points) potrebbe migliorare i protocolli di sicurezza alimentare grazie a un rilevamento accurato e tempestivo. Questa tecnologia potrà offrire, dando priorità alla prevenzione, una promettente opportunità per migliorare la qualità, l'efficienza e la sostenibilità dei futuri processi di produzione alimentare.

Chapter 1 – Introduction

1.1 <u>Tomatoes, history and production</u>

Tomatoes are a widely cultivated vegetable crop that has gained popularity in the last century. They are grown both in outdoor fields and greenhouses around the world. Tomato plants are highly adaptable, and two primary types of crops are grown: fresh market tomatoes and processing tomatoes. In recent decades, global production and consumption of tomatoes have significantly increased. In addition to their delicious taste, tomatoes are highly nutritious and serve as a rich source of vitamins A and C. Vitamin A is crucial for bone growth, cell division, differentiation, regulation of the immune system, and maintenance of the surface linings of various body structures, including the eyes, respiratory, urinary, and intestinal tracts. Vitamin C plays a key role in the formation of collagen, a protein that provides structure to bones, cartilage, muscle, and blood vessels. It helps maintain capillaries, bones, and teeth, and aids in the absorption of iron. Tomatoes are additionally a plentiful source of lycopene, an effective antioxidant preventing various forms of cancer. Cooked tomatoes and their products are the best source of lycopene as it is released during cooking. Nevertheless, both raw and cooked tomatoes are regarded as excellent sources of the antioxidant.[1]

The tomato belongs to the Solanaceae family, which encompasses more than 3,000 species, including numerous economically important plants such as potatoes, eggplants, petunias, tobacco, peppers (Capsicum), and Physalis. From a botanical perspective, the tomato (Solanum lycopersicum L.) is classified as a fruit berry rather than a vegetable (Bergougnoux 2013).

The exact origins of the tomato are not completely clear, but it is thought to have originated in tropical regions of the Americas, possibly in Mexico or Peru. Some specialists propose that the cherry tomato may have been the precursor of our modern cultivated varieties. The term "tomato" has South American roots and comes from the Aztec word "zitomate" or "zitotomate." Native peoples in Mexico partook of the fruit known as "tomati." The tomato

[1] Source: Online interview written by **Zvi Howard Wener, available via link** Importance of the tomato **(last access July 2023).**

was probably brought to Europe from Mexico or Peru in the beginning of the 16th century. The small yellow tomato was brought to Spain by the Spanish conquistador Cortes after capturing Tenochtitlan, the Aztec city now known as Mexico City, in 1521. Later, the tomato was introduced to Italy via Naples, which was under Spanish control during that period (Bergougnoux 2013). The first known mention of the plant by European botanists can be traced back to Matthioli's Herbal (1554), where he reports that it had been recently introduced to Italy and was called pomi d'oro (golden apple) (Gould 1992).

According to Andreas Matthioli, the tomato species has flattened and ribbed fruits that range in color from green to golden yellow and are sometimes consumed fried in oil with salt and pepper, akin to eggplant and mushrooms. Ten years later, Matthioli observes the existence of yellow and red tomato varieties. The Italian term for tomato, "pomodoro," appears to imply that the initial tomatoes to arrive in Italy yielded yellow fruit. In sixteenth and seventeenth century texts, the tomato is referred to by various names, including "mala aurea," the Latin equivalent of "pomodoro."(Dominique Blancard 2012). The tomato gained popularity in France as the "pomme d'amour" (love apple) and was widely cultivated in Italy before becoming a curiosity in England and America. By 1623, there were four recognized tomato varieties: yellow, golden, red, and white (Gould 1992).

In the Old World, the tomato was viewed with suspicion because of its association with other species of the Solanaceae family known to be poisonous, such as belladonna, nightshade, and mandrake, a plant with magical properties. The tomato was first grown as a decorative novelty and is still occasionally utilized for balcony adornment prior to its fruit being consumed. Its culinary use appears to have initially evolved in the form of sauces to enhance cooking. The consumption of tomatoes as a fresh fruit originated in the Mediterranean and then gradually expanded northward in the late 18th century (Blancard 2012).

An Italian artist introduced the tomato to Massachusetts in 1802 but faced difficulties persuading people to give it a taste. The tomato remained relatively unfamiliar as a food in the United States until the period between 1830 and 1840 when its popularity started to skyrocket. This increasing demand led to the creation of new tomato varieties to satisfy the growing market. The number of varieties available to growers significantly increased within a few decades due to the introduction of European varieties and the development of new American ones (Gould 1992).

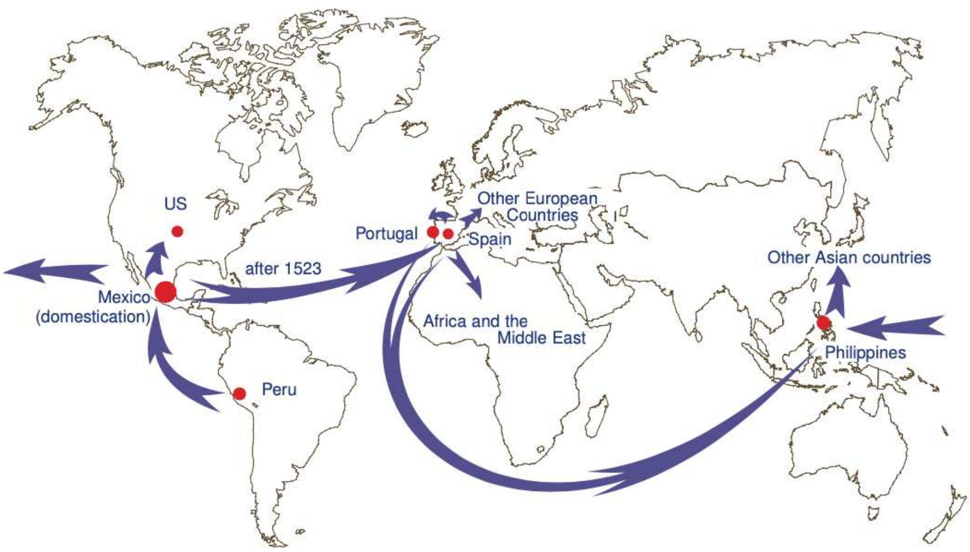

Figure 1 - Map to show the possible expansion of the tomato crop worldwide (Blancard 2012).

The tomato was not known in the Old World until the 16th century, and even during the 19th century, its use was limited. However, in the 20th century, it gained popularity as a star vegetable for commercial cultivation and home gardens alike. It is appreciated for its freshness and used in a variety of dishes, either raw or cooked, as a base or topping. The tomato is a traditional ingredient in sauces, particularly in Italy. Currently, tomatoes rank third globally, behind potatoes and ahead of onions, as one of the most widely consumed vegetables and one of the most popular garden crops. The global production of tomatoes has steadily increased throughout the twentieth century and significantly risen in the past three decades. In 1978, global tomato production was at 48 million tons. This figure increased to 74 million in 1992, 89 million in 1998, and eventually peaked at 124 million in 2006. As of 2011, the worldwide production of tomatoes has approached nearly 160 million tons (Blancard 2012).

Tomatoes are one of the world's most important crops, ranking seventh among key crops such as maize, rice, wheat, potatoes, soybeans, and cassava. Over the last twenty years, both tomato production and cultivation areas have doubled. While Europe and the Americas were the leading producers twenty years ago, Asia now dominates the tomato market. China, followed by India, the United States, Turkey, Egypt, Iran, Italy, Brazil, Spain, and Uzbekistan are the top producers. It is noteworthy that countries in northern Europe, where tomato cultivation is hindered by adverse climatic conditions and limited land availability, have the highest tomato yields. They primarily cultivate their tomatoes in artificial greenhouse environments.

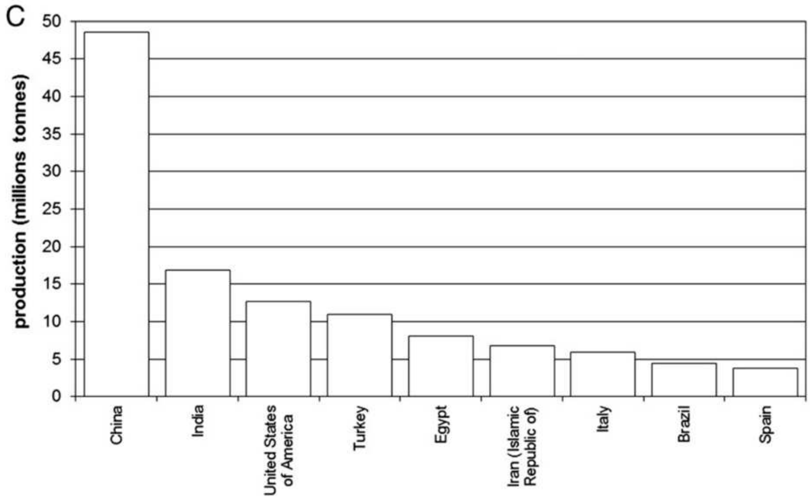

Figure 2 - Production of the nine leading producers in 2011

The increase in tomato production in recent years is primarily attributed to the rising demand for tomatoes. As of 2009, the typical yearly tomato consumption per person was 20.5 kg. Libya, Egypt, and Greece are the top three countries with the highest tomato consumption rates, exceeding 100 kg per person per annum. Generally, the countries that have the highest tomato consumption are those in the Mediterranean and Arabian regions. On average, these countries consume between 40 and 100 kg of tomatoes per person per year (Bergougnoux 2013). The demand for tomatoes is projected to continue growing due to various factors, such as the increase in the human population, the capability of tomatoes to be transported over long distances without spoilage, the advancements in breeding new types of tomatoes, and the evolving dietary preferences of consumers that incline towards this vegetable (Blancard 2012).

1.2 Growing tomatoes

Crop production depends on factors beyond soil quality, all of which must be met to achieve cost-effective yields. Tomatoes are no exception, as their production is heavily influenced by factors such as plant vigor, insect management, and climatic conditions. The encouraging news is that most of these variables can be influenced or controlled by human intervention in tomato cultivation. The success of tomato cultivation ultimately depends on the growers and their effective methods. The selection of suitable fields, careful land preparation, and diligent planting and cultivation practices typically result in a successful harvest (A. Gould 1992).

1.2.1 Climate and geography

The tomato plant, a sub-tropical species, is highly susceptible to frost and flourishes in warmer seasons. It's typically grown during the summer, with a temperature range of about ±18°C to ±30°C ideally supporting its growth. Nonetheless, these numbers act as approximate recommendations; for more specific information, it is crucial to ensure the night temperature never drops below 12°C. Persistent exposure to temperatures below the minimum threshold during fruit development can result in multiple physiological disorders. The same principle applies for tomato's maximum temperature tolerance. To avoid sticky pollination and decreased fruit set, it is recommended that the average maximum temperature does not surpass 32°C, particularly during early morning pollination. Hence, the evaluation of temperature effects requires consideration of qualitative aspects rather than relying solely on a numerical value. While an average determinate tomato plant requires over 3.5 months to grow and yield profitable outcomes, it is important to note that high humidity and elevated temperatures can promote rapid vegetative growth and increase susceptibility to diseases, leading to lower yields. It is worth noting that these responses are linked. On the other hand, in windy, warm, and dry climates, blossom drop occurs, causing a significant decline in yields. Daylight length does not significantly affect tomato plants. However, it is noteworthy that longer days and higher average temperatures lead to better quality and an increased number of fruits per cluster. Tomatoes cultivated under higher light intensity levels have been found to have a more flavorful taste due to higher ascorbic acid content. Additionally, light intensity affects the color of tomatoes, with higher intensity resulting in a greater concentration of carotene in the fruit.[2].

1.2.2 Field selection

The first step in tomato farming involves selecting the appropriate field, as this decision significantly minimizes the likelihood of future issues. The chosen area should be relatively even to allow for proper drainage. Ideal conditions call for fields that are level, with consistent soil composition, well-draining sandy loam, and adequate wind shelter. Conversely, low-lying fields with dense soil are less favorable for direct seeding. To reduce mechanical equipment maneuvers, the shape and size of the field should involve minimal turns. This consideration is especially important when using mechanical harvesting methods. Row lengths less than 200 yards impede harvester effectiveness, while longer rows ease fruit collection, harvesting, and field clearing. Ideally, the tomato field selected for harvesting should have minimal or no stones and large soil clods, as well as a balanced organic matter content. Fields with high weed populations should be avoided to prevent equipment jams and halting of the harvesting process. Measures should be taken to eliminate excessive moisture caused by stagnant water in the field (Gould 1992).

1.2.3 Soil selection

Tomatoes are highly versatile plants, capable of adapting to a variety of soil types. However, some soils are better suited for optimal tomato growth. Typically, soils with high levels of organic matter produce superior yields [3].

Among various soil types, loam is considered the optimal choice for planting tomatoes. Loam is a well-balanced mixture of sand, silt, and clay making it a perfect option for tomato cultivation. The soil's ability to retain and drain water efficiently offers many benefits. Additionally, incorporating organic matter, like manure, further improves the suitability of loam by providing essential nutrients to the plants and enhancing soil composition. Organic

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[2] Source: Online interview written by Antonious Lecuona on 6th May 2016, available via link Basic horticulture of growing tomatoes (last access July 2023).

[3] Source: Official website of GrowFoodEasily via link How to grow healthy tomatoes (last access July 2023).

matter, such as decayed leaves, compost, sawdust, or animal manure, can improve soil water and nutrient retention, promote root growth, and aid water and air infiltration. Composted manure is especially beneficial for growing tomatoes since it has lower nitrogen levels, reducing the risk of root burn (Starke Aires 2019).

Although tomatoes are capable of growing in clay soil, it presents several challenges. Clay soil has a tendency to retain water excessively and exhibit higher alkalinity compared to other soil types. As tomatoes thrive in slightly acidic conditions (around a 6 to 6.8 pH level), clay soil may not be the most ideal choice. Another suitable option for tomato cultivation is silt soil; however, it shares similar downsides to clay soil due to its water-retaining properties. However, adding organic material to silty soil can alleviate its drainage constraints [4].

For successful tomato cultivation, the soil must facilitate adequate root development to sustain the plant, provide water, oxygen, and mineral nutrients, and be devoid of harmful elements. The pace of root growth is determined by the soil's compaction or bulk density, which differs by soil type and location. Tomato plants, both above and below ground, flourish in well-aerated soil. Root density is at its highest in places with optimal oxygen diffusion rates. When soil moisture and plant conditions are optimal, tomato plants can develop extensive root systems, reaching depths of up to 4.9 feet and expanding in width based on plant spacing. Encouraging early root development is crucial since most root growth occurs before fruit set (Starke Aires 2019).

1.2.4 Land preparation

Soil preparation is essential for maximizing the profitability of tomato farming. The primary goal of initial soil preparation is to establish optimal growing conditions for tomato plants, which will allow them to develop a healthy root system within a specific soil profile. The advantages of soil preparation are plentiful. It permits unobstructed root growth, lessens the possibility of compression, enhances oxygen levels in the soil, fosters superior root growth, raises yields, reduces production expenses, promotes vegetative growth, enhances drought and

[4] Source: Official website of GrowFoodEasily via link How to grow healthy tomatoes (last access July 2023).

stress tolerance, diminishes the frequency of root diseases, elevates water retention, and improves the absorption of moisture and nutrients (Starke Aires 2019).

One technique for readying the soil is autumnal ploughing, which allows for complete decomposition of roots and other organic matter within the soil. Ideally, established cover crops should be left undisturbed during autumnal ploughing in order to achieve satisfactory results. The land that has been ploughed in the fall should not be disturbed until spring or alternatively be sown with a winter cover crop that will not hinder early spring preparation and planting. If the land remains unplugged until spring, it should be ploughed as soon as the soil is dry, avoiding any work on wet soil. Tilling wet heavy clay soils can cause significant physical damage. Ploughing should be performed as deeply as the soil allows, gradually increasing the depth by 1.27 cm each season until reaching a minimum depth of 20 cm. This gradual increase in ploughing depth over time enables the deepening of the fertile cropping soil layer without affecting current crops (Gould 1992).

For best outcomes, it is ideal to apply manure before plowing. Alternatively, finely textured and well-decomposed manure can be broadcasted after plowing at a rate of 6 to 8 tons per 1 acre and incorporated into the soil by disking. Higher quantities like 10 or 12 tons can be utilized without any detrimental effects, particularly in instances where the organic content in the soil is low, and plant nutrients are deficient. However, caution must be exercised when applying manure on heavily manured soils or soils with high organic content, as excessive vine growth may occur at the expense of fruit set. (Adekiya e Ojeniyi 2002).

Post-plowing land preparation for tomato planting requires a higher level of thoroughness compared to general farm crops. The topsoil should be well pulverized to a depth of 7.62 cm to 10.16 cm before setting the plants (Cubero e Baquiran 2017).

When preparing the soil, it is crucial to take into account its pH level. The appropriate pH range for growing tomatoes is moderately acidic, between 6.0 and 6.8. If the soil is highly acidic with a pH of 5.0 or below, it is necessary to apply lime before planting tomatoes. Lime serves as a soil conditioner, decreasing acidity created by nitrogen (N) fertilizers, slurry, and heavy rainfall. Studies have proven up to a 50% growth in yield when liming highly acidic or calcium-deficient land for growing tomatoes. In fact, soils with a pH of 5.0 or lower greatly benefit from the application of 1 to 2 tons of finely ground limestone (Gould 1992).

1.2.5 Important tomato soil nutrients and fertilizers

The growth of tomatoes is influenced by three essential nutrients: nitrogen, phosphorus, and potassium (potash), alongside minor nutrients like calcium, magnesium, sulfur, and trace elements such as boron and manganese. Nitrogen plays a significant role in crop quality. Sufficient nitrogen is necessary to generate proper foliage to shield fruit from excessive sunlight exposure. Additionally, nitrogen influences the crop's maturation phase. Early in the season, if there is an excess of readily available nitrogen, the plant may become too vegetative, leading to delayed fruit setting and maturity. It is advisable to avoid late nitrogen treatments to prevent prolonged growth, late fruiting, and split sets. Phosphorus is crucial in tomato fertility programs due to its diverse effects on fruit quality. It facilitates robust root development, resulting in higher utilization of nutrients from the soil, and enhances plant efficiency by producing sturdy stems and healthy foliage. Fertilizer-derived phosphorus leads to a greater yield in a short growing season than in a prolonged growing season because the plant has more time to absorb slowly accessible phosphorus from the soil. We discovered the highest concentration of phosphorus in the top leaves and fruit of the tomato plant. Potassium is absorbed and utilized by the plant in abundance. During the vegetative stage, the concentration of potassium in the leaves is greater (around 3 to 4%), but it diminishes throughout the fruiting period. It is essential for glucose metabolism, translocation, nitrogen metabolism, protein synthesis, and stomatal movement, which helps regulate water in plants. Inadequate potassium results in insufficient lycopene formation in fruit. High temperatures can cause the fruit to sunburn and deteriorate prematurely. Therefore, sufficient and optimal potash fertilization is crucial to producing high-quality fruit. Calcium, magnesium, and sulfur are essential micronutrients. Calcium and magnesium serve a dual purpose in the soil – neutralizing soil pH and acting as essential plant nutrients. Magnesium, in particular, is crucial in chlorophyll synthesis, while sulfur is vital for overall plant development. Iron, boron, manganese, copper, and zinc are trace elements that are recognized as vital for plant growth. Both boron and manganese are also necessary, but only in minute quantities (Gould 1992).

A thorough soil analysis should be performed to identify the ideal type and amount of fertilizer. This study expands our understanding of soil composition and offers practical recommendations for future fertilization. While tomatoes tend to respond positively to significant fertilizer applications, excessive use can cause problems. Commercial fertilizers typically consist of a blend of three essential nutrients in varying proportions. Currently, the most prevalent practice is to fertilize prior to plowing. Nevertheless, fertilization for mechanically harvested tomatoes should differ from that of hand-harvested tomatoes. Fertilization significantly influences the consistency and rate of tomato maturity. For instance, nitrogen plays a critical role in regulating tomato maturity consistency and timing (Gould 1992).

The nitrogen demand for an entire growing season can range from 13 to 45 kilograms per 0.40 hectare, depending on tomato cultivar, soil type, previous crops, and soil fertility. Additionally, nutritional requirements differ among different plant growth phases. Nitrogen is highly needed during the first 0-5 weeks of vegetative development, while the blooming period requires an increase in potassium needs from 6 to 12 weeks. Finally, the need for calcium and magnesium is significant during the 12-20 week period that includes fruit set and filling (Starke Aires 2019).

1.2.6 Planting and cultivation

The decision of when to plant tomato plants or sow them directly in the field is dependent on weather and soil conditions. Various factors, such as geographical and climatic circumstances, transplanting or direct sowing methods, and mechanized or hand harvesting, must be taken into account when selecting the optimal planting period. The most crucial consideration, however, is temperature stability. Planting should commence when the soil temperature has remained at 14°C or higher for three consecutive days. Early plantings exhibit slower seed development rates, whereas later plantings experience accelerated growth, enabling seedlings to progress from the cotyledon phase to the first true leaf stage within a day or two. The duration from emergence to harvest, generally around 125 days, facilitates steady and consistent harvests, contingent on the crop variety cultivated. A wide range of precision planters for direct seeding with uniformly spaced seed distribution within rows are now commercially available. It is recommended to sow seeds directly, spacing them every 20 to 25 centimeters in groups of 4 to 7 seeds, while maintaining rows that are 1.5 to 1.8 meters apart. This corresponds to a seeding rate of approximately 226 grams of seed per 0.40 hectares (Gould 1992).

Transplanting involves carefully moving young, immature tomato plants from their original locations to areas where their growth and ultimate maturity will benefit producers and processors. Even under ideal circumstances, transplanting can cause severe stress to the plants. It is crucial to begin sowing seeds 6 to 8 weeks after the area's anticipated last frost date, as the ground must be warm enough when the tomato plants are placed outside to ensure their survival. Only strong and well-developed plants should be selected for transplantation. It is recommended to adequately hydrate the soil in which they are grown before removing them from the bed. The use of phosphate-rich starting solutions during transplantation may provide benefits.[5].

Weed control is a key objective in tomato gardening as some weeds associated with tomato plants can spread diseases. Hence, it is crucial to prevent them from invading the tomato crop and remove them from neighboring lands. Mechanical cultivation, in combination with chemical control measures, can achieve effective weed control. Additionally, cultivation loosens compacted soil, increasing its permeability to water and facilitating the release of plant nutrients by soil microorganisms, thus enhancing crop growth (Gould 1992).

1.2.7 Irrigation

Providing a proper water supply to tomato plant roots is essential for optimal growth. Objective scheduling of water supply is critical. Both under and over-irrigation can devastate the crop, highlighting the need to irrigate at optimal intervals. Superior crop growth can be achieved through deep, thorough irrigation as opposed to short, frequent watering periods. This can be accomplished via drip or flood irrigation technologies, which are less prone to foliar diseases compared to overhead irrigation. The required water amount varies based on weather conditions. Tomatoes require approximately 25mm of water weekly during colder months, which may increase to 50mm during extremely hot, dry and windy conditions. Nevertheless, it is crucial to refrain from irrigating the crop towards the end of the season to avoid fruit rots and cracks once the crop has matured considerably (Starke Aires 2019).

Tomatoes are prone to flood damage, so it is recommended to moisten the root zone during watering or irrigation, especially from the start of flowering until the final harvest. Quick

[5] Source: Official website of GrowFoodEasily via link How to grow healthy tomatoes (last access July 2023).

furrow irrigation is advised to reduce soil erosion and promote healthy fruit growth. It is recommended to irrigate the plants 4-5 times between transplanting and 14 days before the final harvest. Sprinklers may be used when surface irrigation is unavailable, delivering one liter of water per hill each week (Cubero e Baquiran 2017). Irrigation is imperative to ensure uniform fruit maturation and should be readily accessible for the entire tomato field as needed. Inadequate water availability can hinder achieving consistent fruit maturity. Water is primarily necessary for maintaining overall plant health once the fruits have attained the appropriate size (Gould 1992).

1.2.8 Harvesting

One of the most essential parts of crop cultivation is harvesting. This, like all the other stages of tomato growing seek for maximum output and quality (Gould 1992). Because tomato cultivation provides income for many rural and peri-urban farmers in most of the world's impoverished countries, it's crucial to make the crop profitable while attempting to lower losses, which can surpass 42% worldwide. Harvesting is one of several variables that affect tomato loss rates. Thus, it is crucial to employ sound agronomic harvesting techniques and to be able to identify the optimal time for harvesting. Harvesting is one of the most complex stages of the tomato growth process (Arah et al. 2015). [6]

Tomato fruit harvesting starts 15-20 days after flowering and takes place at weekly intervals depending on market need. Processing tomato harvesting begins in the latter decade of July and the first decade of August and lasts until the end of September. Tomatoes can be harvested in three stages: ripe red (harvested when the fruits are already red. This is the best time to harvest for home consumption); ripe green (harvested when the fruits begin to show cream-colored streaks at the flower tips. This is applicable for far markets); and pink (when the flower end turns pinkish or reddish. This is applicable to the close market) (Cherrybel O. Cubero e Prisca B. Baquiran 2017; Londini et al. 2010).

The first option is to let the tomatoes ripen on the vine. They can grow to full maturity and be harvested at their peak when their color has fully developed, either red, yellow, or orange,

[6] Source: Official website of The Sage – Gardenuity Blog via link: Harvesting tomatoes: the complete guide (last access August 2023).

depending on the type, and the color has spread throughout the entire tomato. In addition, the texture should be firm. This practice results in higher quality since fruits allowed to fully develop on the plant have more flavor than those harvested prematurely. Certain types, like cherry tomatoes, have a tendency to split if left on the plant, resulting in premature spoilage. Therefore, they should be harvested as soon as they begin to turn red, rather than waiting for the peak of redness. [7] It is important to note that as tomatoes ripen, they become more susceptible to bruising. Instead of dropping them, pickers should delicately place the fruits in picking containers to avoid injury. Studies have shown that a 15-centimeter fall on a hard surface can cause internal injuries that are not visible until the tomato is opened. External bruising occurs when pickers transfer tomatoes aggressively from picking buckets to empty bins. Overcrowding the bins should be avoided, as too much weight can cause compression damage. Best practices for hand-picking also involve refraining from burning while waiting for pallets to be unloaded at the packinghouse and avoiding harvesting wet tomatoes, as surface moisture increases heat accumulation in the load and encourages disease growth (Kelley e Boyhan 2010).

The second option is to gather tomatoes when green and allow them to mature in a domestic environment. This practice is commonly carried out under certain conditions such as temperatures above 30°C, sub-15°C temperatures, or industrial-scale conditions. Tomatoes are called "ripe green" when they have reached normal size and are showing signs of color development, based on their particular variety. As the coloring process begins at the base, it is essential to recognize and gather it at the point where the color alteration takes place in this area. [8]

Growers frequently take a representative sample of fruit from their fields and open it to check it internally because the ripe green stage is difficult to judge superficially. A normal mature green tomato has a gelatinous matrix throughout, and the seeds have grown enough that they do not be damaged when the fruit is sliced with a sharp knife (Kelley e Boyhan 2010). Furthermore, mature green tomatoes should be stored below a cover of CaC2+ polyethylene

[7] Source: Official website of The Sage – Gardenuity Blog via link: Harvesting tomatoes: the complete guide (last access August 2023).

[8] Source: Official website of The Sage – Gardenuity Blog via link: Harvesting tomatoes: the complete guide (last access August 2023).

to promote early ripening and color development while preserving the fruit's physicochemical quality throughout storage and marketing (Khandaker et al. 2009).

It is crucial to bear in mind that even at the mature green stage, tomatoes are susceptible to mechanical damage. As a result, harvesting personnel should be instructed and supervised to ensure tomatoes are carefully handled when placed in containers (Brar e Danyluk 2013). Although handpicking and handling tomatoes was prevalent in the 1950s, it is now considered obsolete, with only a few small family enterprises still doing so. Handpicking tomatoes is a time-consuming procedure that requires physical effort, ability, and expertise since employees must be able to select ripe tomatoes and handle them carefully to prevent injury (Gould 1992). Handpicking tomatoes starts by identifying ripe tomatoes based on their color, size, and shape. Ripe tomatoes are usually red or orange and can be easily recognized by their tender texture. It is important for workers to be efficient and able to promptly identify these characteristics. They must use the "snap and pull" method to carefully pick ripe tomatoes from the vine. This method involves pulling the tomato off the vine with one hand while holding the vine with the other to ensure that the tomato is not damaged. It is necessary to remove the tomato from the vine by breaking the stem directly above the calyx or "cap" where it attaches to the stem. After harvesting, the tomatoes should be sorted according to size and quality. It is important to be able to identify any damaged or diseased tomatoes in order to discard them as unsuitable for consumption. [9]

Tomatoes were primarily harvested by hand in Georgia in 2010, with varying procedures employed by producers. There were no subjective evaluations given in the text. Ripe green tomatoes were frequently collected in polyethylene buckets, transported on a platform trailer, and then dumped into plastic bins holding 360 to 550 kg of fruit. Upon loading all the bins, they were transferred to a centralized packing station where the fruit was cleaned, sorted, and packaged (Kelley e Boyhan 2010). The nutritional content and shelf life of fruits are affected by their harvesting stage. Anju-Kumari et al. (1993) noted that harvesting tomato cultivars at the ripe green stage extended their shelf life, thus reducing fruit and vegetable loss. To minimize loss during distant sale, it is recommended to pick tomatoes when they are at the

[9] Source: Official website of Ablison via link: How are tomatoes harvested? (last access August 2023).

ripe green stage, and when meant for immediate consumption, at full maturity. (Khandaker et al. 2009).

Despite this, hand picking tomatoes is time-consuming, inefficient, and impractical for large-scale planting. Given the rising labor costs, automated harvesting has emerged as a potential option over the years. Interest in mechanized tomato harvesting increased during the 1960s. Some reasons for opting for mechanical harvesting include a shortage of affordable labor for manual picking, the necessity for mechanical and automated harvesting, efficient coordination of field and factory operations in a high-speed system, the agricultural machinery industry's curiosity in developing, producing, and operating such machinery, the introduction of novel cultivars adapted to one-time harvesting procedures, enabling in-field fruit preservation, and alterations in cultural practices (Wang Lil et al. 2017; Gould 1992).

Mechanized harvesting is a method utilized by large-scale tomato farmers to increase efficiency and decrease costs. The use of mechanized tomato harvesting provides significant advantages for both producers and processors. Firstly, there is a notable reduction in labor costs. Secondly, provided that the weather allows, the machine can operate around the clock. Thirdly, machine harvesting is considerably less costly than manual harvesting, and, if executed correctly, the equipment can be paid off in three years or less. Fourthly, machine harvesting permits the management of detached tomatoes and reduces damage to the harvested fruit overall. [10] A cultivar requires a minimum of six key features in order to facilitate mechanical harvesting. The fruits must mature simultaneously to ensure optimal production; excessive foliage on plants cannot guarantee a high yield. The tomato stem must be completely intact. Additionally, tomatoes must be solid and resistant to cracking, possess good in-field storage potential after harvest, and remain impervious to mechanical damage (Gould 1992).

[10] Source: Official website of Ablison via link: How are tomatoes harvested? (last access August 2023).

Mechanized harvesting is a process that utilizes advanced machines to pick and sort tomatoes by size and quality. Various harvesting machines exist, each with unique characteristics and capabilities, but they all operate under the "one-time" principle, where the entire plant is cut and moved to the harvester, and the fruits are subsequently harvested. Consequently, the farmers cannot return immature fruits during the harvesting period. As a result, in order to avoid a substantial loss of their crop, tomato producers need to ensure that over 85% of the field is ripe for harvesting simultaneously. All mechanical tomato harvesters comprise four key components: a harvesting mechanism, an area in which to separate the fruit and vine, a section for manual sorting, and a mechanism for loading or unloading containers (Gould 1992).

Figure 3 - The main systems on board a self-propelled harvester for processing tomatoes (Tecnologie e meccanizzazione: I segreti del pomodoro da industria)

In most cases, the harvester cuts the vine at or near ground level. The shoots and any loose fruit that has fallen to the ground are gathered on the machine's feed belt by the collecting discs rotating in the opposite direction. Loose fruit and dirt clods are then separated on the grooved chain and placed on separate sorting belts. On each belt, automated or manual dirt and color sorters ensure that all healthy fruit is retrieved, while discarding any unhealthy produce. The field is scattered with discarded fruit and mud clumps. Simultaneously, conveyor belts transport fruit-laden vines to another mechanism that induces a shaking motion, separating the fruit from the vine. The fruits are separated and transported to a conveyor situated below the shaking device. This conveyor delivers and distributes the fruit to sorting belts located on either side of the machine, where sorters remove rejects and undesired fruits.

To prevent human sorting, modern machines utilize electronic color sorters that can be calibrated to any sorting level. Usable items are directed to a communal discharge conveyor, while discarded vines are expelled onto the field behind the machine (Gould 1992).

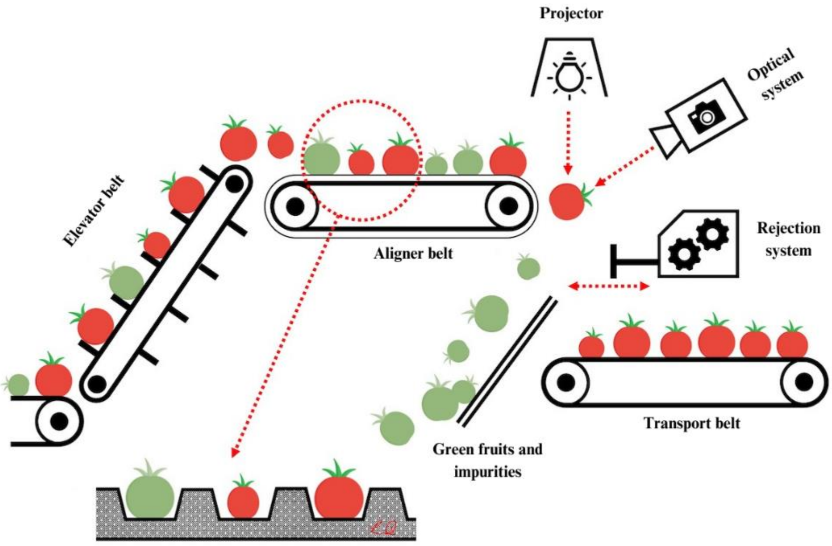


Figure 4 - Schematic of operation of the electronic sorter on board self-propelled harvesters (Tecnologie e meccanizzazione: I segreti del pomodoro da industria)

To enable efficient crew work and prevent unnecessary sorting, the harvester operator must regulate the machine's pace along the rows. Each harvester is equipped with a variable that enables the operator to minimize fruit loss per acre. The sorting crew or operators of the machine's automated color sorter are arguably the most crucial aspect of harvester operation. It is imperative that these individuals are trained on how to sort and what to sort. Excessive sorting or removal of high-quality fruit can lead to a loss of earnings and inefficient use of harvesters. On the other hand, inadequate sorting can incur costs for both the farmer (by having to re-circulate wasted loads) and the processor (due to the costs of re-sorting). To avoid such expenses, sorting employees need to be trained to identify and eliminate flaws such as scald, mold, faulty fruit (insects, illness, fractures, and so on), and fruit of unsatisfactory color (Gould 1992).

However, declining agricultural labor productivity and concerns over global food security have been exacerbated by several factors, including rapid climate change and a shrinking workforce due to an aging population. This problem is leading numerous countries and enterprises to invest in smart farming, which merges information and communication technologies with conventional farming equipment and infrastructure to move away from labor-intensive agriculture and enhance the competitiveness of the agricultural industry. The smart farm employs advanced farming technologies to optimally maintain, manage, and monitor the growing environment. However, technology for facility monitoring and management alone will not be enough to tackle the imminent shortage of competent human resources needed to perform professional agricultural tasks, such as harvesting. Therefore, there has been growing interest in next-generation smart farm technology which utilizes artificial intelligence (AI) and robots, to alleviate the labor shortage problem by automating agricultural operations that require intensive labor. Harvesting is a challenging activity to automate in reality, and as a result, many robotic harvesting systems have been developed over the last decade in response to the increasing demand. For instance, in 2015, Panasonic introduced a robot equipped with pulling hands to pick grape and cherry tomatoes (Kim et al. 2022).

Kyoto University developed a tomato harvesting robot equipped with a 5-degree-of-freedom (DOF) manipulator. Meanwhile, Okayama University created a 7 DOF robot that incorporates a motion system, vision system, end effector, manipulator, and control system. Subsequently, a new tomato harvesting robot was introduced, featuring a vision system, manipulator, control system, and rotating arm. The time lapse from identification to launch averaged around 15 seconds for each tomato, yielding a success rate of 50% - 70%. The robots use tomato surface color detection, assessed by the vision system, to selectively choose ripe tomatoes. However, the robots' poor reaction time, awkward movement, and algorithm restrictions are primary issues that can be affected by light and ambient conditions, making it difficult to detect overlapping fruits. A 2017 study conducted by Beijing University in China developed a robot for harvesting ripe tomatoes in a greenhouse. Equipped with a binocular vision system, the robot recognizes ripe tomatoes with an accuracy rate of 99.3% and launches the picking process in approximately 15 seconds per tomato. The success rate of the system is 86% (Wang Lil et al. 2017).

New research and technical advancements are occurring; thus far, robotic harvesting systems have proven a propitious technology in the past decade and will be increasingly so in the era of deep learning and artificial intelligence (Kim et al. 2022).

1.3 Tomato processing

Tomatoes are a vital crop for fresh vegetables and the production of numerous processed products. Around 80% of fresh tomatoes in developed nations are used for processing. In 2017, each person in the United States consumed 9.2 kg of fresh tomatoes and 33.2 kg of processed tomato products. Canned tomatoes are the most popular canned vegetable in the United States. Sauce and ketchup are the most and second most famous condiments in that order. Also, each year, the global tomato processing business deals with approximately 40 million tons of tomatoes (Dr. S Azam Ali 2008; Wu, Yu, e Pehrsson 2022; Liadakis et al. 2022).

The transformation of tomatoes into products meant to last the entire year has origins dating back to ancient times due to their brief growing season. Tomatoes sliced and sun-dried, or pressed and boiled down, have been present in rural areas since the 18th century. Nevertheless, it was only in the second half of the nineteenth century that the processing of vegetable preserves, starting with artisanal and later industrial methods, increased in the Parma region, accompanied by a shift in dietary preferences. Currently, major canning firms, which are leaders in their respective market sectors, use time-tested processing procedures and technologies to process large amounts of food. [11] Specifically, the aim is to lengthen the shelf life of fresh produce, make out-of-season products available (e.g., canned tomatoes), create products suited to home consumption (e.g., tomato ketchup), produce new food items with alternative, integrated flavor, and texture (e.g., sauces, soups) that have better nutritional properties and ultimately add value for consumers (Esra Capanoglu et al. 2010).

It is crucial to note that high quality "salad" tomatoes are not processed, as they are more valuable when sold fresh and in good condition. Salad tomatoes are exclusively utilized in home settings to preserve surplus during the harvest season. Tomatoes should be ripe, red, and moderately firm to the touch, disease-free (by removing affected areas), and free of stems, leaves, dirt, and other contaminants (by washing). It is possible to store unripe fruits for later consumption. The presence of surface stains or splits/cracks on tomatoes (assuming they are not diseased) is of less importance since they are typically sliced or processed in most cooking

[11] Source: Official Website of Parma, I musei del cibo via link: Le fasi della trasformazione industriale del pomodoro (last access August 2023).

processes (Dr. S Azam Ali 2008). The quality of a tomato product is determined by the color, which is influenced by the redness of the tomatoes used. The red pigment (lycopene) can determine the quantity of tomato utilized in a product. To ensure quality processing, several factors must be taken into account. First and foremost, tomatoes must ripen uniformly on the plant, as yellow and greenish regions not only hide the red color but also cause browning due to oxidation during storage. The high quality of the food makes up for any loss incurred by discarding unripe tomatoes or cutting out partially ripe tomatoes' green parts. Therefore, the fruit's quality is a fundamental and essential factor that determines the final product's quality, including nutritional aspects (Ministry of Food Processing Industries, Govt. of India 2020; Esra Capanoglu et al. 2010). Most tomato product manufacturers add colorants to achieve a bright red appearance of the final product. These colorants mask the natural browning of fresh tomatoes used in making tomato products that aren't fully ripe and red, although browning can still occur during storage (Ministry of Food Processing Industries, Govt. of India 2020).

Processing of tomato yield various products like tomato pulp, tomato puree and paste, dried tomatoes, ketchup, tomato sauce, chutneys, and many more. The processing techniques vary between basic to highly complex, depending on the final product. Fresh tomatoes require essential treatment methods like washing, fruit selection, packaging, transportation, and proper storage at the point of sale. The production process of tomato paste includes several sequential stages like washing, fruit selection, breaking, seed and peel removal, evaporation, pasteurization, canning and longer storage. The manufacturing stages of tomato products may involve several heat treatments and can significantly impact the nutritional properties of the final product (Dr. S Azam Ali 2008; Capanoglu et al. 2010).

As previously mentioned, industrial processing in the United States involves multiple phases and varies depending on the end product to be achieved. To reach full capacity, processing plants must have a steady flow of fresh tomatoes. Otherwise, downtime, whether due to cleaning or operating below capacity, may result in waste — either fresh tomatoes waiting on trucks or tomatoes in different stages of processing. The diagram below illustrates some of the common industrial techniques used to process tomatoes (Wu, Yu, e Pehrsson 2022; Liadakis et al. 2022):

Common preliminary procedures for all items involve evaluating and weighing the fruit. Tomatoes are initially assessed by taking a random sample based on pre-established guidelines

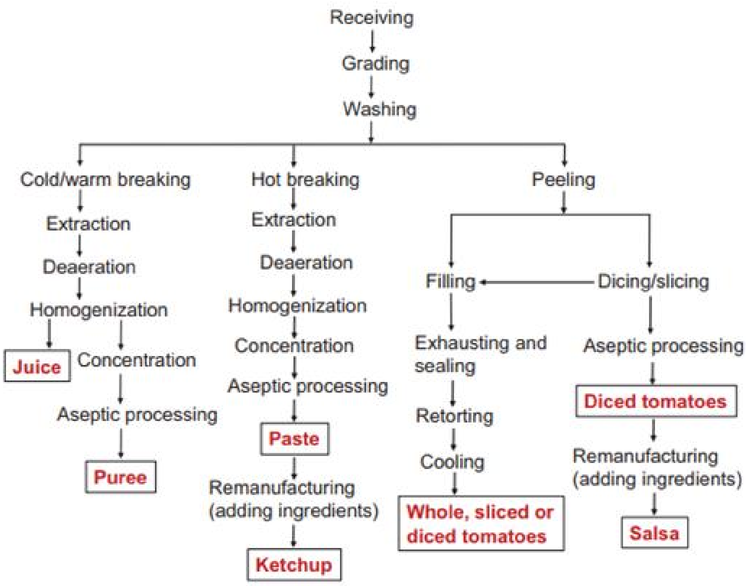


Figure 5 - General industrial processing procedures for different tomato products.
(Wu, Yu, e Pehrsson 2022).

between agricultural and industrial parties. These guidelines specify the maximum allowable percentages of extraneous products, such as green fruit, soil, and stones, and tomatoes with minor defects, such as partially yellow or green ones. After this initial visual inspection, the residual sugar content of the fruit is evaluated, and the combination of these factors determines its final value. Finally, the lot is weighed. [12]

Mildly washing tomatoes by simply rinsing them with water does not suffice in eliminating mold filaments and other microorganisms located in their cracks, wrinkles, folds and stem cavities during this processing stage. To lower the amount of spores in washing water, adding chlorine to the water is a common practice (Dr. S Azam Ali 2008; Wu, Yu, e Pehrsson 2022).

To be more precise, the tomatoes go through a pre-washing stage where they are submerged in water tanks. The tanks are fitted with air insufflators at the bottom that apply pressure to stir the fruits, which helps in better cleaning. The tomato then moves from the first tank to the following tank through an elevator mechanism. The conveyer then takes the fruits in a long roller system where workers perform a final quality check. Afterward, high-pressure water jets are used to remove any remaining contaminants from the tomatoes. A different sorting method

[12] Source: Official Website of Parma, I musei del cibo via link: [Le fasi della trasformazione industriale del pomodoro]() (last access August 2023).

uses fruit-cleaning disks that are mechanically rubbed. This rubbing action cleans the healthy surface of the fruit and eliminates any soft or spoiled areas. This method largely replaces hand sorting.

Tomatoes that are moldy or rotten degrade the quality of the preserve. This reduces its color and aroma and also shortens the shelf life of the product. Unsuitable fruits that were not detected by the optical sorters during previous controls move through the final sorting process. The rotating rollers cause the tomatoes to move, enabling the staff to inspect them closely. This helps the control workers in their task. Afterward, workers assigned to this task manually remove them, while products regarded as unsuitable are placed on small mechanical (or hydraulic) belts located above the washing belt for removal. After this stage, the roller conveyor carrying the tomato moves upwards at an inclined angle, and the final wash using pressurized water jets is carried out here. As the process can strain a person's vision and cause a loss of necessary focus for the employees, an adequate illumination and a regular rotation of sorting personnel is necessary. As a rule, each attendant is designated to perform sorting tasks, such as removing green tomatoes, segregating split or decayed ones, and foreign material. [13]

Certain products, like whole, sliced, and diced tomatoes, undergo peeling before processing. Peeling is possible using steam or lye. The procedure is critical because it affects the taste, quality, and nutritional value of the final products. The peel is removed from the skin using steam or lye before mechanical extraction, which is a common practice. Despite the abnormally high pH values of the discharged wastewater, many tomato processors opt for hot leach peeling due to its higher output and better product quality. Compared to leaching, steam peeling is a chemical-free and ecologically friendly method, but it leads to more peel loss and produces an inferior product. Irregular heating during the procedure results in increased loss of peel and worse quality of the peeled fruit (Liadakis et al. 2022; Wu, Yu, e Pehrsson 2022).

During the breaking step, tomatoes are chopped and crushed. Two methods are available for processing tomatoes: hot and cold breaking. Heated reactions mostly occur between 93 and 99 degrees Celsius. Tomatoes are thinly sliced and briefly heated to increase enzyme activity and yield during the cold process. After being crushed, the diced tomatoes are processed using

[13] Source: Official Website of Parma, I musei del cibo via link: Le fasi della trasformazione industriale del pomodoro (last access August 2023).

an extractor, pulper, or finisher to remove their seeds and skins. The juice is extracted using a screw or paddle extractor. Finally, during the processing procedure, additional processes such as homogenization, concentration, and aseptic packing are carried out. Lastly, it should be noted that processing tomatoes into different end products involves mechanical treatment, several heat treatment procedures, and the use of additives like calcium, oil, or salt; all of which may change the nutritional profiles and bioavailability (Wu, Yu, e Pehrsson 2022).

Drying, heating, and pasteurization all have different goals, such as inactivating microbes or enzymes, reducing moisture content and concentrating the product, or softening the tissue to remove the fruit from the skin. However, processing tomatoes changes not only their physical aspects, but also their nutritional and sensory attributes. It is assumed that processed fruits and vegetables have reduced nutritional value, although this is not always the case. Processing can improve bioavailability of lycopene (the most beneficial component), overall antioxidant activity, and amino acids. Although processed foods are typically considered inferior to unprocessed meals, "processing" is not always a bad term, and processed foods are not always nutritionally deficient or harmful. Food processing can have positive effects such as improved digestibility and nutrient bioavailability, and it certainly promotes food safety (Nasir, Hussain, e Jabbar 2015; Capanoglu et al. 2010; Wu, Yu, e Pehrsson 2022).

When studying tomato processing, we must also consider the by-products of tomato processing. In fact, tomato processing by-products, such as solid and liquid wastes, are a major concern for the tomato industry. Tomato pulp (skin, seeds, and flesh) is a solid waste that remains after tomato processing, while liquid wastes include wash water, peeling chemical solutions and peeling water, cleaning water, and cooling water. Tomato leaves and bruised tomatoes are two other tomato byproducts. Culled tomatoes are fruits that do not meet customer expectations due to aesthetic defects (shape, size, color, etc.). Approximately 2% of the crop is wasted as macerated tomatoes. Tomato pomace is currently being processed to be used as a component in animal feed or as a fertilizer or can be disposed of in landfills. The oil industry utilizes only a small portion of the seed. The tomato processing industry faces significant economic and environmental challenges when it comes to disposing of this waste. The aim is to address this issue by creating a suitable waste management system to recycle and reuse tomato by-products. These by-products contain valuable bioactive compounds, such as proteins, carbohydrates, fatty acids, dietary fiber, and phenolic compounds, which promote human health (Liadakis et al. 2022).

1.3.1 <u>Changes in color and flavor</u>

The plant pigment lycopene gives the attractive red color to tomatoes and their products. Lycopene's composition is similar to that of the famous yellow plant pigment carotene, which produces vitamin A (Ministry of Food Processing Industries, Govt. of India 2020).

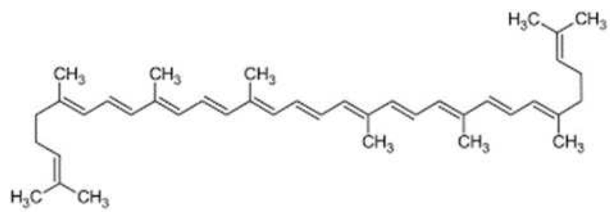


Figure 6 - Structure of lycopene (https://www.licofarma.com/licopene)

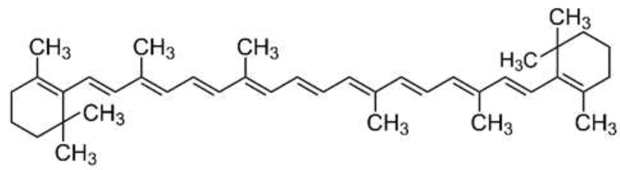


Figure 7 - Carotene structure (https://it.m.wikibooks.org/wiki/File:Beta-carotene.svg)

Contrary to popular belief, lycopene is located in the insoluble pulp or pericarp of the tomato, instead of in the clear serum component. It is most abundant in fully ripe red tomatoes. When heated, the pulp experiences significant oxidative changes, especially in the presence of air (Ministry of Food Processing Industries, Govt. of India 2020).

As the color is the first thing a customer notices, even the slightest change in it is discernible. During processing, the browning processes may cause the color of tomato paste to become slightly darker and less vibrant. The development of red pigment caused by these processes has little impact on the quality of tomato paste, as it eventually contributes the red color to it. The shift in color is mainly caused by pigment loss, nonenzymatic browning (Maillard processes), sugar hydrolysis, and caramelization. High processing temperatures can cause caramelization. Tomatoes contain a high concentration of ascorbic acid, commonly known as vitamin C, which is believed to be the main reason for whey color darkening during processing. However, browning can be minimized by decreasing both the pH and temperature during processing. Color variation increases as temperature increases; in fact, solar drying yields the least color change because it is conducted at lower temperatures (Nasir, Hussain, e Jabbar 2015; Nikita S. Bhatkar et al. 2021).

Iron and copper equipment should be avoided at every stage of the operation. Lycopene, a self-oxidizing acyclic isomer of carotene, turns brown when it comes into contact with iron. Iron also produces black compounds with the tannin in tomatoes and the spices used. Therefore, the equipment used should have a lining of glass or stainless steel. Tannins found in spices like cloves, cinnamon, and other spices used in making ketchup, sauces, and soups negatively affect their color. Therefore, limiting the absorption of such tannins through spices is crucial. To achieve that objective, it is recommended to use spice oils instead of whole spices (Ministry of Food Processing Industries, Govt. of India 2020).

The flavor of processed tomato differs from that of fresh tomato due to the transformations that occur during processing. This could be attributed to the loss of volatile chemicals or the formation of new compounds. Two necessary chemicals that impact tomato taste, Cis-3-hexenal and hexenal, are lost during processing. Moreover, the conversion of Cis-3-hexenal to trans-2-hexenal significantly contributes to tomato flavor loss. The breakdown of sugars and carotenoids produces chemicals that may cause the cooked aroma in processed tomatoes (Nasir, Hussain, e Jabbar 2015).

1.3.2 Effects on nutrients

The growing demand from consumers and producers to comprehend the nutritious components available in our meals and their potential impact on human health, especially from industrial processing processes, is driving up research interest in this field. Tomatoes are a significant ingredient in the Mediterranean diet that is thought to promote a healthier lifestyle. Tomatoes are a rich source of various nutrients, including lycopene, an antioxidant; vitamin C; and a range of polyphenols. The tomato components are mostly stabilized in vivo by the acidic pH of the fruit tissue, and a significant portion of the nutrients are preserved even during the most delicate and vulnerable processing stages. During transport and storage, both fruits and vegetables experience detrimental changes caused by respiratory, metabolic, and enzymatic processes, as well as drying, pests, microbial spoilage, and temperature-induced damage. Several of these modifications can have a harmful effect on the antioxidant quality of tomato products (Capanoglu et al. 2010).

Various processing methods have different impacts on the nutrients present in tomato products. In fresh tomatoes, lycopene exists as the most stable thermodynamic form, all-trans. However, it is known that lycopene concentration is affected by isomerization and oxidation during the processing. Under thermal conditions, the trans form transforms into the cis form by isomerization. Recent research from 2021 shows that the cis form is unstable, but it has higher solubility in organic solvents than the trans form. It has also been shown that the cis form is more bioavailable. However, impacts might appear contradictory and vague when comparing different scientific studies, which highlights the need for further research in this field in the coming years. It has been found that a specific dehydration method can increase lycopene content in some instances, while decreasing it in others (Ministry of Food Processing Industries, Govt. of India 2020; Nikita S. Bhatkar et al. 2021).

For example, in 2020, the Indian Institute of Food Technology reported that processing tomatoes into value-added products can increase the bioavailability of some carotenoids, such as beta-carotene, lycopene, and phenolics. Additionally, it was found that processed tomato paste retains around 65 percent of the flavonoids that are present in fresh tomatoes. As per a 2015 analysis, lycopene remains relatively stable throughout the process of tomato processing and preservation. Extended exposure to oxygen, low water activity, and relatively high processing temperature can destroy lycopene. Experts agree that in terms of degradation and isomerization, this molecule is relatively stable during commercial production and processing (Nasir, Hussain, e Jabbar 2015; Ministry of Food Processing Industries, Govt. of India 2020).

A study published in 2022 reveals that heat treatment increases the bioavailability and bio accessibility of carotenoids by breaking down the cell wall and organelle membranes where these compounds are found. Heating denatures the protein-carotenoid complexes that constrain the bio accessibility of carotenoids and promotes the release of these compounds from the dietary matrix. Consequently, heat processing has a direct impact on tomato carotenoid profile and quantity. The raw tomato has a lycopene concentration of 2 mg t-lycopene/g, and heating (at 88°C) can raise it by over 150%. In contrast, a 2010 study found significant decreases (9-28%) in lycopene and vitamin C in samples obtained from a commercial facility that processed tomatoes into paste (Pereira Lima et al. 2022; Capanoglu et al. 2010).

Furthermore, the 2015 analysis conducted an in-depth examination of the changes in numerous nutrients. Concerning amino acids, the amount of amino acids present in tomato juice is significantly increased when treated at temperatures above 100 °C for 20 minutes due to partial hydrolysis and protein denaturation. The concentration of amino acids increased the most for glutamic acid followed by aspartic acid, threonine, and alanine. During processing, some amino acids such as glutamine and asparagine were lost completely due to acid conversion.
During tomato preparation, the oxidation process causes the majority of ascorbic acid (vitamin C) to be lost. The rate of ascorbic acid oxidation is affected by various factors such as dissolved copper, oxygen, enzymes, and processing temperature. Studies have shown that the decomposition of ascorbic acid is closely related to temperature and air, while reduced sugars are also transformed. In reality, their amount decreases due to chemical reactions such as caramelization and the Maillard reaction. The method used determines the amount of sugar lost. Studies have shown that reducing sugars in processed tomato juice leads to a 19% decrease. During juice processing, the concentration of acids increases. Studies have demonstrated that concentrations of acetic acid can increase by as much as 32.1%. One possible reason for the increased concentration of acids may be attributed to the oxidation of aldehydes, alcohols, and other chemicals. It is believed that the primary reason for the increased acid level in processed tomatoes is the decomposition of amino acids into their constituents (Nasir, Hussain, e Jabbar 2015).

Non-thermal treatments have been shown to change the nutritional content of tomato products. Operations like cutting, homogenization, and peeling may affect the antioxidant components. Fresh-cut tissues are mainly exposed to oxidative stress, which is believed to harm cell membranes and alter the composition and amount of antioxidant chemicals. Several tomato products' hydrophilic antioxidant capacity was increased by homogenization, according to a 2010 study. However, the exact process is unclear. Furthermore, in industrial processing, the "breaking" or homogenization stage was proven to considerably alter the biochemical composition (Capanoglu et al. 2010).

Considering all of these factors, the question "Are processed tomato products nutritionally equivalent to fresh tomatoes?" may not be a suitable one because the answer depends on several variables, such as the types of fresh tomatoes, the tomato products compared, and the method of data analysis and interpretation used. A straightforward "yes" or "no" answer to this question may be misleading. Responses based on comparing some fresh tomatoes and different tomato products or focusing on specific components (e.g., lycopene) may be misleading. Currently, there is insufficient evidence to fully comprehend all aspects and their impact on nutrients and bioactive compounds in processed tomatoes (Wu, Yu, e Pehrsson 2022).

A research conducted in 2022 states that various practical drying techniques have an impact on many chemicals, including antioxidants. Therefore, additional research must be conducted to bridge the knowledge gap and stay current with the development of new tomato cultivars and advancements in industrial processing technologies (Bakir et al. 2023; Wu, Yu, e Pehrsson 2022).

1.3.3 Drying

Tomatoes are rich in carotenoids, lycopene, calcium, zinc, vitamin C, and calcium, and can be consumed in fresh or dried forms. Their consumption has been associated with a reduced risk of chronic diseases and some types of cancer. Fresh tomatoes are known for being highly rich in vitamin C (on average 20 mg/100 g), providing 40% of the daily requirement. However, fresh tomatoes have a high water content, which makes them susceptible to damage during harvest. Natural product degradation may occur during cold storage, underscoring the importance of drying tomatoes to prevent these losses (Hamdi et al. 2023; Bakir et al. 2023).

The objective of drying is not just to prevent spoiling and prolong shelf life. It also reduces weight and volume of the shipment, which in turn, improves handling and reduces transportation costs. Dried tomatoes serve as raw materials in ketchup, sauces, soup premixes, canned goods, drinks, and other products. Dried tomatoes are used as spices in various cooking recipes for the culinary sector. All types of dried tomato products (whole dried tomatoes, concentrate, powder) have various uses such as nutraceuticals, drugs, oil extraction, animal feed, and cosmetics (Bhatkar et al. 2021).

Conventional methods in arid and hot areas comprise sun-drying, which is feasible only in hot and dry regions. This is a thermodynamic approach to control moisture content through a free and sustainable energy source. Sun-drying is the earliest approach that involves slicing tomatoes, putting them cut side up on a level and sanitary surface (e.g., a roof), or hanging them on strings under the sun from a branch or a beam. The duration to decrease the moisture content to less than 15% varies between 3-4 days to 20 days, depending on the external drying conditions, type of the variety, and its initial moisture content. Prolonged exposure to sunlight results in a loss of ascorbic acid, lycopene, and phenolic content, and poor color retention. In contrast, sun-drying has been shown to maintain fat-soluble vitamins A and E. Sun-dried tomatoes are deemed high-quality because this method preserves the aroma and concentrates it, while preventing the undesirable caramelization of natural sugars that often causes a burnt aftertaste and undesirable browning in more intensive drying techniques. Moreover, the use of solar energy reduces operational costs and resolves environmental concerns related to traditional fuels (Dr. S Azam Ali 2008; Hamdi et al. 2023; Bhatkar et al. 2021; Bakir et al. 2023; Hadibi et al. 2023).

Even in Tunisia, sun-drying tomatoes is a common practice owing to its cost-effectiveness. However, this method has numerous issues, such as the risk of spoilage and quality degradation since the dried products are exposed to the sun for long periods, subjected to sudden showers and uncontrollable climatic conditions, and lack of proper supervision during the process. The use of this method is significantly limited due to the unpredictability of weather, uncontrollable drying temperatures and periods, high manpower costs, and the requirement of vast surfaces to carry out the process. Moreover, under certain conditions, the ultimate quality of the dried products can be significantly impacted by insect or virus infestation, sand or dust contamination, or other foreign objects present in the atmosphere (Hamdi et al. 2023; Bakir et al. 2023).

To overcome these problems, newer approaches have significantly reduced drying time while improving quality. For instance, a solar dryer can be employed as a cost-effective technology for the drying process, which has several benefits such as the even distribution of drying products and high hygienic quality. In the drying field, solar dryers can be used to prevent tomatoes from atmospheric agents like dust, insects, and rain, ensuring exceptional quality (Bhatkar et al. 2021; Hamdi et al. 2023).

The hot air dryer is another example, used most frequently to economically dry fruits and vegetables. These methods are widely used to dry tomatoes due to their impact on drying kinetics, the quality of the resulting dried product, and the influence of temperature and speed. Temperatures between 50 and 70°C are typically utilized. However, the food products may be subject to high temperatures during the process, leading to significant shrinkage, cracking and hardening, as well as reduced rehydration capacity and bulk density. Moreover, the hot air drying method might adversely impact the final flavour, color, and nutritional content of the product produced (Nikita S. Bhatkar et al. 2021; Bakir et al. 2023; Mencarelli et al. 2023).

Heat pump drying is an alternative option that functions at lower temperatures and could be more energy-efficient. Furthermore, the drying process is carried out at lower temperatures, which allows for the retention of more thermolabile chemicals. Other techniques comprise fluidized bed drying (mainly used in research to dry tomato processing waste), spout bed drying, microwave drying, infrared drying, cold drying, and osmotic drying. Recently, infrared drying has been proposed and provides multiple advantages over traditional drying methods, including faster drying times, higher energy efficiency, and a reduced airflow through the sample product (Bhatkar et al. 2021; Liadakis et al. 2022).

On a mass scale, the drying procedure starts with tomato sorting, followed by sorting based on size and washing in order to remove surface bacteria, pesticide residues, insects, grubs and dirt. The tomatoes are then submerged for 3 minutes at 54 degrees Celsius to dislodge any foreign substances that remained stuck to the surface prior to washing. The soaking process occurs in tanks and can be made more effective by adding wetting agents, detergents, soda solution, or caustic soda, and washed after treatment. Sorting and pruning are the final stages. Tomatoes can be dried in slices, halves, quarters, or any other desired shape. Various factors affect the drying kinetics and quality of dried tomatoes, including external environmental conditions, the type of drying machine, pre-treatment, as well as intrinsic features of the samples such as variety, ripeness and shape. In fact, the shape of the dried samples affects both the duration of the drying process and the quality of the finished product (Bhatkar et al. 2021).

Dried tomatoes

Process details	**Flow sheet**
Select firm, ripe tomatoes. Reject any that are over-ripe, rotten or damaged.	Preparation of the tomatoes
You can leave the skin on, or remove it from the tomatoes. If you remove the skin, the fruit will dry more evenly. Plunge the tomatoes in boiling water to loosen the skins. Remove from the hot water, cool in cold water and peel the skin. If you leave the skin on, the drying process will take longer as it is difficult for the tomatoes to lose water through the skin. The final product will have a wrinkled leathery skin with curled up edges (see figure 2). If the unpeeled pieces of tomato are too big, it might be difficult to remove all the moisture from the centre of the pieces and they will have a short shelf life.	↓ Plunge in hot water (optional step) ↓
Chop in half or quarters depending on the size of fruit. Smaller pieces dry more quickly so give a better dried product. Do not make the pieces too small (no less than 20mm thick) or they will shrivel and become crisp during drying.	Chop/slice ↓
Place the cut pieces of tomato cut side upwards on the drying platform or tray. If you are not peeling the tomatoes, make sure the side with the peel is in contact with the tray. Place the pieces close together to get as many as possible in the dryer. But do not let the pieces touch or overlap. Sun drying. Place the trays of fruit in a shaded sunny position. Do not dry in direct sunlight or the colour will fade. Choose a spot where there is good ventilation to speed up drying. Solar drying. Place the trays of fruit into the dryer and dry until the pieces are soft and leathery.	Drying ↓
Conditioning is an important step if you leave the peel on the tomato and there is the risk of some moisture remaining in the dried pieces. Let the dried fruit pieces cool then place in a large plastic or glass container. Fill the container to about two thirds full. Stand in a warm, dry, well ventilated place for up to 10 days. After this time, inspect the pieces of tomato. If there are beads of moisture on the pieces, return to the dryer until they are fully dry. Once you are sure that the pieces are all dry, pack them in moisture proof packaging	Conditioning and packing

Figure 8 - Process details and flow sheet of dried tomatoes (Dr. S Azam Ali 2008)

The resulting product is dark red, leathery pieces with a flavorful tomato taste. In case of low humidity, the dried product can be preserved for months without requiring specialized packaging. In case of increased humidity, the product is susceptible to mold growth and requires an appropriate packaging method such as sealed plastic bags or ceramic jars.

Alternatively, the pieces can be carefully dried over a fire until they contain minimal moisture and are hard and brittle. The appropriate drier type depends on the quantity of tomatoes, local availability, and climate (Dr. S Azam Ali 2008). Dried fruits and vegetables can often be consumed as they are, or they can be rehydrated by boiling or cooking. In recent times, semi-dried goods have been gaining popularity because of the desire of consumers for a softer texture and food quality more closely resembling that of fresh fruits (Bakir et al. 2023).

In certain situations, dehydration is used to treat waste generated by the tomato processing industry. This practice not only reduces waste from a sustainability standpoint, but also yields products that are just as promising as actual tomatoes. In certain aspects, it is a crucial step in the valorization of tomato waste. A crucial component involves processing trash, which comprises of seeds, peels, fibrous portions, and pulp remnants. This waste contains a high concentration of bioactive components like lycopene and phenolic compounds, making it useful for manufacturing functional foods (Bhatkar et al. 2021).

Drying is now a feasible solution for managing byproducts and waste from the tomato processing industry in the long-term. The Business is worried about the high transportation cost of tomato pulp waste, combined with its high moisture content. To tackle these challenges, we propose thermally drying industrial tomato waste before using them as livestock feed or as boiler fuel in the form of pellets (Liadakis et al. 2022).

One of the main challenges facing the dried tomato industry is the limited shelf-life resulting from yeast and mold growth. Numerous studies have demonstrated the efficacy of preservatives in mitigating such issues. Specifically, a 2003 study found that chlorine treatments are highly effective in reducing microbial growth. It has been demonstrated that when a typical drying temperature of 60°C is used and the initial microbial load is high, there is a risk of the dehydrator serving as an incubator for further microbial growth. This highlights the significance of pretreatment to reduce the initial microbial load before beginning the drying process (May e Fickak 2003).

1.4 Mold

Molds are living organisms within the fungus kingdom, with eukaryotic cells unlike bacterial cells, which are prokaryotic. The term "mold" typically denotes a specific type of fungus that grows on plants and appears white, downy, or silvery. Mold is also used to describe fungi that grow on textiles, leather, or building exteriors. In reality, small mold particles exist in both indoor and outdoor settings. Approximately 100,000 fungi have been described so far, but the total fungal diversity is expected to be at least 7-10 times larger. Other estimates suggest that there may be up to 5 million fungal species awaiting research, description, and categorization, though the true value likely falls somewhere in between. Fungi, including molds, can be found ubiquitously. In reality, fungi are present in and on every human individual. The oral cavity alone may host more than 20 of the over 100 fungal species discovered (Mencarelli 2016; Parrott 2009; Borchers, Chang, e Gershwin 2017). Molds are saprophytic microorganisms, meaning they decompose and absorb dead and moist organic matter. Consequently, they play a crucial role in the ecosystem by reducing natural waste accumulation and providing essential nutrients such as nitrogen and phosphate to other bacteria. In fact, without mycorrhiza, a symbiotic association between the fungus mycelium and plant roots, most plants would not survive because mycorrhiza aids plants in obtaining vital nutrients and water (Parrott 2009; Borchers, Chang, e Gershwin 2017).

Molds, which are obligate aerobes, possess a thick cell wall composed of 75% chitin and 25% protein/lipids. They propagate by extending hyphae, which are microscopic root hairs or multicellular filament strands. The hypha is a branching tubular structure with a diameter of 2 to 10 µm, significantly larger than that of a bacterial cell. These hyphae proliferate and interweave to form a mass called mycelium. The mycelium buried in food or on surfaces is crucial for nutritional uptake, while the visible aerial mycelium contains spores or reproductive cells, hence why it is referred to as the reproductive mycelium (Laura Mencarelli 2016). In reality, molds reproduce asexually through sporification and budding. This means that tiny cells are released into the atmosphere. Mold colonies spread via spores, which act like seeds. Because many spores are so small, they can easily float in the air and be carried long distances by even the slightest breezes. Mold spores can remain inactive for long periods until the right circumstances for growth arise. Conversely, molds and yeasts can also multiply through sexual reproduction (Parrott 2009; Mencarelli 2016). [14]

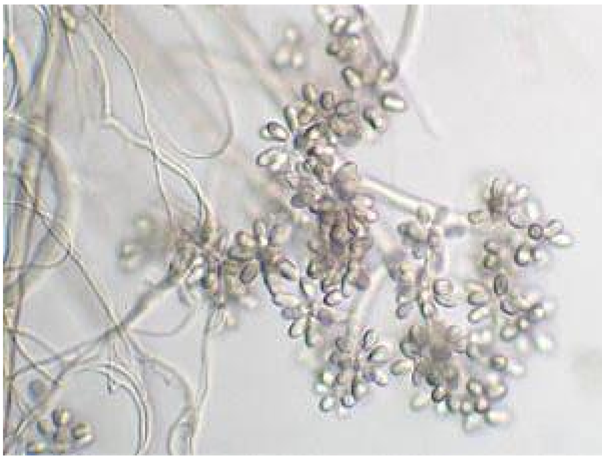


Figure 9 - Mould spores under the microscope (Laura Mencarelli 2016)

Humans benefit from yeasts, single-celled fungi, and molds in the production of various foods such as bread and certain cheeses, as well as beverages like beer and wine. In addition to this, they also serve as sources for medications, including antibiotics, immunosuppressants, and statins. Some species present on the skin of salamis play an important role in the maturation and aging of sausages by interfering with numerous processes, such as moisture control, deacidification, and proteolysis, and have a significant impact on the creation of the product's flavor. However, some molds produce mycotoxins, which are secondary metabolites that can cause a toxic reaction in vertebrates if ingested in large amounts. (When these poisons affect microorganisms, they are referred to as antibiotics.) Mycotoxins are not essential for primary growth or reproduction and their precise function is unknown; they can only be formed under specific conditions, and some scientists hypothesize that they serve as a defense mechanism. Mold growth and mycotoxin production can occur during primary production, which involves plant cultivation in soils, as well as during secondary production, which includes food handling, processing, and storage. It is important to note that these processes may contribute to the development of mold and mycotoxins.

Several hundred mycotoxins have been discovered thus far. Only a small proportion of them affect global agriculture as they lower crop yields and jeopardize food security. These

[14] Source: Official Website of North Central District Health Department via link: What are molds? (last access August 2023).

mycotoxins are mostly produced by Aspergillus, Penicillium, and Fusarium fungi and include major aflatoxins such as AFB1, AFB2, AFG1, and AFG2; OTA (ochratoxin A); some trichothecenes; and fumonisins B1 and zearalenone. Molds capable of producing mycotoxins manifest as white, greenish, or black powdery forms on various types of food, primarily cereals and nuts, as well as animal feed, such as forages, silage, and extracted meal (Borchers, Chang, e Gershwin 2017; Mencarelli 2016).

But what types of health problems can mold cause? Because there are so many different types of molds, the number of compounds produced that can harm individuals is vast. The health effects are impacted by the amount and duration of exposure. Additionally, some individuals are sensitive to molds. Infants, children, the elderly, and individuals with respiratory disorders, weakened immune systems, or known susceptibility to pollution are the most at risk. It is important to keep in mind that mold can sensitize individuals Exposure to mold can lead to increased sensitivity to future exposures. It may not require equivalent amounts or durations of mold exposure to elicit symptoms in the future. The potential health effects of mold can be classified as irritants, allergies, and asthma. Under certain circumstances, mold can also lead to illness or infection in humans (Parrott 2009).

Damage caused by mycotoxins can be evident in human health. Although acute toxicoses are infrequent, an example is the 2004 aflatoxicosis epidemic in Kenya, which resulted in 317 instances of acute liver failure and at least 125 deaths. In some people with heavy intake of specific dietary products, chronic mycotoxicosis is difficult to prevent, even in developed nations. Due to genetic variations in the enzyme pathways responsible for mycotoxin bioactivation and metabolism, as well as the varying impacts of age, gender, weight, diet, nutritional status, chronic infections, and potentially other lifestyle and environmental factors, humans exhibit diverse levels of susceptibility. The International Agency for Research on Cancer (IARC) has categorized the main types of aflatoxins as carcinogenic to humans (Borchers, Chang, e Gershwin 2017).

Mold can have adverse effects on human health and cause food spoilage, posing a food safety concern due to the formation of mycotoxins or allergies. To minimize or reduce mold spoilage, various methods can be used, such as reducing food water activity, applying heat treatment, adding preservatives, reducing oxygen in packaging using vacuum, and storing items in a chilled environment. These hurdle technologies have varying effectiveness against different groups of spoilage fungi. Using multiple barriers reduces the amount of fungal decay. In many countries, the maximum levels of the primary mycotoxins found in frequently contaminated foods are regulated, and acceptable levels of dietary consumption have been established. It is crucial to utilize preventative mycological detection techniques to mitigate the damage caused by these microorganisms to the fullest extent possible. Currently, classical methods utilizing well-validated protocols are able to identify a wide spectrum of fungi, but they are time-consuming, with results taking days or even weeks. New molecular detection techniques are faster, but require good DNA isolation procedures and expensive equipment. They can identify live and non-viable fungus that are unlikely to harm a given product. Therefore, it is crucial to employ specialized personnel and conduct research in this field (Rico-Munoz, Samson, e Houbraken 2019; Borchers, Chang, e Gershwin 2017).

1.4.1 Tomato mold types

Fruits and vegetables are living organisms that derive energy through respiration after harvest. Post-harvest metabolism causes the products to ripen, ultimately leading to senescence. While fruits' beneficial properties make them edible, they also make them susceptible to disease. During this stage of ripening, the fruit is at risk of rotting due to bacteria that hasten ripening, damage internal and/or external appearance, cause unpleasant smells, produce mycotoxins, and contaminate adjacent produce. Rotting is the result of fungal and bacterial infections, although fungal infections are believed to have a greater ability to infect a wider range of hosts during the post-harvest period (Silvia 2014).

Mold contamination presents an ongoing challenge in tomato processing, requiring comprehensive monitoring in both fields and processing facilities to ensure the production of high-quality end products. Tomatoes, a delicate crop with thin skin, are particularly vulnerable to parasitic infection during transportation, preparation, and storage. Regardless of their variety, tomatoes have a pleasant taste derived from their high carbohydrate content and free water matrix, which also renders them susceptible to disease (Doan et al. 2016; Hegazy 2017; Rodrigues e Furlong 2022).

The reference list contains extensive research on the prevalent fungi found in tomatoes. A 2017 study carried out in the United States revealed that the most frequently isolated fungi in tomatoes are *Alternaria, Aspergillus, Botrytis, Cladosporium, Geotrichum, Fusarium, and Penicillium*. Among the 39 fungal species detected in an assortment of 116 healthy organic tomato products collected from the Asyut market in Egypt in 1994, *Aspergillus Niger* was identified as the most prevalent fungal infection. As per the published 2022 review, the major challenges to tomato output are black spot produced by *Alternaria sp*. and late blight caused by *Phytophthora infectants*. A wider investigation showed the existence of fungi belonging to *Penicillium, Aspergillus, Fusarium, and Alternaria genera* (Hegazy 2017; Rodrigues e Furlong 2022).

In California, there are two widely used technologies for detecting and quantifying molds in processed tomatoes. The first method involves visual inspection of whole, unprocessed fruit at processor receiving stations (PTABs). The second is the Howard Mould Count (HMC), which involves examining a small drop of homogenized juice under a microscope. Using the PTAB method, a tomato is considered moldy if visible mold infection extends into the seed cavity or if more than 10% of the tomato's volume is clearly contaminated. The HMC, on the other hand, involves looking for mold particles in approximately 25 circular areas on a microscope slide containing a drop of juice. The percentage of fields with mycelial fragments of a minimum aggregate length is then calculated. Both procedures are performed subjectively by seasonal workers, who often have to perform the tests quickly due to the pressure of seasonal production schedules. The study included two types of samples of processed tomatoes: those reported by inspectors for the presence of visual indicators of severe mold contamination and a random sample of tomatoes. Mold was found in more than half of the fruit with visible mold symptoms and in about one-quarter of the randomly sampled fruit. *Alternaria, Fusarium* and *Geotrichum spp*. were the most common fungi found in both types of samples. *Alternaria, Fusarium*, and *Geotrichum* were found in 29.1%, 16.8%, and 9.2% of the samples with obvious symptoms, respectively, while 6.5%, 5.8%, and 4.1% were found in the random sample group (Doan et al. 2016).

It is essential to note that post-harvest infections typically have a necrotrophic or saprotrophic lifestyle leading to a breakdown of host tissue and decreased marketable output. Ripe fruit is highly susceptible to infection by necrotrophic fungi, resulting in rapid onset of disease symptoms. These fungi feed on dead host cells, secreting enzymes, toxins, and other virulence factors that degrade cell walls, inducing necrosis. These pathogens, however, often do not infect unripe fruit or remain inactive until host conditions promote effective infection. Three fungal diseases that display necrotrophic activity, in particular, are *Botrytis cinerea, Fusarium acuminatum, and Rhizopus stolonifer*. Necrotrophic infection is multidimensional, involving various traits previously believed to be limited to biotrophs, such as immune system suppression or symptomless endophytic development. The ability of necrotrophic fungi to easily infect ripe fruit but not unripe fruit or to enter a dormant phase until favorable environmental and host conditions promote a successful infection highlights the significance of host-pathogen compatibility in necrotrophic infections. Ripe fruit contains higher levels of total soluble solids, has greater titratable acidity (TA), reduced hardness, and different secondary and volatile metabolites compared to unripe fruit (Petrasch et al. 2019).

Grey mold (*Botrytis*) is one of the most extensively studied molds. *Botrytis* is a Greek word that means "*grape cluster*". This name is based on the fungus' single-celled spores carried on conidiophores that resemble the structure of a grape cluster. According to a recent study, the fungus *B. cinerea* ranks second in scientific and economic importance among the world's top ten diseases. Because it reduces yield, tomato grey mold is a widespread and potentially devastating disease that can harm the entire crop and cause post-harvest fruit rot. This disease, caused by the fungus *Botrytis cinerea*, can be found anywhere tomatoes are grown. *B. cinerea* has a broad host range, rapid growth rate, high reproductive capacity, and high genetic variability, which make it easier to develop medication resistance, including multiple drug resistance. Damage attacks are most common during extended periods of rain, when crop tilling is minimal, in unheated or partially heated crops, in older greenhouses with limited space above the crop, near vents or dripping gutters, and towards the end of harvest. *B. cinerea* mainly infiltrates the plant through wounds and aging tissues (O'Neill 2012; Anum et al. 2023; Silvia 2014; Song et al. 2023).

The fungus is a typical wound infection that thrives on the moisture and carbohydrates present in damaged tissue. Its hyphae can infiltrate plant tissue through wounds or natural openings, spreading from previously infected dead tissue to healthy tissue. The mycelium of *B. cinerea* is branching, septate, and hyaline to brown in color. Conidiophores grow straight from mycelia or sclerotia, and are tall and thin. They have irregularly branching terminal sections, with expanded or rounded apical cells that carry clusters of conidia on short denticles. The conidia are smooth, hyaline or gray, egg-shaped, averaging 10m in length and 5m in width. Cool

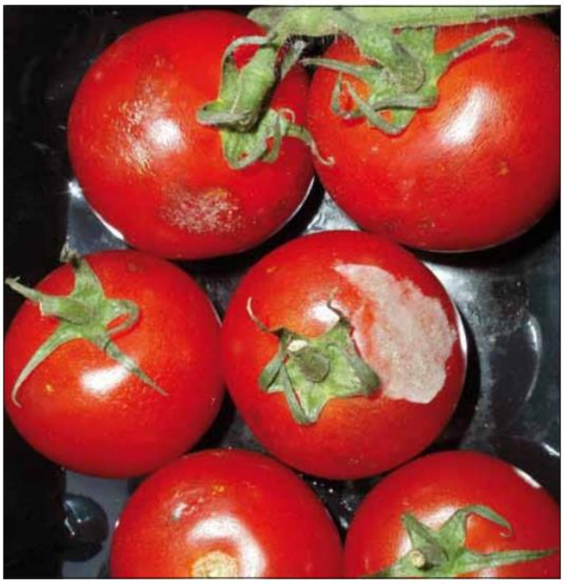


Figure 10 - Post harvest fruit Botrytis (O'Neill 2012)

temperatures and humidity can facilitate infection. Spore germination occurs within the temperature range of 0 to 25°C, with 10-20°C being the optimal. To trigger spore germination, free water on the plant's surface or very high humidity (above 90%) is required. Furthermore, the plant's age and condition also affect infection susceptibility. Young plants grown in low light, old plants approaching the end of the season, and plants already affected by another disease seem to be more susceptible (O'Neill 2012; El Oirdi et al. 2011; Silvia 2014).

Botrytis can infect various parts of the plant, including leaves, petioles, stems, flowers, fruit, fruit shoots, roots, and seeds. The primary symptoms are commonly found on leaves and stems, affecting both young and mature growth. Lesions of varying shades, from light to dark brown, appear on leaves, petioles, and stems, frequently in concentric circles from the front margin. The dense gray-brown spores that emerge on necrotic tissue are a distinct characteristic of the disease. If the tissue is disturbed in humid environments, it will expel clouds of spores. When spores infect green fruit without causing decomposition, a sign called "*ghost spot*" appears. The presence of ghost spot indicates that the host's resistance is effective, but unfortunately, the fruit becomes unmarketable due to the unsightly symptom. Each spot has a necrotic core surrounded by a halo of light. The fruit's appearance is ruined due to the presence of ghost spot. Phantom spot emerges when there is condensation on the fruit, which typically occurs in the early morning. This phenomenon occurs more often in cultivars with larger fruit, which have a greater thermal inertia, causing them to heat up more slowly. As a result, conditions that reach the dew point persist for longer periods of time. Small-fruited cultivars are less vulnerable to the fungus, although they may still exhibit spots without the halo effect. In such cases, increasing heat input to elevate the plant and fruit temperature above the dew point is more effective and efficient than increasing ventilation to prevent condensation. The fungus primarily damages greenhouse-grown tomatoes near pruning wounds, leading to potential stem rot (O’Neill 2012; Williamson et al. 2007).

The structure and chemical composition of the fruit enable the accumulation of high levels of mold. Furthermore, the fruit's delicate and thin skin results in rapid degradation after harvest. Post-harvest *botrytis* of the fruit may also result from contaminated harvest containers. The possibility exists for contaminated greenhouse tools and buildings to transmit disease from one season to the next. Fungal spores can survive for several days or even weeks, with their longevity dependent on the temperature, humidity, and sunlight exposure. Survival is most favorable during cold weather and at night. Objective temperature requirements for growth indicate a minimum of 0°C, an optimal of 20°C, and a maximum of 30°C. Thus, *B. cinerea* flourishes during the cold storage of fruits and vegetables (Song et al. 2023; O’Neill 2012; Silvia 2014).

B. cinerea sclerotia, or resting structures, can persist for multiple years and produce spreading spores or fungal filaments that lead to illness. Additionally, *B. cinerea* disperses primarily through spores, or conidia, carried by air currents and dispersed via splashing water. When free water from sources like rain, mist, fog, or irrigation comes into contact with the plant surface in the field, spores fall onto tomato plants, germinate, and cause infection. The optimal temperature for sporulation of *B. cinerea* on infected tissue is between 13-17°C, with minimal spore formation below 10°C or above 22°C. Only temperatures exceeding 28°C can hinder the formation of spores for this fungal strain. Sporulation is triggered when the humidity exceeds 85%. It has been established that the disease can remain dormant for some time until conditions allow for rapid spread and sporulation, underscoring the need for careful surveillance, rapid response, and preventive control at the start of the season. Growing plants out of season in heated or unheated greenhouses and plastic tunnels, which are increasingly used to supply fruit, vegetables, herbs, and flowers in northern latitudes, significantly increases the risk of infection, particularly for tomatoes (O’Neill 2012; Anum et al. 2023; Williamson et al. 2007).

Botrytis cinerea has implemented a strategy recognized in 2011. In general, plants have sophisticated mechanisms to detect and respond to pathogen attacks. The activation of the salicylic acid (SA) signaling system is primarily against biotrophic pathogens, whereas the Jasmonic acid (JA) signaling pathway is necessary for resistance against necrotrophic pathogens. The SA signaling can be antagonistic to JA signaling, and vice versa. According to reports, the exchange of Salicylic Acid (SA) and Jasmonic Acid (JA) assists the plant in reducing fitness costs and creating a versatile signaling network. This network enables the plant to precisely regulate its defense mechanisms against external threats. The SA and JA signaling pathways may have antagonistic or synergistic effects, leading to either negative or positive functional outcomes. *Botrytis cinerea*, a necrotrophic pathogen, infects senescent or dead plant tissue, causing grey mold in vegetables and fruit softening. It leverages the antagonistic relationship between the SA and JA pathways to induce disease progression. Particularly, *B. cinerea* produces an exopolysaccharide that can elicit the SA pathway. The SA route, in turn, hinders the JA signaling system, enabling the fungus to inflict tomato disease. This highlights an innovative strategy adopted by B. cinerea to bypass the plant's defense mechanism and proliferate within the host (El Oirdi et al. 2011).

Additionally, susceptibility to *B. cinerea* varies depending on tissue growth and age. Unripe green fruits tend to be more resistant to rot caused by *B. cinerea*, but ripe fruits are notably vulnerable, although the rot can infect at least some unripe fruits as well. The interaction between plants and necrotrophy is widely studied, and B. cinerea is commonly used as a model species for this research. B. cinerea produces toxins, CWDE, reactive oxygen species (ROS), and other virulence factors in appropriate hosts, such as ripe fruit, leading to rapid death and destruction of plant tissue. In unsuitable hosts, such as unripe fruit, *B. cinerea* produces dormant infections by suppressing the host's immune system and increasing its vulnerability. *B. cinerea* activates fruit ripening processes by altering plant hormone production and signaling and stimulating host CWDEs that soften the fruit. This promotes fungal growth and colonization (Shah et al. 2012; Petrasch et al. 2019).

Fusarium is a fungus that can contaminate tomatoes. *F. acuminatum* infects roots and fruits and is considered one of the most hazardous species of Fusarium. This fungus produces potent mycotoxins such as trichothecene and fumonisins, which can damage host cells and cause tissue necrosis. *F. acuminatum* has the ability to infect both mature green (MG) and red ripe (RR) fruit due to its unusually broad host range, which includes insects and fruit. The fungus can germinate in artificial medium at a temperature of 5°C, forming colonies up to 3mm in diameter in certain conditions. However, growth does not occur at a temperature of 37°C. Various volatile metabolites including limonene, valencene, ethylene, ethyl alcohol, ethyl acetate, and methyl acetate have been detected. The conidial apparatus is delicate, often breaking up into multiple cellular components. Terverticulate conidiophores emerge from subterranean or aerial hyphae. They are irregularly branched and consist of short stipes. The conidiophores have a few metulae and branches that culminate in whorls of three to six phialides which are typically solitary and cylindrical with a short neck (Petrasch et al. 2019; Silvia 2014).

Another fungus found in tomatoes is *Alternaria alternata*. Due to its synthesis of toxins, the fungus is associated with cases of food poisoning. Some of these toxins are harmful; for example, alternariol and alternariol methyl ester can promote the breaking of DNA in human cancer cells by impeding DNA relaxation and raising DNA cleavage. Furthermore, this species has been linked to fungal infections in the human eye. Morphological studies indicate that *A. alternata* colonies display hues ranging from lettuce green to olive green with a noticeable white edge (2-5 mm) when grown on potato dextrose agar. Within 7-10 days, isolates frequently develop colonies larger than 70 mm in diameter. *A. alternata* is distinguishable by its sporulation pattern of single-pore colonies, characterized by the generating of conidial chains six to fourteen conidia long. Additionally, the fungus produces various secondary chains and sometimes tertiary chains, with two to eight conidia. Chain branching occurs sympodially, starting with the extension of secondary conidiophores from the distal terminal conidial cells, and culminating in the production of conidia. This species is recognized for producing small conidia (20-50m in length). These conidia are oval-shaped, separated by transverse and vertical walls, and have minimal apical extension growth. *Alternaria* ulceration has a dark brown-black color with concentric zoning on stems close to the ground or on tomatoes (M. Hegazy 2017; Silvia 2014).

Alternaria is a fungus with resilience that permits it to survive in harsh environments. *A. alternata* can overwinter in numerous environments such as soil, seeds, infected agricultural residuals, and even perennial host tissues like bark, knots, and scaly leaves, where it continues to exist as mycelia and/or conidia. Certain strains have the ability to construct survival structures in order to persist in hostile environments. In contrast to other *Alternaria* species that require specific triggers to induce conidiophore development and sporulation, *A. alternata* readily sporulates without such stimuli. The spores of *A. alternata* can be spread through the air due to changes in moisture levels, exposure to red light, or a shift from wet to dry

Figure 11 - Alternaria Solani [(https://extension.umd.edu/resource/alternaria-fruit-or-pod-rot-vegetables)](https://extension.umd.edu/resource/alternaria-fruit-or-pod-rot-vegetables)

conditions. The presence of free moisture promotes germination of *Alternaria* species. High relative humidity can promote germination, particularly when temperature changes cause temporary condensation of water vapor. Fungal infection of fruit can occur not only during the growing season but also at various stages such as harvesting, handling, transportation, post-harvest storage, marketing, and even after consumer purchase. It is clear that *A. alternata* is a necrotrophic and damaging fungus that causes black spots on numerous fruits and vegetables after they are harvested. It is a non-active fungus that appears during marketing after being developed in cold storage of the fruit. This pathogen enters the fruit through wounds or natural openings and persists until the fruit ripens and conditions are more suitable for disease growth. In addition to the fruit, this fungus affects other plant components such as seeds, leaves, stems, and flowers (Silvia 2014).

To summarize, conducting thorough research and swiftly identifying harmful microorganisms in agricultural produce like fruits and vegetables are crucial for implementing successful prevention and control measures. Additionally, comprehending pathogenic activity, the interactions with host plants, and environmental factors that foster disease transmission is crucial in creating effective preventative interventions throughout the post-harvest pipeline, from cultivation to storage and consumption. Research aimed at identifying species, features, and dispersion methods of microbes enables early and targeted actions, aiding in the preservation of food quality, safety, and availability. Monitoring and controlling pathogenic microorganisms in agricultural goods is critical to ensuring healthy production and consumption in a future increasingly focused on sustainability and food safety.

1.4.2 Consequences for human health and product quality

Each year, 20-25% of all cultivated fruits and vegetables are lost due to fungal infections in the fields and post-harvest supply chain worldwide. *Botrytis cinerea* causes considerable harm after harvest due to its latent nature, resulting in losses after being transported to distant markets. Post-harvest losses make up 15-20% of the total yield in affluent countries and up to 50% in underdeveloped nations, due to insufficient preventative measures and conservation conditions (Bu et al. 2021; Brian Williamson et al. 2007; Stefan Petrasch et al. 2019). Fungi on tomato crops not only affect productivity as an external illness but are also a significant source of mycotoxin contamination. Mycotoxins are highly toxic secondary metabolites produced by a diverse range of fungi that are projected to impact up to 25% of global food consumption annually. For instance, in 2021, the European Food Safety Authority identified *Alternaria* toxins as a severe risk to public health (Hegazy 2017).

Contamination with hazardous mycotoxin-producing species (even if inactivated) has raised concerns since their heat-resistant toxins may persist even under heat-processing conditions. The fungal genus *Alternaria* is commonly found in tomatoes and significantly affects crop production (50-80%). It produces over seventy secondary metabolites, including mycotoxins. The European Food Safety Authority (EFSA) identifies alternariol (AOH), alternariol monomethyl ether (AME), tentoxin (TeA), and tenuazonic acid (TEN) as the main toxins produced by *Alternaria* sp. TeA is deemed the major mycotoxin present in dried and fresh tomatoes, as well as tomato-based items like sauce, juice, pulp, soup, and ketchup (Rodrigues e Furlong 2022).

An examination of mold strains obtained from rotting tomatoes was reported in a 1979 study. Objective evaluations were emphasized and the positive results for crayfish larvae toxicity from some of the isolates could be attributed to poisonous compounds, like citrinin, tenuazonic acid, and T-2 toxin. For example, one instance showed that an *Alternaria alternata* isolate produced tenuazonic acid at levels up to 106 g/g in all seven tomatoes tested and alternariol methyl ether at 0.8 g/g in one of the seven tomatoes. Another isolate of *A. alternata* produced tenuazonic acid or alternariol methyl ether in only three out of seven tomatoes at significantly reduced levels. One strain of *Penicillium expansum* produced patulin and citrinin at levels of up to 8.4 and 0.76 g/g, respectively. An isolate of *Fusarium sulphureum* produced T-2 toxin, HT-2 toxin, and neosolaniol at levels of up to 37.5, 37.8, and 5.6 g/g, respectively, in tomatoes incubated at 15°C. If these mycotoxins are heat-resistant, they could be present in measurable amounts in tomato products made from partially moldy tomatoes. The report emphasizes the significance of mycotoxins in tomatoes and the need for further toxicological research in this field (Joost et al. 1979).

In conclusion, losses of fruits and vegetables due to fungal diseases throughout the supply chain represent a global issue, with Botrytis cinerea and Alternaria inflicting significant damage. To tackle this issue, collaborative efforts are needed to establish preventative policies, improve storage practices, and uphold global food security.

1.4.3 <u>Prevention and management</u>

Depending on the type of fungi, various preventive and management techniques are available. Cold chain transportation is one of the most commonly used storage systems. However, the impact of low-temperature transit is unclear, even when environmental conditions are regulated to slow down post-harvest fruit losses due to senescence. This approach is insufficient in preventing fruit rot. Some psychrophilic microorganisms, such as *Bacillus, Pseudomonas*, and *Listeria monocytogenes*, can thrive even in extreme cold conditions. However, the quality of fruits tends to decline due to changes in the cell wall caused by low temperatures (Bu et al. 2021).

The most effective and cost-efficient treatment for *Botrytis cinerea* is to prevent stem and fruit infections, which are the most harmful forms of the disease. The main preventive measures are to control greenhouse humidity and manage the crops carefully. All of these factors must be considered meticulously for efficient management of gray mold. The goal is to evade prolonged periods of high humidity in the crop canopy and on the plant surfaces to prevent condensation. As a general rule, it is recommended to avoid days with relative humidity exceeding 85% for more than 6 hours to prevent unfavorable outcomes. Additionally, ensuring that the morning air temperature does not increase too quickly to avoid the formation of condensation on cold plant surfaces (e.g. fruits and stems) is crucial. The temperature should not rise more than 2°C per hour. To avoid dew point formation and restrict temperature rise, ventilation is a more beneficial approach than increasing heat input, as previously stated. It is crucial to utilize fans for air circulation and/or a fan-and-duct system to achieve a uniform temperature throughout the house and prevent cold spots; *botrytis* often develops in cold spots (like near an exterior wall or at the end of a heating system), where condensation is more prone to occur (O'Neill 2012).

In crop management, it is important to achieve balanced growth while avoiding weak and flimsy stems and leaves, peeling wounds, and aging leaves. To prevent excessive softness, practitioners should strive for adequate solution conductivity and balanced nutrition, with limited nitrogen input and sufficient potassium. Additionally, removing leaves from the plant head, utilizing generative temperature conditions, and meticulously removing dead material to eliminate inoculums can be effective methods for avoiding overly lush and soft growth. Plants with low levels of calcium have been found to be more susceptible to *Botrytis*, likely due to weaker cell walls, which can also increase the likelihood of leaf scorch. Gray mold is worsened by high humidity, inadequate light, and moderate temperatures. Therefore, promoting an open canopy in crop management can be advantageous for sufficient air circulation and optimum light reception, enabling rain or irrigation droplets to evaporate quickly. High relative humidity fosters the growth, germination, and infiltration of conidia into the host (Silvia 2014; O'Neill 2012).

In addition, management strategies for *Botrytis Cinerea* range from synthetic chemical fungicides to non-harmful alternatives like potassium bicarbonate, chlorine treatment, and biocontrol agents (G. Dal Bello et al. 2007).

Botrytis can be treated with a range of fungicides and biofungicides. Research shows that treatment is more effective when applied at the onset of an epidemic, rather than when *Botrytis* is already established in a crop. Early spring (March-May) is a critical period for protecting crops with preventive fungicide applications due to the wide range in daytime and overnight temperatures and the potential for condensation/high humidity during this time. *B. cinerea* has already developed resistance to fungicides, including thiophanate-methyl, pyraclostrobin, and fenhexamid. The frequency of fungicides with the same mechanism of action used is one of the influencing factors in the development of resistance. As a result, it is crucial to adhere to product guidance for preventing resistance and substituting chemical groups (O'Neill 2012).

Fungicides containing the same active components, *Difenoconazole* and *Cyprodinil*, were evaluated for their effectiveness against tomato gray mold disease in a 2020 study. Results indicate that the treatment rates of the fungicides were effective, particularly when applied three to four times. The biological effectiveness was high in these instances, ranging from 80.5% to 87.5%. Fungicides containing the active ingredient *Difenoconazole* outperformed those containing *Cyprodinil* in terms of biological effectiveness. Although both fungicides were applied, *Difen Super* at 0.08% and *Skor* (250 g/l EC) at 0.05% showed the highest biological efficacy against gray mold disease in tomatoes. Given the minimal difference in biological efficacy between the third and fourth spraying, it is recommended to use *Difen Super* at 0.08% and *Skor* (250 g/l EC) at 0.05% for controlling gray mold in tomatoes. It is recommended to apply the product three times with a 10-day interval, considering economic factors, the cumulative effects of the fungicide, and the potential emergence of resistant isolates of *Botrytis cinerea* (M S Mamiev et al. 2020).

B. cinerea is challenging to manage due to its numerous attack mechanisms, diverse hosts as sources of inoculum, and the ability to persist in crop debris as mycelia and/or conidia, or as sclerotia for extended periods. Thus, a single control approach is unlikely to be effective, and a comprehensive understanding of the host-pathogen relationship, the environment in which the fungus operates, and its microbial competitors on the host is necessary (Silvia 2014).

Fungicide residues in tomato tissues may have adverse effects on human health, cause environmental pollution, and promote resistance to disease biotypes. Thus, it is crucial to identify safer and more sustainable alternatives to combat fungal infection in tomatoes. Contemporary agriculture emphasizes the identification, screening, and utilization of biological control agents (BCAs) that promote growth and enhance plant defense. Microbial bioagents, such as fungi, bacteria, and yeasts, have been demonstrated to effectively control plant diseases through antibiosis, competition for resources and space, and/or the production of volatile chemicals and extracellular enzymes. Biological control is a proven and ecologically sound method of managing diseases, involving the introduction of an organism that combats the pathogen, rather than the use of chemical pesticides. Microbial biocontrol agents use their metabolites to prevent, preserve, and manage disease by restricting pathogen growth. Gram-positive Bacillus bacteria, found in soil, water, and air, produce an array of antifungal and antibacterial chemicals that are particularly effective in controlling disease. *Bacillus* species have been used in biocontrol to combat various diseases, such as *Fusarium oxysporum f. sp. Lycopersici, Alternaria alternata,* and *B. cinerea*, as reported in the literature (Rodrigues e Furlong 2022; Song et al. 2023; Zheng et al. 2023; Bu et al. 2021; Lee et al. 2006).

Bacillus altitudinis B1-15, which was isolated from saline-alkaline soils, exhibited significant antifungal activity against B. cinerea based on a 2023 research study. Strain B1-15 demonstrated considerable biocontrol effectiveness against tomato gray mold in pot trials at the 3-leaf (87.63%) and 6-leaf (76.43%) stages, as well as at 39.83% after 35 days of inoculation at the 6-leaf stage. Furthermore, administering strain B1-15 through inoculation with or without wounding resulted in significant improvements in stem diameter, plant height, dry weight, and fresh weight in tomato plants. Studies suggest that strain B1-15 may effectively suppress gray mold and prolong the post-harvest shelf life of tomato fruits. Strain B1-15 displays potential as a biocontrol agent for managing tomato gray mold and enhancing tomato yield and storage quality in practical environments. A 2021 investigation found that another *Bacillus* species may hold promise. *Bacillus subtilis*, in particular, could prevent gray mold and other postharvest diseases during storage. *B. subtilis* L1-21 showed strong suppression of tomato gray mold, resulting in an 86.57% control effect. It was found in this study that inoculating the bacteria prior to the fungal spores led to increased occupation of space by the strain, resulting in intense competition for resources and space with the pathogen. The biocontrol strains' volatile chemicals heavily inhibited spore germination and germ tube elongation in the pathogenic fungus (Song et al. 2023; Bu et al. 2021).

In 2023, researchers conducted a study to evaluate the antifungal effectiveness of eight biocontrol strains from tomato rhizosphere soil against *B. cinerea*. These strains demonstrated noteworthy antifungal activity, with inhibition rates ranging from 19.30% to 69.88%. The strain with the highest impact was D50, which had an inhibition rate of 69.88%. Further analysis of its morphology, physiology, and biochemistry led the researchers to identify it as *Bacillus mojavensis*. *Bacillus mojavensis* D50 fermentation supernatant (BMFS) inhibited mycelial growth and conidia formation, causing alterations in mycelial morphology. Additionally, BMFS exhibited remarkable stability (Zheng et al. 2023).

According to a recent study by Faiza Anum et al., the use of nanoparticles has emerged as an effective technique for protecting plants from harmful microbes. Nanoparticles are being effectively utilized in modern and sustainable agriculture techniques for products such as nano fertilizers, nano pesticides, and nano fungicides. Nanotechnology shows great potential for addressing and managing agriculture-related issues. Silver nanoparticles have garnered considerable attention for their catalytic, antibacterial, antifungal, and anticancer properties applicable in medical and agrochemical fields. For the production of nanoparticles, the chosen method was biological or green synthesis. The main objective of this study was to utilize green synthesis in order to create silver nanoparticles and assess their antifungal capacity against *Botrytis cinerea* by using extracts from *A. viridis* (which includes a range of functional phytochemicals like phenols, tannins, flavonoids, steroids, and saponins that are known for their antioxidant and antimicrobial qualities). The use of green-synthesized silver nanoparticles has shown the ability to mitigate the negative impacts caused by the pathogenic fungus, with effectiveness depending on the concentration. Ultimately, this approach enables us to decrease the dangers associated with environmental pollution and toxicity brought about by chemical fungicides (Anum et al. 2023).

A 2008 study proposes yeasts as a final option for biological control. In postharvest scenarios, yeasts reduce the incidence of fungal infections significantly. Due to their potent inhibitory ability, rapid colonization of fruit wounds, and method of action based mainly on resource competition, direct physical interaction with fungal hyphae, and cell wall lytic enzyme synthesis, yeasts are an excellent choice for postharvest use. Disease management incorporating biological control seems to decrease the selection pressure on the *Botrytis* population while deterring the development of fungicide resistance (G. Dal Bello et al. 2007).

The search for environmentally friendly methods of disease control has been prompted by the need to avoid fruit loss while causing minimal harm to human health. This involves understanding crop plant defense mechanisms and stimulating secondary metabolism in plants to produce chemical compounds that confer resistance to biotic and abiotic stresses. Additionally, the benefits of these chemicals on human health are being explored in tomato. A 2022 study will investigate the efficacy of bioactive compounds in tomatoes, including polyphenolic compounds, minerals, hormones, phytoalexins, defense enzymes, and amino acids, in defending against pests in the absence of pesticides. Food safety, environmental protection, and low production costs are all advantages. Fruit loss in the field and during post-harvest processing due to pathogen infection presents a significant concern for the global food supply chain. Quick and efficient activation of natural defense mechanisms, known as Constitutive Resistance or Induced Resistance, is crucial in inhibiting fruit-pathogen interactions. These mechanisms are complex and consist of multiple structural and biochemical barriers. Abiotic stressors, such as salt, dryness, and nutritional limitation or excess, can also occur when fruits are exposed to them. These stresses can often combine, leading to conditions of combined stress in the field. Research indicates that these abiotic stressors can impact plant resistance to infections, either positively or negatively (Rodrigues e Furlong 2022; Yuling Bai et al. 2017).

The physical and chemical barriers present in a fruit's inherent defenses, such as cell walls, waxy cuticles, and peel, provide constitutive resistance. If the fruit becomes infected, it emits multiple systemic signals, which activate specific defense responses against the virus, protecting other tissues. This process is called acquired systemic resistance (ASR) and is triggered by the salicylic acid (SA) hormone, as opposed to induced systemic resistance (ISR), which is activated by the jasmonic acid (JA) hormone. The defensive chemicals within the fruits vary based on their ripeness stage. The composition of mature fruit plays a crucial role in the development of postharvest illnesses. Although, certain pathogens have the ability to overcome these fruit defenses and result in infections (Rodrigues e Furlong 2022).

Genetic modification is an intriguing option for improving fruit output, plant performance, and disease resistance. The transfer of disease resistance genes from wild tomato cousins to cultivated tomato types has been a critical feature of tomato breeding procedures since the 1950s. This has resulted in increased resistance to the most damaging pests and viruses. The transfer of disease resistance genes from wild tomato cousins to cultivated tomato types has been a critical feature of tomato breeding procedures since the 1950s. Currently, genes for resistance obtained from a limited group of wild species, *including S. pimpinellifolium, S. habrochaites, S. pennellii, S. chilense,* and *S. peruvianum*, can be utilized to genetically control around 20 infections (Yuling Bai et al. 2017; Rodrigues e Furlong 2022).

In conclusion, the multitude of prevention and control measures available to address the various issues related to fungal infection in fruits and vegetables highlights the essential importance of protecting food quality and safety. Efforts to decrease post-harvest losses and maintain consumer health encompass regulating growing and storage conditions, identifying biological control agents, and developing innovative technologies. Simultaneously, advances in biotechnology and sustainable agriculture are facilitating safer and more efficient strategies to combat these challenges. Moreover, the collective implementation of these solutions represents an essential progression towards mitigating post-harvest losses and achieving sustainable, high-quality food production.

1.5 HACCP

Food safety is a significant public health concern, and guaranteeing a safe supply presents significant challenges for organizations in the food chain industry. Numerous foodborne hazards, both acknowledged and unknown, raise health concerns and obstruct global food trade. These hazards must be assessed, evaluated, and controlled effectively to manage the ever-expanding and intricate worldwide food networks. (H. Khalaf et al. 2021).

HACCP is a food safety management system that focuses on prevention. This involves identifying potential risks before they occur and employing control measures to guarantee food safety during all stages of food production and handling. Meaning "hazard and critical control point analysis," HACCP is a globally recognized method for ensuring food safety. Endorsed by national and regional agencies, this science-based approach is highly systematic, addressing biological, chemical, and physical hazards throughout the entire food chain, from primary production to ultimate consumption. Implementing HACCP provides increased systematic controls, resulting in a higher degree of product safety assurance. Its global recognition enables communication between processes, which allows audits to follow a standardized protocol. This simplifies communication between food companies and inspectors or auditors, creating opportunities for mutual learning regarding hazard control (Food and Agriculture Organization of the United Nations 2023).

Quality control has traditionally relied on inspection and testing. While comprehensive inspection may seem like the optimal method for ensuring product safety in theory, it is not always feasible in practice. For example, fruit manufacturing lines often rely on visual inspection by operators to identify physical and biological contaminants such as leaves, stones, insects, and infections. Several issues lower the effectiveness of this approach, such as employee distraction caused by noise, surrounding activities, and conversations, as well as the limited attention span when working on repetitive tasks and people's differing observational abilities (Mortimore e A. Wallace 2001).

The Pillsbury Company, NASA, and the United States Army developed a "zero defects" approach in the 1960s to ensure the microbiological safety of food for space travel. This method was based on the engineering concept of failure mode and effect analysis (FMEA), which evaluates potential issues at every stage of an operation and implements effective controls. In the early days of the United States' manned space program, this idea was utilized for a microbiological safety system to guarantee food safety for astronauts and decrease the likelihood of a foodborne illness outbreak while in space. Food safety and quality systems were previously reliant on end-product testing, but limitations in sampling and testing hindered the ability to ensure food safety. The development of the HACCP method provided a preventative and practical approach to address this need, guaranteeing a high level of food safety. Pillsbury initially introduced the HACCP method in 1971 at the United States National Conference on Food Protection; since then, the concept has progressively gained acceptance as a practical solution. To combat significant botulism problems in the canning industry, the FDA implemented HACCP principles in its regulations for low-acid canned goods as early as 1973. Even though the approach was not officially established until the 1970s, it has since gained global backing, and the World Health Organization (WHO) has acknowledged the HACCP methodology for safe food manufacturing as the most successful means of decreasing foodborne illnesses (Food and Agriculture Organization of the United Nations 2023; Mortimore e A. Wallace 2001; L. Hulebak e Schlosser 2002).

The Codex Alimentarius Commission recognized HACCP as a valuable tool for improving food safety in 1993 and established Codex guidelines for implementing HACCP. This had a significant impact on the dissemination of the HACCP system. Upon the formation of the World Trade Organization (WTO) in 1995 and its implementation of the Agreement on Sanitary and Phytosanitary Measures, the Codex regulations and recommendations became the global standard for national food safety regulations. To promote food safety, many major trade blocs now require domestic and exporting food enterprises to have HACCP-compliant food management systems. Additionally, the concepts of the HACCP system are now included in the national law of many countries (ISO, 2005). To ensure food quality and safety, various food quality assurance systems are necessary at each stage of the food chain and across all sectors of the food industry. Governments are responsible for developing the standards, laws, and enforcement programs necessary for ensuring food quality and safety. Meanwhile, the industry is accountable for implementing quality assurance systems, including HACCP as applicable, to ensure compliance with standards and laws (Food and Agriculture Organization of the United Nations 2023; H. Khalaf et al. 2021).

The HACCP system reduces instances of foodborne illness, enhances food safety, and offers tangible advantages to food establishments, including: Improving food production and handling efficiency through detailed operational analysis, maximizing food safety resources by focusing on critical areas and reducing expensive final product inspections and tests, preventing recalls by detecting issues before products are released, ultimately resulting in more efficient food safety management systems, enhancing the market competitiveness of HACCP-affiliated companies nationally and internationally, building trust in food safety to promote trade, and advancing science-based goals to facilitate international trade (Food and Agriculture Organization of the United Nations 2023).

Setting goals or standards encourages innovation and change to minimize risk from all sources of food hazards – biological, chemical, and physical. This approach also provides a tool to hold establishments accountable for achieving acceptable levels of food safety performance. The Hazard Analysis and Critical Control Points (HACCP) system and its application instructions are described in detail in the Codex General Principles of Food Hygiene (CXC 1-1969) (L. Hulebak e Schlosser 2002).

The successful implementation of the HACCP system requires the dedication and engagement of both top management and personnel. It is best to involve staff members from multiple departments with varied expertise in performing the gathering of essential information, documentation, and danger analysis. Finally, before implementing HACCP principles, food companies should establish well-defined precursor programs, such as GHP (good hygiene practices), to ensure basic environmental and operational conditions. If executed properly, these preparatory programs will establish the foundation for a successful implementation and execution of the HACCP system. Without proper execution of precursor programs, the HACCP system will not be effective. Inclusion of hygiene factors necessitates proper execution of preparatory programs, as their lack or poor execution might result in more complicated HACCP plans with more critical control points (CCPs) to monitor. The greater the number of CCPs, the more challenging it becomes to manage the plan, which could compromise its efficacy in ensuring food safety (Food and Agriculture Organization of the United Nations 2023).

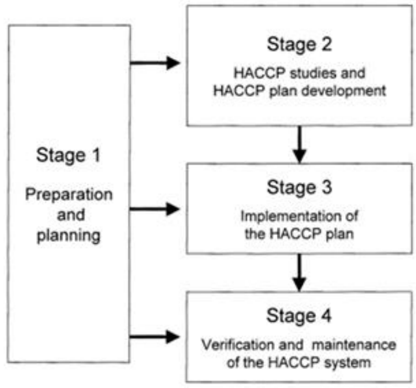


Figure 12 - The four key stages of HACCP (Mortimore e A. Wallace 2001)

The HACCP system is highly versatile, making it feasible for businesses of any size to implement. The system follows seven HACCP principles, but careful consideration must be given to the unique characteristics of each food operation, including its personnel, financial resources, infrastructure, procedures, knowledge, practical limits, and associated hazards when designing the system. These are the seven principles (Food and Agriculture Organization of the United Nations 2023):

- Principle 1: Performing a risk assessment and establishing control strategies is the primary step in building a HACCP system. This involves thorough investigation of the product creation process from start to finish, identifying potential risks that could occur and determining when they are likely to happen. Controls need to be put in place to avoid their occurrence. To begin, all potential risks, whether biological, physical, or chemical must be identified. The hazard must be significant enough so that eliminating it or reducing it to acceptable levels is crucial for producing safe food.
- Principle 2 involves identifying critical control points (CCPs) or the essential measures for maintaining food safety.
- Principle 3 requires setting established critical limits for operating these controls.
- Principle 4 entails implementing a monitoring mechanism to ensure that CCP control is effective and that the safe limit is not surpassed.
- Principle 5: Specify corrective actions to be taken when monitoring indicates a deviation from a critical limit in a CCP.
- Principle 6: Validate the HACCP plan and establish verification procedures to ensure the effectiveness of the HACCP system. This involves setting criteria and recording results at the time of creation.

- Principle 7: Document all procedures and records related to these principles and their implementation. This requires conducting regular performance evaluations and audits to confirm the proper functioning of the system.

The principles aim to identify potential hazards at every stage of the food supply chain and establish preventative measures to avoid their occurrence (Mortimore e A. Wallace 2001; Food and Agriculture Organization of the United Nations 2023; L. Hulebak e Schlosser 2002).

In addition, there are twelve steps to implement a reliable HACCP plan:

1. Bring the HACCP team together and identify the scope of application.
2. Describe the product.
3. Identify the intended use and users.
4. Construct the flowchart.
5. On-site confirmation of the flowchart.
6. List all potential hazards that may occur and are associated with each step, conduct a hazard analysis to identify significant hazards, and consider all measures to control identified hazards (Principle 1).
7. Determine critical control points (CCPs) (Principle 2).
8. Establish validated critical limits for each CCP (Principle 3).
9. Establish a monitoring system for each CCP (Principle 4).
10. Establish corrective actions (Principle 5).
11. Validate the HACCP plan and verification procedures (Principle 6).
12. Establish documentation and record keeping (principle 7).

During steps 2 and 3 of the HACCP process, all relevant information, including product specifications, should be objectively evaluated. Abbreviations should be clearly defined upon first usage. The resulting findings should be clearly documented in a concise, two-page paper. The objective is to provide all HACCP team members with a comprehensive understanding of the product and procedure being considered, ensuring logical connections between statements and consistent use of technical terminology. The product description stage involves assessing the potential applications, materials and technology utilized, primary categories of hazards to consider, and necessary control measures. This document is a valuable resource not only for the HACCP team, but also for future HACCP plan auditors. When integrating food safety into

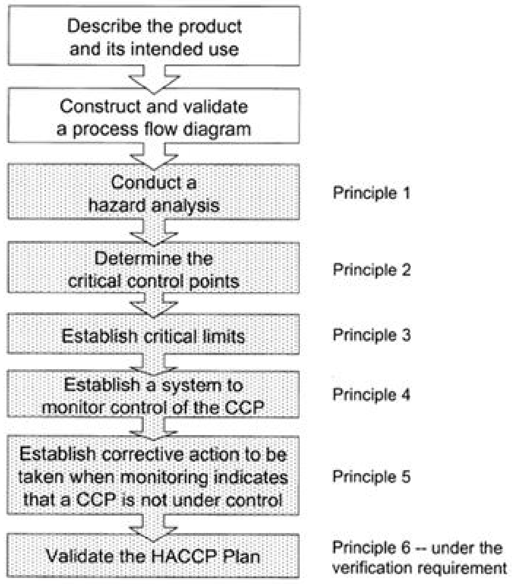


Figure 13 - The HACCP study (Mortimore e A. Wallace 2001)

a product, it is vital to consider the product's composition and the process technology utilized. At this juncture, the HACCP team typically examines these specifications. Instead, to determine how raw materials and product formulation affect safety, it is necessary to understand the inherent characteristics of the product. Intrinsic variables in food safety include compositional features such as pH and acidity levels, the use of preservatives, water activity (a_w), and the ingredients themselves. These characteristics are crucial to consider when assessing the safety of food products. The next step is to develop the process flowchart, which will establish the basis for conducting the risk analysis. It provides a comprehensive depiction of the entire procedure. If the modular method is used, it can be presented as a comprehensive diagram that encompasses the entire process or a series of smaller diagrams. This should furnish enough technical information for team members to comprehend each phase of the process, starting with the raw material supply and ending with the final product delivery. The process flow diagram must feature all process activities, storage conditions, temperature and time profiles, and raw material and packaging details (Mortimore e A. Wallace 2001).

Step 7, as well as Principle 2, involves the identification of critical control points. A critical control point is defined as a stage when "control can be applied and is essential to prevent or eliminate a food safety hazard or reduce it to an acceptable level" (Codex 1997b). Only significant food safety concerns are addressed by critical control points. To differentiate between CPs and CCPs, ask yourself this simple question: Is there a risk of a health hazard if control is lost? If the answer is "yes," the point should be managed as a CCP. If the answer is "no," indicating that food safety is not necessarily compromised, the issue can be managed as a control point (CP). Cooking, refrigeration, specific sanitation methods, prevention of cross-contamination, formulation controls, and personnel and environmental hygiene are all examples of critical control points (CCPs). All CCPs must be carefully planned and documented. CCPs, especially, can be identified using tools like decision trees, which provide an organized approach (Mortimore e A. Wallace 2001; L. Hulebak e Schlosser 2002).

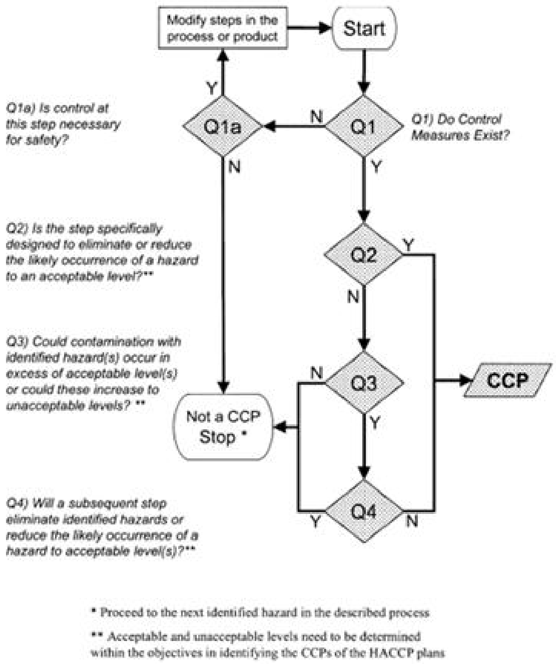


Figure 14 - Example of decision tree for process steps (Mortimore e A. Wallace 2001)

After identifying all CCPs, the team needs to determine criteria that differentiate between "safe" and potentially "unsafe" CCPs for each one, which are represented by parameters called critical limits. If the product surpasses specific limits, the CCP becomes uncontrollable, and a safety risk could arise. Critical limits can be determined through regulations, safety requirements, or scientifically confirmed values. In addition to critical limits, operational limits are often utilized to provide a buffer or action zone for process control. These parameters are intended to permit a certain level of variation in normal process operation, while simultaneously ensuring food safety (Mortimore e A. Wallace 2001).

Monitoring is covered in Principle 4, which entails performing observations or measurements to determine whether a CCP is under control. Monitoring is used to identify deviations in a

CCP and should be conducted at regular intervals so that the CCP is always under control. Nevertheless, in a processing operation, optimal conditions are not always present and deviations occur. To regain control over the CCP, corrective action plans must be implemented. These plans will determine the appropriate disposal method for nonconforming products and identify and address the source of deviations. Finally, the HACCP plan of an establishment, along with all accompanying data, must be retained for record-keeping purposes and inspection. The ultimate audit involves utilizing various techniques, processes, or tests besides those for monitoring in order to evaluate whether the HACCP system aligns with the plan or requires revising and revalidating (L. Hulebak e Schlosser 2002).

If the company is sizeable, a multifaceted team is typically responsible for conducting HACCP research. Four to six members receive training in diverse areas like quality control, manufacturing, engineering, microbiology, R&D, and supplier quality assurance. It is essential that every team member comprehends the production process thoroughly (Mortimore e A. Wallace 2001).

How do we know the HACCP system is working? Companies using HACCP can verify that the system is working in a number of ways. Typically these are: number of customer complaints (using information provided by customers as evidence that food preparation is not causing problems); audits and test results (routine and specially planned tests can be used to verify the effectiveness of the HACCP system) (Mortimore e A. Wallace 2001).

Using systematic techniques for food risk control, such as HACCP together with strong GHP, is now considered the most effective and efficient way to ensure food safety. To reduce the risk of foodborne illness, many countries have acknowledged the need for proactive, science-based food regulation regimes. This method introduced noteworthy scientific and policy considerations, including the establishment of objectives or criteria (referred to as microbiological limits or performance standards). Setting specific quantitative limits for each significant pathogen was not feasible because the scientific understanding of the relationship between specific levels of many pathogens and the risk of foodborne illness is insufficient. The standards cannot be based on public health considerations without this understanding. The Food Safety and Inspection Service (FSIS) adopted the strategy of establishing pathogen reduction goals that were believed to be achievable using current research and technology, and mandating facilities to meet these standards on a continuous basis. FSIS acknowledged that if advancements were made in knowledge and procedures, additional illnesses could be considered, and the objectives could be strengthened (Food and Agriculture Organization of the United Nations 2023; L. Hulebak e Schlosser 2002).

HACCP is often thought of as a challenging task that requires significant resources and skills like those found in larger corporations. While some specialized skills are necessary to apply HACCP principles, the fundamental requirement is a thorough understanding of the product, raw materials, and manufacturing processes, along with a comprehension of potential situations that could occur in the product or process being evaluated, which may pose health hazards for the consumer. All personnel involved in the use of HACCP should possess the capability to comprehend and implement its principles via instruction and instruction. Nevertheless, the implementation of HACCP concepts within small to medium-sized enterprises (SMEs) and underdeveloped organizations can occasionally pose more formidable challenges than anticipated. There are several reasons for utilizing the HACCP system in SMEs, and a study is currently underway to assess its suitability. Per the authors, the challenge stems from inadequate knowledge and skills among company personnel, as well as insufficient implementation of current protocols, including proper hygiene practices. Such circumstances can arise in any type of business (Mortimore e A. Wallace 2001).

There are no case studies in the bibliography on the application of HACCP in a farm setting for the industrial production of sun-dried tomatoes. Nevertheless, it is important to underscore the theoretical significance of the experimental section of this thesis for possible CCP control of postharvest mold contamination.

The utilization of AI software for identifying mold through picture recognition is an innovative strategy for overseeing a Critical Control Point (CCP) in the production of dried tomatoes. The software can be deployed at multiple stages throughout the manufacturing process to detect mold presence and take necessary preventative or corrective measures in real-time. After drying, during inspection and sorting, before packaging, as a final quality control, and for storage and monitoring are some possible connection points. To obtain a reliable outcome, choose a suitable AI program for mold recognition and train it using a set of pictures showcasing common molds that might occur at each point of the production process where it will be utilized.

In practice, this would have numerous benefits, such as the ability to quickly analyze vast amounts of photos, ensuring speedy diagnosis of mold on dried tomatoes. This would reduce the need for lengthy manual checks, speeding up the manufacturing process, and improving problem detection timeliness. Additionally, AI can identify mold with high accuracy, surpassing human limitations such as fatigue or human error. This could help decrease false positives and false negatives, enhancing the dependability of quality control. Additionally, it would enable better allocation of human resources. Human operators could focus on more advanced and demanding quality control tasks, while AI automatically handles mold recognition. Lastly, artificial intelligence could identify molds before they spread significantly. This will enable early detection and separation of contaminated batches, preventing the spread of mold to other products and reducing waste of raw materials and finished goods. Incorporating AI into a HACCP plan could also promote environmental sustainability and waste reduction, while offering significant cost savings related to product recalls or company reputation. Integrating AI software for mold detection can significantly increase the efficiency, quality, and sustainability of the tomato production process. However, appropriate implementation planning is essential, including employee training and ongoing evaluation of the system's effectiveness.

1.6 Artificial Intelligence

Man-made machines are capable of performing a variety of high-intensity tasks. However, humans have attempted to instill human intelligence into machines in several instances, driven by the need for increased production or perhaps just curiosity, which is the basis of artificial intelligence (AI). Without our automated technologies, our civilization would not have progressed very far. These technologies have made life as we know it possible, from the wheel that revolutionized agriculture to the pulley that facilitated more complex construction projects to today's robotic production lines. Despite their seemingly limitless uses, humans have always been wary of machines, particularly the possibility that they would one day possess human intelligence and operate autonomously (Jiang et al. 2022; McKinsey Explainers 2023).

The era before 1956 is considered the period in which AI was incubated. Prior to this, scientists and engineers had endeavored to supplant certain aspects of mental labor with robots. In 1936, mathematician Alan Turing developed a mathematical model for an ideal computer, which established the theoretical basis for subsequent electrical computers. In 1943, neurophysiologists W. McCulloch and W. Pitts created the first neural network model, known as the M-P model. The M-P model is considered the initial mathematical model for simulating the structure and functioning of organic neurons. It is recognized as the first artificial neural network. In 1949, Hebb proposed a learning process rooted in neuropsychology. Hebb's "learning rule" is an unsupervised learning algorithm that can extract statistical characteristics from training sets and classify data based on similarity. It is the earliest concept in machine learning (ML) and closely resembles human cognitive processes. In 1952, IBM scientist Arthur Samuel developed a checkers algorithm that could learn implicit patterns from the current position and suggest next moves. Checkers programs were among the first studies in evolutionary computing in this field. Several factors are fueling AI's resurgence. Firstly, the success of machine learning is a primary driver. Numerous key ML concepts and techniques have been proposed since the late 1980s, with many being essential components of modern ML textbooks. Secondly, vast amounts of data are readily accessible to train models. Thirdly, the rise of artificial intelligence is concomitant with a significant boost in processing power. Fourth, several AI systems that have outperformed leading human competitors in competitions and contests have impressed the public and reinstated confidence in AI (Jiang et al. 2022).

Rule-based expert systems were commonly used in the 1980s and 1990s, while artificial neural network models and fuzzy inference techniques took over around 1990. Hybrid systems, such as neuro-fuzzy or image processing systems combined with artificial neural networks, have been increasingly applied in recent times. These technologies aim to achieve better automation and precision by operating in real-time. The replication of human intelligence in computers to think and act like humans, encompassing learning and problem-solving, is known as artificial intelligence (AI). This field encompasses machine learning, which is the methodology used to identify, understand, and evaluate patterns in data. In contemporary computer science, AI is a critical subject of study (Das et al. 2018; Sharma 2021),

AI research has been ongoing for over 65 years, with notable achievements in both theoretical studies and practical applications. AI is now being utilized across various industries and is viewed as an essential skill for the future. The AI industry is projected to reach $190 billion by 2025, with a CAGR (compound annual growth rate) of more than 36% between 2018 and 2025. Due to its rapid technological advancements and widespread usefulness in addressing challenges that often strain traditional computer architectures and human capabilities, this technology is gaining momentum (Jiang et al. 2022; Sharma 2021).

Artificial intelligence (AI) has various definitions. In the Turing test, AI refers to the ability of computers to converse with humans (through electronic output devices) without revealing non-human identities, where the primary evaluation criterion is binary. According to one of AI's pioneers, Marvin Minky, AI is the ability of robots to perform tasks that require human intellect. According to the symbolic school, AI involves the manipulation of symbols, where the most basic symbols correspond to physical realities. Although definitions of AI vary, the concepts, methodologies, technologies, and research applications used to simulate, expand, and advance human intellect are considered central to AI (Jiang et al. 2022). Going through the definitions again, it is still unclear how to distinguish between AI and ML. AI is the science and engineering of creating robots that can act like humans, including understanding and imitating human intellect. Simply put, AI can be defined as the ability to develop a program that enables a computer to exhibit human-like behavior. However, the aim of an intelligent machine is not limited to accomplishing a specific task. It also encompasses the interaction of the machine with its surroundings, which may significantly impact the final result. This is where machine learning comes into play. An intelligent machine not only performs tasks, but also analyzes data to adapt to its environment (Ramli et al. 2020).

Companies utilizing AI can increase efficiency and profitability. Nevertheless, the real value of artificial intelligence does not rest in the systems themselves, but rather in how organizations utilize this technology to aid humans, and in their ability to articulate to shareholders, the public, and peers how these systems function in a way that instills trust. Machine learning, a subset of AI, uses trained algorithms to process data. Instead of being given explicit programming instructions, these algorithms can recognize patterns and learn to make predictions and suggestions by analyzing data and experiences. Deep learning is a form of machine learning that can analyze a wider range of data resources, including pictures and text, with less human interaction. Additionally, it often produces more accurate results than classical machine learning. Deep learning processes data through multiple iterations using neural networks modeled after how neurons interact in the human brain. The network makes decisions based on the data and learns if they are accurate, applying this knowledge to make decisions based on new data. For instance, once the network has "learned" how to detect an item, it can recognize it in a new image. Machine learning utilizes numerous artificial neural networks, wherein convolutional neural networks (CNNs) are widely used and popular. A CNN is a type of feed-forward neural network patterned after the structure of the visual cortex of animals, which performs image processing. As a result, Convolutional Neural Networks (CNNs) are well-suited for perceptual tasks such as identifying bird or plant species based on photos. In the corporate world, use cases include recognizing a company's logo on social media to manage the brand's reputation or uncover possible collaborative marketing opportunities (McKinsey Explainers 2023).

To date, AI has played unprecedented roles in industry, healthcare, transportation, education, and many other public-facing fields, both consciously and unconsciously. AI study includes systems and engineering, brain science, psychology, cognitive science, mathematics, computer science, and many more subjects. AI applications include speech recognition, image processing, natural language processing, intelligent robotics, autonomous vehicles, energy systems, healthcare, and other fields. AI is believed to be a significant catalyst for change in both social and economic realms. Historically, each scientific and technological revolution has brought about changes not only in technology, but also in human social structures, moral values, laws, and education. The corporate sector is exploring options to address potential problems related to AI, and legislative proposals have been introduced to address these issues as well (Jiang et al. 2022; Wang 2019). Artificial intelligence (AI) will be crucial in the development of symbiotic systems in the future. Human-machine symbionts would assist individuals by surmounting limitations, enabling them (also referred to as "human augmentation"), and improving their intellectual capacity. With the current information overload, it has become increasingly challenging to navigate through available resources. However, a cognitive digital twin (CDT) can provide great value by collecting and pre-screening relevant data and performing tasks on behalf of humans (Jiang et al. 2022).

1.6.1 Artificial intelligence in agriculture

Artificial intelligence (AI) is a significant area of research in computer science. Due to its rapid progression and extensive range, AI is increasingly becoming widespread due to its ability to tackle problems that people and conventional computer systems are unable to solve. Agriculture is a crucial sector, with approximately 30.7% of the world's population directly employed in working on 2,781 million hectares of agricultural land. To meet demand, it is predicted that the global population will exceed nine billion by 2050, requiring a 70% increase in agricultural production. Presently, agricultural operations are the main source of income, contribute to GDP, act as a cornerstone for national commerce, reduce unemployment, provide raw materials for other sectors and contribute to overall economic growth. Despite being challenging from seeding to harvesting, this task is critical. Climate change, rising production costs, restricted irrigation water supplies, and a dwindling agricultural workforce have all presented significant challenges to agricultural production systems in recent decades. Additionally, the COVID-19 pandemic has negatively impacted food security through the disruption of food supply chains and production. These variables collectively pose a threat to the sustainability of the environment and the future food supply chain. The major concern currently faced is how best to generate sufficient quantities of high-quality food to meet the demands of an ever-growing global population. Therefore, comprehending the meaning and significance of AI in agriculture and food may prove to be pivotal in guaranteeing the security of the world's food supply. Substantial changes are required to mitigate this challenge. Therefore, comprehending the meaning and significance of AI in agriculture and food may prove to be pivotal in guaranteeing the security of the world's food supply. Indeed, the crucial aspects of AI in agriculture are its flexibility, high performance, accuracy and cost-effectiveness. Objective evaluation of these aspects is important (Das et al. 2018; Eli-Chukwu 2019; Sharma 2021; Sahni, Srivastava, e Khan 2021).

In 1983, the first documentation of computer usage in agriculture was recorded. Several approaches have been suggested to tackle current agricultural difficulties, including databases and decision support systems, with pest and disease infestation, unsuitable chemical application, incorrect drainage and irrigation, weed control, yield prediction, among others, being the primary concerns. Among the available options, artificial intelligence-based systems have been shown to be the most successful in terms of accuracy and resilience. Agriculture is a dynamic subject, and its circumstances cannot be generalized to suggest a common remedy. AI approaches have enabled us to comprehend the deep aspects of each circumstance and deliver the best solution to that specific challenge. With the development of various AI approaches, increasingly complex issues are gradually being resolved (Das et al. 2018).

McKinion and Lemmon first applied artificial intelligence techniques to crop management in their 1985 essay 'Expert Systems for Agriculture'. Boulanger developed another expert system for maize crop protection in his dissertation. In 1987, Roach presented POMME, an expert system designed for apple planting management. Stone and Toman created COTFLEX, another expert system for crop management. In order to obtain crop metrics in cultivated areas, the application of 3D laser scanning, hyperspectral imaging, and remote sensing techniques is necessary. This has the potential to revolutionize the way farmers manage their land, thereby saving them valuable time and effort (Sharma 2021).

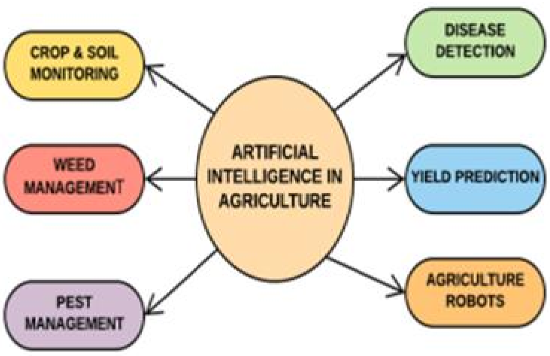


Figure 15 - Application of AI in agriculture (Eli-Chukwu 2019)

Smart agriculture, also referred to as 'Agriculture 4.0,' encompasses several technologies and advancements that can improve crop yields and reduce water and energy consumption. This can be achieved through the integration of environmental sensors and predictive tools. Smart agriculture facilitates the optimization of farming processes to increase productivity whilst conserving natural resources. This is possible through a variety of technologies and platforms that allow farmers to implement new techniques (Shaikh, Rasool, e Lone 2022).

The most up-to-date machine learning implementations tackle three main areas: pre-harvest, harvest, and post-harvest. By evaluating sources of soil management data, such as temperature, weather, soil analysis, moisture, and historical crop performance, artificial intelligence systems will be capable of providing predictive information regarding the crops that should be planted in a given year, and the optimal dates for planting and harvesting in a specific area. This will result in enhanced agricultural yields while using less water, fertilizer and pesticides. The implementation of AI technology could reduce the impact on natural ecosystems and guarantee worker safety in addition to sustaining food production and stabilizing food costs. According to recent predictions by the United Nations Food and Agriculture Organization, the global population is expected to increase by 2 billion by 2050 while agricultural land will rise by only 4%. In this context, more dependable farming methods are necessary, utilizing modern technological advancements and tackling the limitations still hindering agriculture. The use of artificial intelligence is becoming increasingly prevalent in the farming sector, with the aim of improving efficiency and accuracy of production through analysis of agricultural data (Meshram et al. 2021; Eli-Chukwu 2019; Sharma 2021).

Crop diseases are a significant worry for farmers. Plant diseases have three primary causes: fungi, bacteria, and viruses. While some diseases are highly destructive and can result in the complete loss of plants, others are challenging to identify due to their subtle symptoms. The use of AI, particularly machine learning, for identifying and categorizing plant diseases holds vast potential for enhancing crop management techniques, reducing crop losses and enhancing food safety. As a result, the employment of AI in agriculture is irrefutable in order to improve sustainable food production and meet the increasing global demand for food. Pests and diseases obliterate 35% of crops in India alone, leading to substantial losses for farmers. Human health is jeopardized by the unchecked use of pesticides since some can become toxic. Effective crop surveillance, disease diagnosis and appropriate treatment procedures can help to negate such adverse consequences. Identifying a diseased plant and implementing the necessary recovery steps requires a high level of competence and experience. Plant diseases significantly limit potential production gains. Different factors contribute to the development of various animal and plant diseases, including genetics, soil type, rainfall, dry environment, wind, temperature, and other factors. Due to these variables, in addition to the unforeseeable nature of certain pathogenic agents, managing their effects is challenging, especially in extensive agriculture. Computerized systems are widely used worldwide to detect diseases and offer management strategies. Disease detection involves analyzing images of leaves, where leaf images are segmented into categories such as non-diseased, background, and diseased. The affected leaf is subsequently gathered and dispatched to a laboratory for further examination (Ramli et al. 2020; Sundararaman, Jagdev, e Khatri 2023; Sharma 2021; Eli-Chukwu 2019).

The ongoing automation and deconstruction of the food supply chain emphasizes a new normal and renders the old reality unachievable. The food sector is being revolutionized by robots, augmented and virtual reality, 3D printing, sensors, computer vision, drones, blockchain, and the Internet of Things, all of which highlight the crucial role of artificial intelligence. The use of artificial intelligence to enhance food production is on the rise as the world transitions from the COVID-19 pandemic, and the demand for speed, efficiency, and sustainability is growing in tandem with the rapid population growth (Sahni, Srivastava, e Khan 2021).

The bibliography lists various instances of AI employed in agriculture. For instance, multiple artificial neural network models have been fashioned for disease control in a range of crops. Moreover, there have been a number of hybrid systems put forth. A certain research, for example, proposed an image processing technique backed by an artificial neural network model to diagnose illnesses in orchid seedlings. In the agricultural industry, solutions based on artificial intelligence (AI) such as drones, robots and wireless ground sensors are gaining in popularity. Microsoft, for instance, worked alongside the International Crop Research Institute for the Semi-Arid Tropics (ICRISAT) to develop an AI-powered planting tool. In a similar vein, Nature Fresh Farms, a US-based technology company, is devising data analysis with AI-based technology to produce precise crop predictions on a large scale. The duration required for the maturation of flowers is determined via an AI system. In addition to pest and disease surveillance, crucial aspects of agriculture include crop preservation, desiccation, and classification (Das et al. 2018; Sharma 2021).

Moving on to the details of this project, references regarding the application of AI in tomato cultivation can be found in the bibliography. Artificial intelligence has shown potential for precise identification and categorization of tomato leaf diseases, enabling farmers to take necessary measures to avoid crop damage and yield reduction. AI algorithms are capable of interpreting vast volumes of data objectively and without human bias. This makes them a useful tool for detecting even the most minor alterations in plant diseases, which traditional approaches may overlook. The combination of AI algorithms and developments in computer vision has led to considerable breakthroughs in current literature on the classification of tomato leaf diseases using AI approaches (Sundararaman, Jagdev, e Khatri 2023).

Artificial intelligence has significant potential in agriculture. However, there is a general lack of understanding of modern high-tech machine learning solutions in agriculture. Additionally, AI systems require a vast amount of data to train robots to make accurate predictions. While collecting geographical data over vast areas is relatively straightforward, obtaining time data is more challenging. Creating knowledge-based rules and effectively organizing them for multiple factors can be equally challenging. Crop-specific data is often only available once a year during the growing season, and building a robust AI machine learning model takes time as the database needs time to mature. This is why artificial intelligence is employed in agricultural products like herbicides, fertilizers, and seeds. Additionally, numerous cognitive agriculture solutions are quite costly, potentially restricting their widespread acceptance. More widely available AI-inspired solutions are crucial to ensure that AI technology benefits the farming community. Open-source platforms could enhance accessibility to these technologies for farmers, promoting quicker adoption and improved understanding (Sharma 2021).

The main objective of this study is to propose a novel application of artificial intelligence (AI) in tomato farming, with the aspiration that this technology can eventually be implemented as a viable and sustainable solution on farms. As demonstrated in this research, AI holds great potential for streamlining crop administration, eradicating diseases and pests, boosting harvests, and reducing the use of resources such as water, fertilisers and pesticides. Adoption of AI in agriculture could be a potential solution to overcome these challenges and ensure global food security in a world where the global population continues to grow, and environmental issues become more critical. With its flexibility, efficiency and ability to process large amounts of data, artificial intelligence has the potential to shape the future of agriculture and make it more sustainable and resilient. Objective evaluations suggest that with further research, funding and efforts to make AI more accessible to farmers, this technology will continue to improve and contribute to a safer and more efficient future for food production.

Chapter 2 – Objectives

Food safety is a crucial concern in our society today. As food production becomes increasingly complex, ensuring that the food we consume is free of biological, chemical, and physical hazards has become a key issue. This means not only preventing potential threats to human health, but also instilling confidence in the food production process for consumers.

To achieve this, prioritizing prevention over correction is fundamental. The Hazard Analysis and Critical Control Point (HACCP) method is a beneficial tool that focuses on preventing potential hazards at each stage of the production process. This approach shifts the focus from post-production analysis to proactive hazard management.

Unlike traditional monitoring methods that can be costly and time-consuming, the HACCP system relies on effective surveillance at critical control points.

Fortunately, advances in technology have enabled us to handle food safety issues more effectively and efficiently. Artificial intelligence and machine learning technologies have the potential to improve industrial processes, promote sustainability, and reduce costs.

The automated procedures and improved risk detection process implemented by AI ensure higher quality food products that require fewer recalls once they are placed on the market.

In this thesis, we examine the use of AI software in a critical control point phase of tomato production. The software's objective is to detect molds during the drying phase to ensure quality in the production process. Our research aims to determine if AI can be more widely utilized in the food industry to create safer, better quality products while minimizing food waste.

Drying plays a crucial role in both enhancing the product's sensory characteristics and preventing mold formation. However, a prolonged drying process that enhances the product's quality may heighten the mold risk. The application of preservatives is a typical way to avert mold formation, but proper process control is crucial in managing drying conditions. Our objective is to create a control system utilizing computer vision (CV) and artificial intelligence (AI) for the early detection of mold to enhance process control. Studying AI integrated with HACCP plans in the food industry can determine whether we can guarantee the quality, safety, and sustainability of our food supply for future generations from a broader "One Health" viewpoint.

Chapter 3 – Materials and method

For the experimental part of this paper, different procedures were carried out at different times.

The goal was to "train" the image recognition software so that when the experiment was finished, it would be able to recognize spoiled tomatoes from healthy ones on its own. To do this, it was necessary to collect as many photos as possible of healthy and unhealthy tomatoes and of different shapes.

In a first trial, photos already owned by the research team of the TESAF department of the University of Padua that depicted mostly healthy tomatoes, dried healthy tomatoes, and dried spoiled tomatoes were used (tomatoes all of the same variety).

Figure 16a – 16b Photo held by the TESAF department of the University of Padua

These photos, a total of 232 in number, were labeled thanks to YOLOv7 (further explanation in subchapter 3.1) into 3 labels: healthy, uncertain and spoiled. We thus obtained 4645 labeled tomatoes.

At a later stage of analysis of these first data, it was seen that the category "uncertain" could be confusing and an unclear classification for the algorithm, so it was decided to do a second trial (still keeping 232 photos) and all the subsequent ones with only two labels: healthy (green) and spoiled (red).

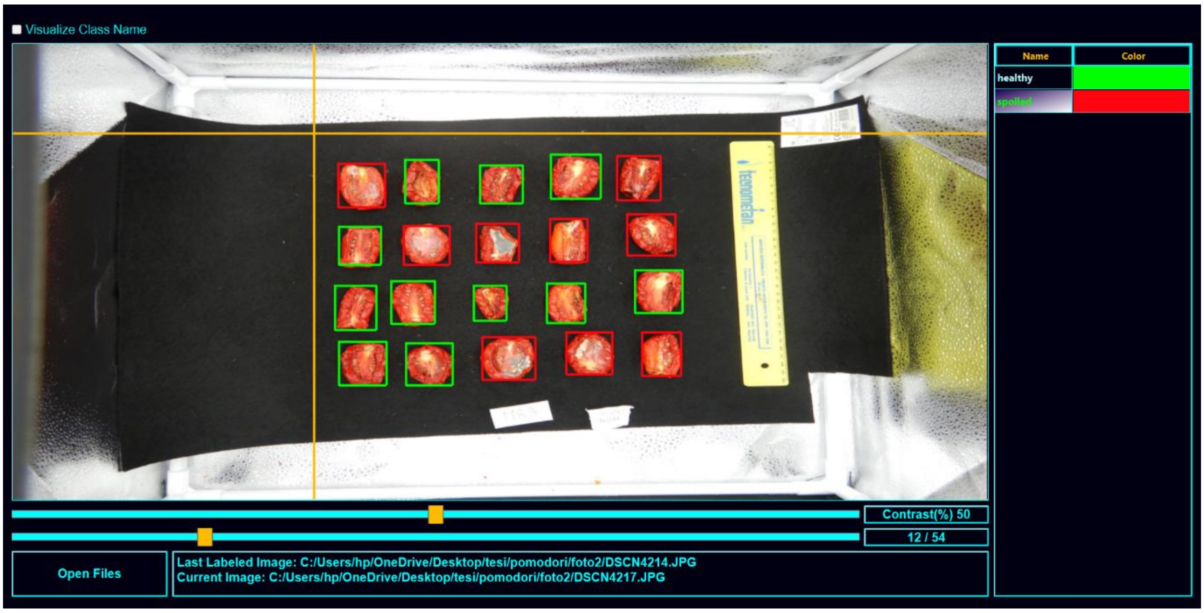


Figure 17 - Photo labelled with YOLOv7

Following the outcome of the analysis with only two labeling, it was realized that it was necessary to increase the number of photos that contained spoiled tomatoes, as, in the first two labeling there were only 344 spoiled tomatoes against 4281 healthy ones.

After buying new tomatoes of different varieties, new photos of them were taken. The tomato varieties examined were Beefsteak, Cherokee Purple, San Marzano, Plum, Brandywine, Grape, Cocktail, and Cherry. Approximate measurements of each were taken to clarify the limits and application range of the model as indicate in the Table 1:

	Grape	Cherry	San Marzano	Cherokee	Beefsteak	Plum	Brandywine	Cocktail
Width (cm)	3,36	4,85	4,17	8,14	8,85	6,05	10,44	4,35
Length (cm)	5,33	4,28	8,62	7,63	7,12	10,66	14,28	4,75

Table 1 - Approximate measurements of each variety of tomato

The process took 3 days using: a stove (which would allow us to dry the tomatoes), a camera, a scale and a photo light box. First the tomatoes were cut and placed in aluminum baking trays to hold food. The trays were weighed both with and without the tomatoes to keep track of water loss throughout the drying process.

Since the ultimate goal of this step was to increase the number of spoiled tomatoes, contamination by rubbing was performed between the present tomatoes that already had mold and those that did not.

Photos were taken of both individual tomatoes on a black background and inside the aluminum trays (a total of 11 trays) to increase the variables that the algorithm would then have to identify.

Figure 18 - Tomatoes inside the tray

The trays containing the tomatoes were placed inside the stove with a set temperature of 40°C for 24 hours. On the second day, the same photos and weighing of the trays were repeated, observing that mold had expanded on all the tomatoes inside the different trays.

Figure 19 - Spoiled tomatoes after 24h

As on the previous day, the trays were placed in the stove at 40°C for another 24 hours. The third day was worked in two stages. In the morning, all photos and weighing of the 11 trays were still repeated, which were then placed in the stove again, but this time with a set temperature of 80°C.

Two and a half hours passed and the last photos and weighing of the trays were taken.

Figure 20 - Tomatoes after two and a half hours in the stove at 80°C

At the end of these three days there were 115 new photos obtained, including 76 photos of tomatoes inside the trays and 39 of tomatoes on the black background.
Before adding the new photos to the old ones, the latter were rechecked and the photos that were repeated several times were removed thus arriving at a final total of no longer 232 but 114. To these were added the 115 new photos and another 18 photos also already in the possession of the TESAF department of the University of Padua. This brought the total to 247 photos (including those with tomatoes in trays and not).

The new photos were labeled, again using the YOLOv7 algorithm, and a total of 3392 labeled tomatoes were obtained of which 2055 were healthy and 1337 were spoiled. Thanks to these new labeling subsequently the third data analysis was started.

Following the creation of this new dataset, it became necessary to take additional photos portraying both healthy and dried tomatoes of different varieties. Therefore, new photos were searched that portrayed both healthy and spoiled dried tomatoes of each variety. This, to make sure that the algorithm had been trained to recognize both healthy and unhealthy dried ones of the same variety. To achieve this, new tomatoes were then bought and all the steps already performed last time were repeated.

This time, however, the photos were taken on 4 different days and using the stove with a fixed temperature of 40°C every 24 hours.

The initial goal of obtaining photos of dried and healthy tomatoes of the same variety unfortunately failed as mold contamination again affected all the trays but, nevertheless, all photos were taken.

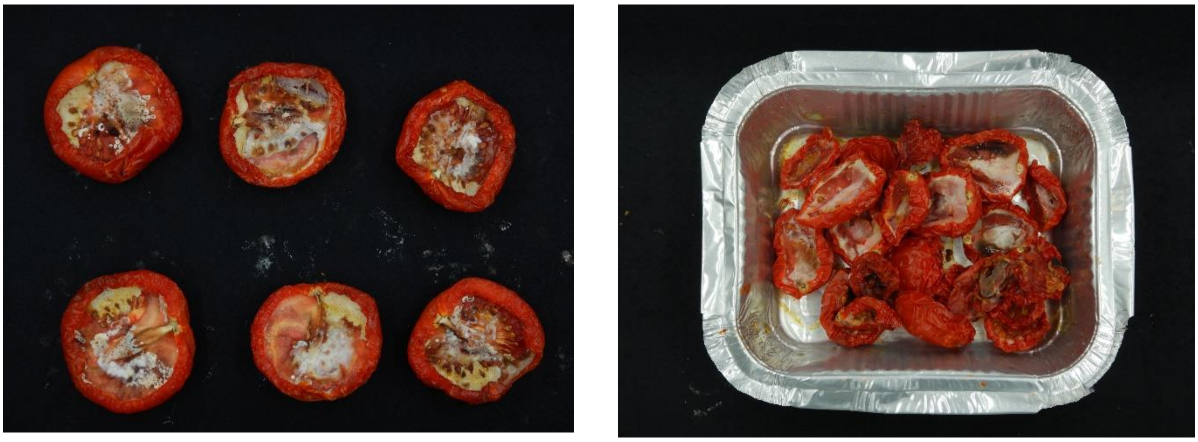


Figure 21a - 21b - Fourth trial tomatoes

After 4 days, a total of 194 photos was obtained, 124 of which had the tomatoes inside the tray (a total of 18 trays) and 70 photos of individual tomatoes with the black background.

These new 194 photos were labeled with YOLOv7 and added to the previous ones. This resulted in 441 photos to which another 21 photos (with only dry and healthy tomatoes) were added, again already in the possession of the TESAF department of the University of Padua, to try to increase the amount of dry and healthy tomatoes. As a result of labeling, 4644 labeled tomatoes were then obtained, of which 2688 were healthy and 1956 were spoiled. Again, thanks to this data, the fourth analysis was started.

3.1 Object detection and neural networks

Object detection is a process within computer vision that involves the classification and localization of objects in images or videos. Computer vision represents one of the fastest-growing areas in the field of artificial intelligence. Notably, Tesla has taken the lead in developing autonomous and self-driving vehicles, with other major automakers following suit by experimenting with similar technologies. Image identification and classification have been a long-standing concern, particularly due to the challenges of a standard algorithm in recognizing the same object from different viewpoints and angles. Although visual image recognition and discrimination come easily and automatically to us, it is challenging to perceive the difficulties encountered in automating this process. Initially, two types of difficulties must be differentiated: classification and localization. The less sophisticated challenge already arises with the former. For instance, recognizing a chair is easy but describing it unambiguously can be difficult. A chair, which is a piece of furniture for sitting, typically has four legs, armrests, and a backrest. Nevertheless, various issues exist: some have only three legs, some possess two legs, and some chairs in an office come with wheels. Regardless, we can immediately identify all of them as chairs. It is impossible to train a machine to recognize all potential exceptions. Consequently, rule-based recognition is bound to yield poor results, including both false positives (identifying chairs that do not exist) and false negatives (failing to recognize chairs that do exist). When presented with multiple orientations or missing sections, the situation becomes significantly more challenging. [15]

In other terms, object detection is the process of creating bounding boxes around observed items in order to identify them in a scene (or comprehend how they move within it). The distinction between picture recognition and object detection must be clarified.[16] Image classification entails labelling an image with a class name, whereas object location entails creating a bounding box around one or more objects in an image. Object detection is more difficult and combines these two tasks by constructing a bounding box around each object of

[15] Source: Online interview by Paolo Costa on 26 June 2018, available via link: [YOLO, un algoritmo ultra veloce open source per la computer vision in tempo reale]() (last access September 2023).

[16] Source: Online interview by Alberto Rizzoli on 10 June 2021, available via link: [The ultimate guide to Object Detection]() (last access September 2023).

interest in the picture and labelling it. Object recognition refers to the combination of these challenges. Object recognition is a broad word that refers to a group of related computer vision tasks that include identifying items in digital pictures. Image classification entails guessing the class to which an object in an image belongs. Identifying the position of one or more items in a picture and drawing a bounding box to their extent is referred to as object location. These two tasks are combined in object detection, which locates and classifies one or more things in a picture.

However, the tasks of computer vision can be summarized as follows: Image classification is the process of estimating the type or class of an object in an image. Object localization: detect the existence of items in a picture and mark their position with a selection rectangle. Object detection: identify the presence of items in an image using a bounding box and the kinds or classes of objects found. [17]

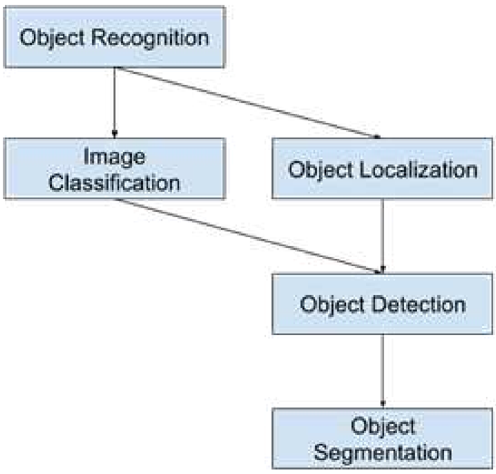


Figure 22 - Overview of Object Recognition Computer Vision Tasks
https://machinelearningmastery.com/object-recognition-with-deep-learning/

[17] Source: Online interview by Jason Brownlee on 22 May 2019, available via link: A gentle introduction to object recognition with Deep Learning (last access September 2023).

Classification offers benefits as a preferred alternative to tags without physical limits, such as "fuzzy" or "sunny." However, object detection systems consistently outperform classification networks in recognizing items with a physical presence, like an automobile. [18]

Figure 23 - Image Classification vs. Object Detection
https://www.v7labs.com/blog/object-detection-guide

Object segmentation, also referred to as "object instance segmentation" or "semantic segmentation," is a computer vision technique that involves highlighting object-specific pixels to identify recognized object instances instead of relying on a crude bounding box. Picture segmentation is a related concept that involves defining the pixels in an image belonging to a specific class of objects. Semantic image segmentation identifies all pixels corresponding to a particular label but does not define the boundaries of individual objects.

In contrast, object detection does not segment the object itself, but instead employs bounding boxes to precisely locate each object instance. When combining semantic segmentation and object identification, the result is instance segmentation. This method first recognizes object instances and subsequently identifies them inside specified windows, also known as areas of interest. [19]

[18] Source: Online interview by Alberto Rizzoli on 10 June 2021, available via link: The ultimate guide to Object Detection (last access September 2023).

[19] Source: Online interview by Jason Brownlee on 22 May 2019, available via link: A gentle introduction to object recognition with Deep Learning (last access September 2023). Source: Online interview by Alberto Rizzoli on 10 June 2021, available via link: The ultimate guide to Object Detection (last access September 2023).

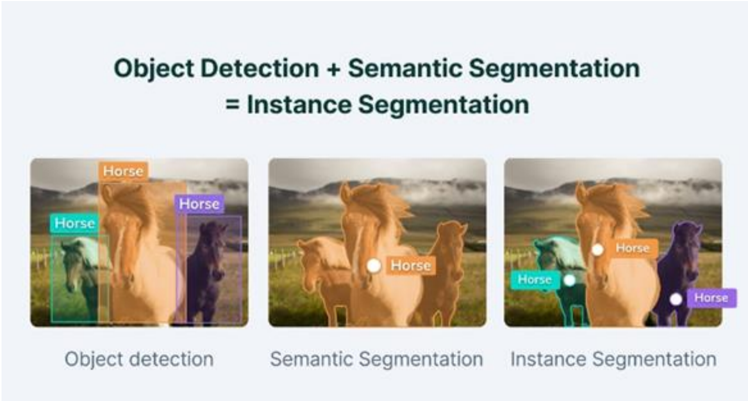


Figure 24 - Object detection and Segmentation
https://www.v7labs.com/blog/object-detection-guide

Prior to 2013, most object identification was conducted using traditional machine learning algorithms. The Violet-Jones object recognition approach, Scale Invariant Feature Transformation (SIFT), and Histogram of Oriented Gradients (HOG) were the most widely used methods. These algorithms detected common features in the image and categorized them into clusters using logistic regression, color histograms, or random forests. However, contemporary deep learning-based approaches outperform these techniques by a wide margin.[20]

Object detection techniques are classified into two types based on the number of times a network processes the same input image: single-shot detectors and two-stage detectors.

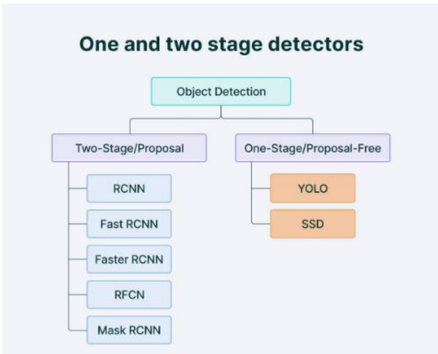


Figure 25 - One and two stage detectors
https://www.v7labs.com/blog/yolo-object-detection

[20] Source: Online interview by Alberto Rizzoli on 10 June 2021, available via link: [The ultimate guide to Object Detection](#) (last access September 2023).

Single-shot object detection predicts the presence and placement of objects in an image through a single pass of the input picture. This approach processes the entire image in a single pass, which enhances computational efficiency. However, single-pass object detection may be less precise than other methods and can struggle with recognizing small objects. Nevertheless, these algorithms are capable of detecting objects in real-time, even in situations where resources are limited. Two-shot object detection predicts object presence and placement using a two-pass method on input images. The initial phase generates a set of ideas or potential item positions, followed by a secondary refinement period that fine-tunes the suggestions and generates definitive forecasts. Despite the fact that this process is more precise than single-shot object detection, it is also more computationally demanding. Generally, single-shot object identification is preferable for real-time situations, while two-shot object detection is more appropriate for precision-intensive applications. [21]

Standard quantitative measurements are essential for assessing the performance of object detection models. When evaluating such models, these metrics are indispensable. The Intersection over Union (IoU) and Average Precision (AP) are the most commonly used metrics. IoU is a key indicator for estimating location errors and measuring location accuracy in object recognition algorithms. It calculates the intersection between two bounding rectangles: one representing an expected bounding rectangle and the other representing the ground truth bounding rectangle. [22]

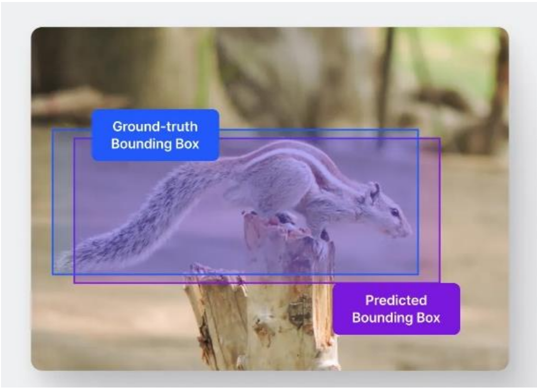


Figure 26 - Bounding rectangles
https://www.v7labs.com/blog/intersection-over-union-guide

[21] Source: Online interview by Rohit Kundu on 17 January 2023, available via link: YOLO, algorithm for Object detection explained (last access September 2023).

[22] Source: Online interview by Deval Shah on 30 May 2023, available via link: Intersection Over Union (IoU): Definition, Calculation, Code (last access September 2023).

IoU is the ratio between the junction of the two boxes' areas and their combined area. The union area, which is the denominator, is included in both the ground truth selection rectangle and the predicted selection rectangle. In the numerator, we compute the overlap between the ground truth and anticipated selection rectangles. We write the following for binary classification:

$$Intersection\ over\ Union\ (IoU) = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN} + \mathrm{FP}}$$

Where TP denotes true positive, FN denotes false negative, and FP denotes false positive. In particular: True positive: The model correctly predicted the existence of a bounding box at a certain place (positive). False positive: The model predicted the presence of a bounding box at a specific point (positive), but it was incorrect (false). False negative: The model predicted the existence of a bounding box at a particular place but was incorrect (false), indicating that a ground truth bounding box existed at that point. True negative: The model predicted a bounding box but was incorrect (true). This relates to the backdrop, the region without bounding boxes, and is not utilized in the final metrics calculation. [23]

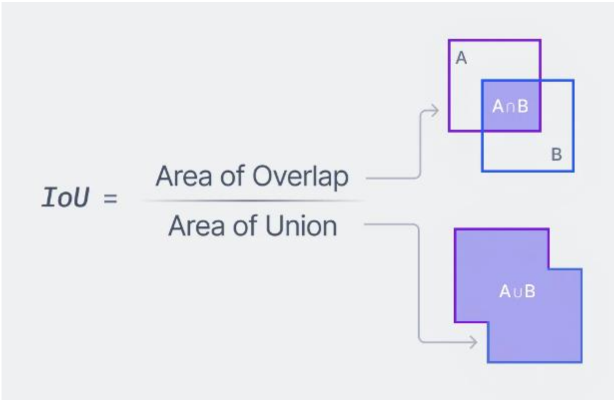


Figure 27 - Intersection Over Union
https://www.v7labs.com/blog/intersection-over-union-guide

[23] Source: Online interview by Deval Shah on 30 May 2023, available via link: Intersection Over Union (IoU): Definition, Calculation, Code (last access September 2023). Source: Online interview by Aqeel Anwar on 13 May 2022, available via link: What is Average Precision in Object Detection & Localization Algorithms and how to calculate it? (last access September 2023).

If there is significant overlap between the expected and ground truth boxes, the IoU score will be high. Conversely, a low overlap will result in a low IoU score. An IoU score of 1 indicates a perfect match between the projected and ground truth boxes, while a score of 0 suggests that the boxes have no overlap. Let us take the example of using a deep learning model to detect a squirrel, for which the model will provide an estimated selection rectangle. However, it is important to note that the actual truth box, which has been accurately marked around the object, may differ from the predicted rectangle. The Intersection over Union (IoU) measure is used to evaluate the accuracy of the model by assessing how well the predicted rectangle matches the actual one. As shown in Figure 28, three instances arose from the computation of IoU. The model performs with high accuracy in the initial squirrel example. However, the second example, with an IoU of 0.79, is average. Finally, the third case shows poor performance with an IoU of 0.45, indicating that the object was not successfully detected. [24]

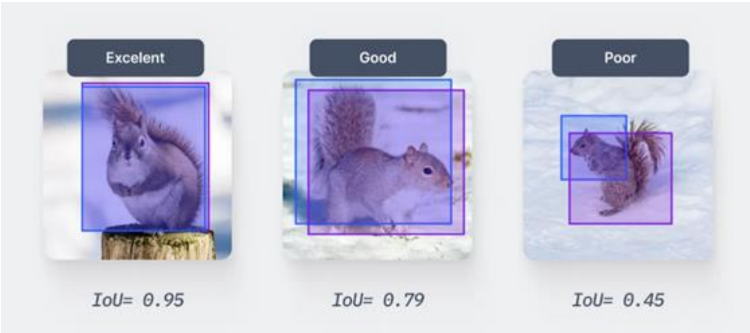
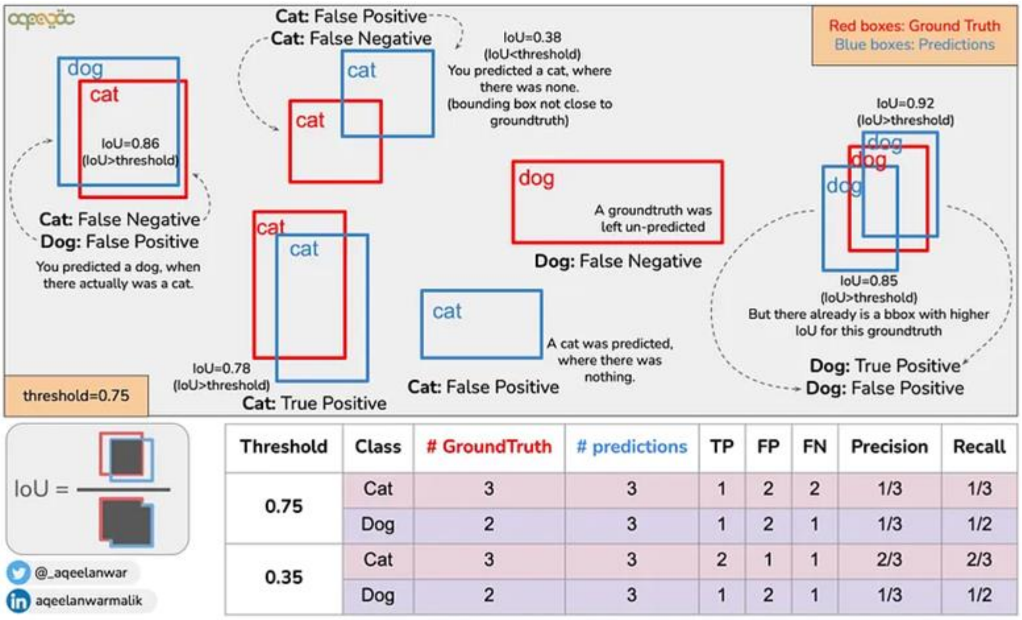


Figure 28 - IoU comparative performance
https://www.v7labs.com/blog/intersection-over-union-guide

The IoU metric is crucial as it provides a numerical assessment of a model's competency in recognizing objects in images. Moreover, a minimum IoU score is essential to consider a projected box as an accurate positive detection while training the model, allowing IoU to be utilized for establishing a threshold for object identification. The threshold choice controls the balance between detection accuracy and false positives. There is no universally accepted threshold for Intersection over Union (IoU) as it depends on the specific item detection task and dataset. Nevertheless, a prevalent criterion in practice is 0.5, which suggests that a predicted box can be considered a true positive detection only if its IoU with a ground truth box is at least 0.5. In conclusion, IoU assists in evaluating our algorithms' performance and

[24] Source: Online interview by Deval Shah on 30 May 2023, available via link: Intersection Over Union (IoU): Definition, Calculation, Code (last access September 2023).

establishing acceptable levels of detection accuracy. The actual or accurate values of the evaluated objects or regions are known as ground truth data in Intersection over Union (IoU). The expected values generated by a model or algorithm are compared to the ground truth data. Ground truth information in object detection, for instance, consists of the precise bounding boxes encompassing the elements of interest in an image, which human experts manually designate. Obtaining accurate and reliable data is crucial for evaluating the efficiency of machine learning models and algorithms, as well as for comparing various models to determine the best performer. Additionally, TP, FP, and FN can be utilized to obtain two parameters for each labeled category - accuracy and recall. [25]



Threshold	Class	# GroundTruth	# predictions	TP	FP	FN	Precision	Recall
0.75	Cat	3	3	1	2	2	1/3	1/3
	Dog	2	3	1	2	1	1/3	1/2
0.35	Cat	3	3	2	1	1	2/3	2/3
	Dog	2	3	1	2	1	1/3	1/2

Figure 29 - Object Detection and Localization – IoU
https://towardsdatascience.com/what-is-average-precision-in-object-detection-localization-algorithms-and-how-to-calculate-it-3f330efe697b

Precision demonstrates the accuracy of the model, specifically the number of identified cats. Illustrated below, it represents the ratio of true positives to the total number of cat predictions produced by the model (equal to the sum of true positives and false positives).

Recall: This metric measures the model's ability to correctly identify cat images, or in other words, the number of cats it was able to recognize in the input image. The model calculates

[25] Source: Online interview by Deval Shah on 30 May 2023, available via link: Intersection Over Union (IoU): Definition, Calculation, Code (last access September 2023).

the ratio of accurately identified cats (true positives) to the total number of actual cats (sum of true positives and false negatives) as shown below. [26]

Precision and Recall in Machine Learning

For each class

$$Precision = \frac{Correct\ Predictions}{Total\ Predictions} = \frac{TP}{TP + FP}$$

$$Recall = \frac{Correct\ Predictions}{Total\ GroundTruth} = \frac{TP}{TP + FN}$$

Class	# GroundTruth	# predictions	TP	FP	FN	Precision	Recall
Cat	10	5	4	1	6	4/5 (80%)	4/10 (40%)
Dog	10	10	8	2	2	8/10 (80%)	8/10 (80%)

Figure 30 - Precision and Recall in Machine Learning
https://towardsdatascience.com/what-is-average-precision-in-object-detection-localization-algorithms-and-how-to-calculate-it-3f330efe697b

The classifier is accurate as shown in the above image, with an 80% accuracy when predicting whether an image contains a cat or a dog. However, if a cat or a dog is present, the classifier can only identify it correctly 50% (80%) of the time. This leads to difficulty in recalling cats (cut image) in the model. Our goal is to achieve high accuracy and recall, meaning that all occurrences of a class are correctly identified by the model. The accuracy and recall values are determined based on the number of true positives detected by the model. The assignment of a bounding box TP, FP, or FN is determined by the following two factors:

- The predicted label versus ground truth label.
- The IoU between the two boxes.

The model provides the conditional probability that the selection rectangle belongs to a specific class for a multiclass classification problem. As the probability for a class increases, the likelihood of the selection rectangle containing that class also increases. To classify a selection rectangle, the probability distribution is used along with a user-defined threshold value (ranging from 0 to 1). Lowering the probability confidence threshold will increase the model's detections, decrease the likelihood of missing ground truth labels, and thus improve overall recall (although not always consistently). Increasing the confidence threshold results in a more certain prediction from the model, leading to higher precision (although not always).

[26] Online interview by Aqeel Anwar on 13 May 2022, available via link: What is Average Precision in Object Detection & Localization Algorithms and how to calculate it? (last access September 2023).

This trade-off is dependent on the value of the confidence threshold. However, there is a trade-off between precision and recall as we aim for maximum accuracy and feasibility.[27]

The precision-recall curve enables us to visually comprehend the suitable confidence threshold for our application. A basic example of the PR curve is illustrated in Figure 31.

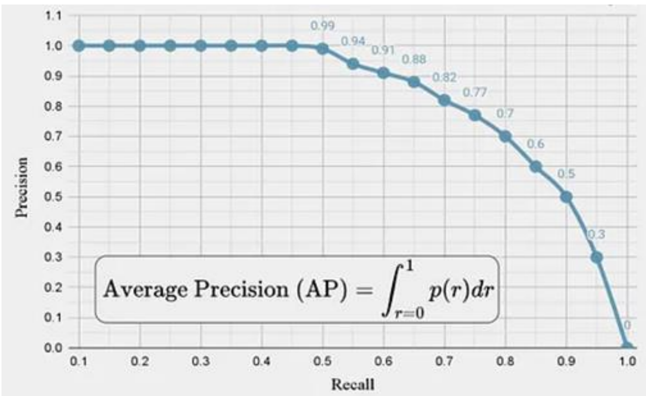


Figure 31 - Precision Recall Curve (PR Curve)
https://towardsdatascience.com/what-is-average-precision-in-object-detection-localization-algorithms-and-how-to-calculate-it-3f330efe697b

The second evaluation metric, referred to as average precision (AP), is derived from this. Average accuracy, a crucial performance metric aimed at reducing dependence on selecting a confidence threshold value, is defined by the area beneath the PR curve. AP provides a scalar value that summarizes the PR curve. Average precision is high when both precision and recall remain high within a range of confidence thresholds, and low when either is low. The mean accuracy (mAP) of AP, which ranges from 0 to 1, is the average score across all classes in object detection. Precision and recall are not utilized for class prediction in object detection. The prediction model uses precision and recall evaluating the decision performance of boundary box predictions. Predictions with an IoU value above 0.5 are classified as positive, while those with values less than 0.5 are deemed negative. [28]

Another concept that requires explanation in the extensive field of machine learning is neural networks. An artificial neural network (ANN or NN) is a mathematical model composed of artificial "neurons" inspired by a biological neural network. In detail, ANNs are a technique

[27] Source: Online interview by Aqeel Anwar on 13 May 2022, available via link: What is Average Precision in Object Detection & Localization Algorithms and how to calculate it? (last access September 2023).

[28] Source: Online interview by Rohit Kundu on 17 January 2023, available via link: YOLO, algorithm for Object detection explained (last access September 2023).

utilized to solve intricate problems that are challenging to design, and they establish the basis of current machine learning. "Neural networks" are so called because their component nodes exhibit similar activity to actual neurons. A neuron processes incoming information from neighboring neurons via synaptic connections. If the resulting activation reaches a particular threshold, an Action Potential is generated and transmitted along the axon to one or more neurons. A neural network can be envisioned as a black box, consisting of inputs, intermediary layers where processing occurs, and outputs that constitute the final outcome. The network comprises individual "units," known as neurons, which are arranged in layers. Weighted connections join each neuron to every neuron in the subsequent layer. A connection is simply a numeric value, or "weight," multiplied by the value of the connected neuron. Each neuron adds its bias value to the sum of weighted values from all linked neurons. An "activation function" is then applied to this result, modifying the value mathematically before forwarding it to the next layer. This process allows the input values to be transmitted through the network until they reach the output neurons, which is essentially the core function of a neural network. If a node's individual output exceeds the designated threshold value, it activates, and subsequently sends data to the next layer within the network. Conversely, if the output falls below the threshold value, no data is transferred to the subsequent network layer. [29]

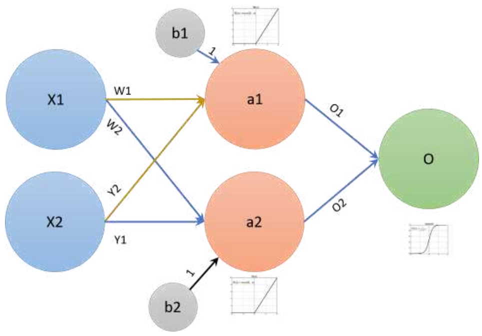


Figure 32 - Neural Networks
https://www.spindox.it/it/ml1-reti-neurali-demistificate/

As a result, neural networks comprise three layers: an input layer (which stores the input data), one or more hidden layers (which perform the actual processing), and an output layer (which saves the final outcome). The term "deep learning" originated from this neural network concept as this method employs "deep" neural networks, implying that they have multiple

[29] Source: Online interview by Paolo Costa on 20 February 2018, available via link: Machine Learning – Reti neurali demistificate (last access Septembre 2023).

layers. The multiple layers in the algorithm are necessary because each layer gradually "generalizes" more than the previous one. In the context of identifying geometric shapes, for instance, the initial layer simply distinguishes individual pixels, the next layer "generalizes" edges, the third layer begins recognizing basic shapes, and so forth. [30]

Convolutional neural networks (CNNs) are a type of neural network that is especially beneficial for categorizing and computer vision purposes. Prior to the advent of CNNs, pinpointing objects in photographs was an onerous task requiring time-consuming feature extraction methods. Now, CNNs offer a more scalable solution to image classification and object identification applications by utilizing linear algebra concepts, specifically matrix multiplication, to identify patterns within an image. However, training these models can be computationally intensive, and thus the use of Graphical Processing Unit (GPU) cards is often required. Convolutional neural networks outperform other types of neural networks in processing images, speech, and audio signals. They consist of three types of layers: convolutional, pooling, and fully connected (FC) layers. The first layer of a convolutional network is the convolutional layer. While convolutional layers may be followed by additional convolutional or pooling layers, the final layer is the fully connected layer. With each level, the complexity of the CNN improves, as does the percentage of the image that is detected. The initial stages concentrate on fundamental aspects like colors and shapes. As the visual data passes through the CNN stages, it detects greater details or shapes until the object is recognized. [31]

3.1.1 YOLO

To be truly effective, object recognition must be capable of identifying complex scenarios that we encounter in our daily lives. The extensive use of neural networks in the age of big data, coupled with the emergence of deep learning, has completely transformed the field. Specifically, convolutional networks have led to a significant improvement. The "sliding window" approach, which scans the whole image region by region and accurately examines

[30] Source: Online interview by Paolo Costa on 20 February 2018, available via link: Machine Learning – Reti neurali demistificate (last access Septembre 2023).

[31] Source: Official website of IBM via link: Cosa sono le reti neurali convoluzionali? (last access September 2023).

one area at a time, has been employed by nearly all algorithms. The goal of convolutional neural networks (CNNs) is to iterate the process using various window sizes, resulting in predictions for the content with varying levels of confidence. Subsequently, the predictions with the least confidence are removed.
YOLO introduced single-pass decoding. It is a straightforward object detection framework with the acronym "you only look once." This is a unified neural network that takes as input an image and predicts bounding boxes as well as class labels for each of them, end-to-end. YOLO is a conventional one-stage detector. Today's requirements exceed basic classification or localization in static photos. Instead, real-time analysis is imperative. No passenger wants to be in an autonomous vehicle that takes several seconds or even minutes to recognize images. Thus, utilizing single-pass convolutional networks, which concurrently examine all picture areas, is a viable solution as it eliminates the need for the sliding window. [32]

Yolo was developed in 2015 by Redmon and Farhadi during their doctoral studies. Their approach involves analyzing a picture with a single glance to determine the objects present and their locations. A single convolutional network predicts multiple bounding boxes and class probabilities simultaneously. YOLO trains on complete photos and instantaneously enhances detection performance. This unified model surpasses previous object identification methods in various aspects. Firstly, YOLO is remarkably fast. Secondly, when generating predictions, YOLO takes into account the entire image. During both training and testing, YOLO views the entire image, thereby implicitly encoding contextual information about classes and their appearance. Lastly, YOLO acquires generalizable object representations (Redmon et al. 2016).

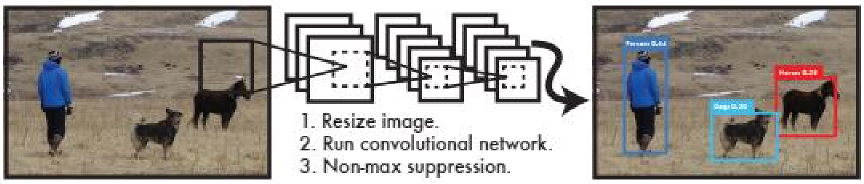


Figure 33 - The YOLO Detection System (Redmon et al. 2016).

Unified detection combines various components of object detection into a single neural network. The network predicts each chosen rectangle by utilizing information from the entire image. It simultaneously predicts the bounding boxes for all classes in the image, meaning

[32] Source: Online interview by Paolo Costa on 26 June 2018, available via link: [YOLO, un algoritmo ultra veloce open source per la computer vision in tempo reale] (last access September 2023).

that it considers the full image and all its objects together. It simultaneously predicts the bounding boxes for all classes in the image, meaning that it considers the full image and all its objects together. In brief, the approach utilizes a sole end-to-end neural network, which is trained to receive an image as input and then to directly forecast the class labels and bounding boxes for each bounding box. The method yields lower prediction accuracy, as in a higher occurrence of localization mistakes, but functions at a speed of 45 frames per second. The model's speed-optimized version operates at up to 155 frames per second. The model divides the input image into a cell grid, with each cell predicting a bounding box when the center of a bounding box is within the cell. Each cell predicts a bounding box with x, y, width, and height coordinates, as well as confidence. The confidence prediction represents the IoU of the anticipated box with any ground truth box. Additionally, each cell predicts a class. For instance, an image can be divided into 77 cells, and each cell can predict two bounding boxes, which results in 94 bounding box predictions. Afterward, the confidence map of classes and bounding boxes integrates into a final set of bounding boxes and class labels (Redmon et al. 2016). [33]

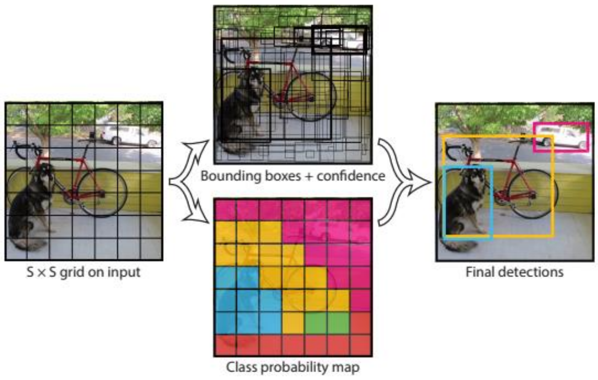


Figure 34 - The Model (Redmon et al. 2016)

The YOLO technique receives an image as input and identifies objects within it through a deep convolutional neural network. The CNN model serves as the foundation of YOLO and is depicted in this section. The initial 20 convolutional layers of the model were trained in advance with ImageNet, including a transitory mean pooling and a fully connected layer. [34]

[33] Source: Online interview by Jason Brownlee on 22 May 2019, available via link: A gentle introduction to object recognition with Deep Learning (last access September 2023).

[34] Source: Online interview by Rohit Kundu on 17 January 2023, available via link: YOLO, algorithm for Object detection explained (last access September 2023).

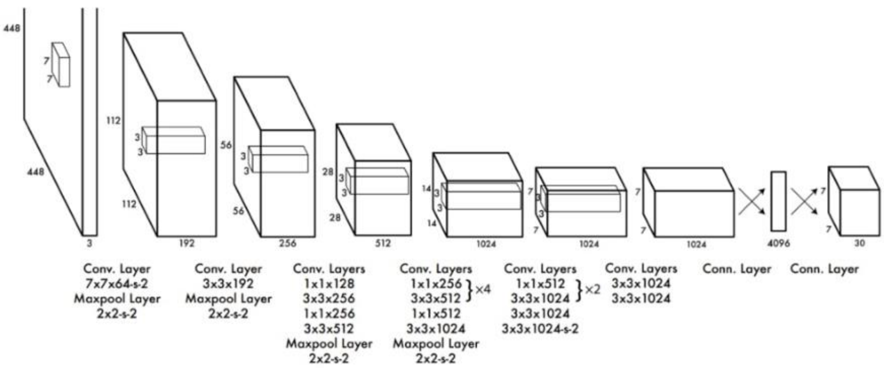


Figure 35 - YOLO Architecture
https://www.v7labs.com/blog/yolo-object-detection

The final, fully linked layer of YOLO predicts both class probability and selection rectangle coordinates. YOLO splits the input picture into S grids. If the center of an item falls within the boundaries of a grid cell, that cell is in charge of detecting the object. Each grid cell forecasts bounding boxes B and their confidence ratings. These confidence ratings represent the model's belief that the bounding box includes an item as well as the prediction's accuracy. Nonmaximal suppression (NMS) is a fundamental approach in YOLO models. NMS is a post-processing procedure used to increase object detection accuracy and efficiency. Multiple bounding boxes are frequently created for a single item in an image during object detection. These bounding boxes may overlap or be located in various places, but they all represent the same item. NMS is used to detect and delete redundant or incorrect bounding boxes, resulting in a single bounding box for each item in the picture. The experimental part of this work utilized the YOLO software v7 version, which boasts significant enhancements over previous versions. One of the primary improvements includes the use of anchor boxes, a set of preconfigured boxes with varying aspect ratios that are used to identify objects of various forms. YOLO v7 utilizes nine anchor boxes to identify a broader range of item shapes and sizes than earlier versions, thus reducing the occurrence of false positives. A noteworthy improvement in YOLO v7 involves the implementation of a novel loss function called "focal loss." Previous versions of YOLO utilized a standard cross entropy loss function, which has been shown to be less effective at identifying small objects. Focal loss mitigates this problem by minimizing the loss for accurately classified samples while prioritizing difficult cases, such as hard-to-detect objects. Additionally, YOLO v7 features higher resolution than previous iterations. The algorithm analyzes images at 608 x 608 pixels, an improvement from the previous 416 x 416 pixels used in YOLO v3. This increase in resolution allows YOLO v7 to detect smaller objects with greater accuracy. Moreover, YOLO v7's rapid processing speed is one of its chief advantages. With a processing speed of 155 frames per second, YOLO's basic model from the beginning qualifies it for sensitive real-time applications such as surveillance and self-driving automobiles, being substantially quicker than other cutting-edge object identification systems, which can only reach a maximum speed of 45 frames per second. Processing pictures, YOLO v7 outperforms other object detection algorithms in terms of accuracy, reaching an IoU (intersection over union) threshold of 0.5 and an average accuracy of 37.2%. [35]

[35] Source: Online interview by Rohit Kundu on 17 January 2023, available via link: YOLO, algorithm for Object detection explained (last access September 2023).

3.2 Data processing – Colab

Google Colab processed the data obtained from YOLO algorithm. It is a cloud-based platform that leverages the computational power of Google to execute codes. Jupiter Notebooks are used within this platform which allows users to create and run code in interactive cells that can complete a single analysis or processing procedure with a logical flow of information. Python is the most widely used and suitable programming language. To configure the notebook in Colab, the initial step is to utilize the GPU, followed by installing other Python modules and connecting Colab to Google Drive. This enables the creation of workbooks. Due to its features, Colab is highly advantageous for any data scientist or machine learning developer. Utilizing the power of the Cloud is crucial when handling massive amounts of data for analysis and processing. In essence, using Google Colab to run YOLO creates a user-friendly environment for training, evaluating, and exploiting object detection models while harnessing Google's cloud computing capabilities. [36]

Training starts by setting up the configuration on Colab and linking it to Google Drive to get the YOLO data files and source code. Adequate data preparation is vital for the model to learn correctly. To begin with, compile a collection of photos labeled with the objects you intend to identify, which is outlined in the "Materials and Methods" section before this chapter (the labels should specify both the object classes and their locations in the images). Then, organize the material into a folder structure on Google Drive. A main folder, such as "YOLO_Dataset," is created with three subfolders designated as "Train" (for 60% of the training data), "Test" (for 30% of the test data), and "Validation" (for 10% of the validation data). In order to assess the model's efficacy, the data should be sorted into sets for training, testing, and validation. The "Training" directory is utilized for the purpose of training the model, while the "Testing" directory is utilized to appraise the model's performance. Finally, the "Validation" directory is used to fine-tune the model's parameters throughout the training process. The train-validation-test split is a standard practice when training machine learning models. Its purpose is to ensure the model can generalize well to new (test) data and was not overfitted on the training data, which could lead to subpar performance on unknown data.

[36] Source: Online interview by Vito Gentile on 31 December 2019, available via link: Google Colab per il Machine Learning: cos'è e come si usa (last access September 2023).

The training parameters, including the model architecture, number of classes to be identified, training file names, and pre-trained weights, are defined in a configuration file. Once the YOLO model has been trained on Colab, it can recognize objects in images. The "Train" folder data is used to train the model, while the "Test" folder data is utilized to assess its performance. This metric measures the model's success in identifying objects in previously unseen data. Finally, the "Validation" dataset allows us to modify and optimize the model parameters to prevent overfitting (accurate predictions for training data but not for new data) and improve performance.

The paper presents the results of a series of training sessions, as outlined in the accompanying table that indicates the relevant train-validation-test split:

	Training sessions			
	1	**2**	**3**	**4**
(Total number of photo)	232	232	247	462
TRAIN	139	139	148	277
TEST	70	70	74	139
VAL	23	23	25	46

Table 2 - Number of photos by session number

Chapter 4 – Results

The initial findings outside the YOLO algorithm's training output relate to the dehydration patterns of tomatoes. As outlined in the "Materials and Methods" chapter for the third and fourth sets (that purchased the tomatoes), we recorded the weight reduction of the tomatoes on the trays and therefore the loss of moisture after each incubation in the oven. Table 3 presents the weight loss data for the third set along with their corresponding incubation temperatures and resulting dehydration curve.

TRAY	TRAY WEIGHT ONLY g	TOMATO WEIGHT g	T. WEIGHT AFTER 24H 40°C g	T. WEIGHT AFTER 24H 40°C g2	T. WEIGHT AFTER 2.5H 80°C g
A	12,2	418,6	276,4	181,4	94,4
B	12,3	532,8	376,9	270,2	164,3
C	12,3	266,9	184,4	116,2	62,9
D	12,4	377,9	257,2	193	113,7
E	12,4	383,6	264,3	185	115,8
F	12,4	417,7	309	201,4	108,6
G	22,9	689,3	463,6	296,6	182,2
H	22,4	828,1	581,7	419,4	311,9
L	5,6	168,1	113,2	72,7	47
M	22,5	859,8	650,3	403	246,5
N	22,4	802,5	555,4	373,6	242,1

Table 3 - Weight loss data for the third set

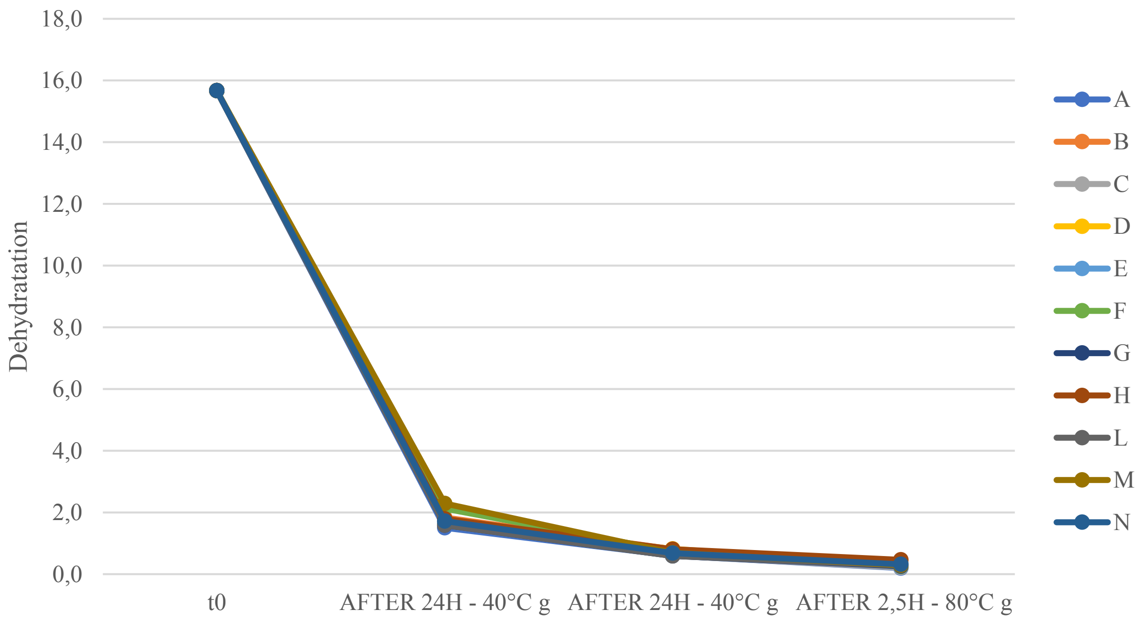


Table 4 - Dehydration curve for the third set

The dehydration curve of tomatoes shows the dehydration that occurred on a dry basis throughout the process. The graph shows a reduction in moisture content over time as tomatoes are dehydrated. The x-axis displays the duration between drying procedures, measured in hours for this example. The y-axis represents the dehydration value expressed on a dry basis by making the ratio of water weight to dry weight for each tray. As oven incubation and time spent in a temperature-controlled environment increased, a significant decrease in moisture content for individual trays of tomatoes was observed. During the early period, the curve was steeper, indicating a quicker loss of moisture from the tomatoes. However, as the moisture content decreased, the curve became less steep due to the difficulty in removing remaining moisture. The fourth group underwent an identical study, with the findings presented in Dehydration Curve Graph and Table No.5.

TRAY	TRAY WEIGHT ONLY	TOMATO WEIGHT g	T. WEIGHT AFTER 24H 40°C g	T. WEIGHT AFTER 24H 40°C g	T. WEIGHT AFTER 24H 40°C g
A	14,1	458,1	347,4	266	181,9
B	13,8	480,7	386,9	271,1	167,6
C	13,8	462,2	342,4	226,2	124,3
D	13,7	262,6	189,7	115,1	53,5
E	13,8	229,4	148,4	83	40,9
F	13,8	288,3	213,9	113,5	62,4
G	13,7	266,3	159,3	96,6	30,7
I	13,7	315,2	237,5	108,4	43,4
L	5,6	99,5	56,7	20	3,8
M	5,5	159,3	103,1	38,3	6,3
N	5,6	276,8	227,6	168,8	84,9
O	5,6	211,4	165	91	36
P	5,5	253,3	193,3	127,9	61,7
Q	5,6	258,3	196,1	132,8	82,6
R	5,7	125,4	90	46,3	23
S	5,4	126,7	92,6	42,2	16,9
T	5,6	252,7	200,5	146,2	86,8
U	5,6	220,7	174,4	97,3	52,6

Table 5 - Weight loss data for the fourth set

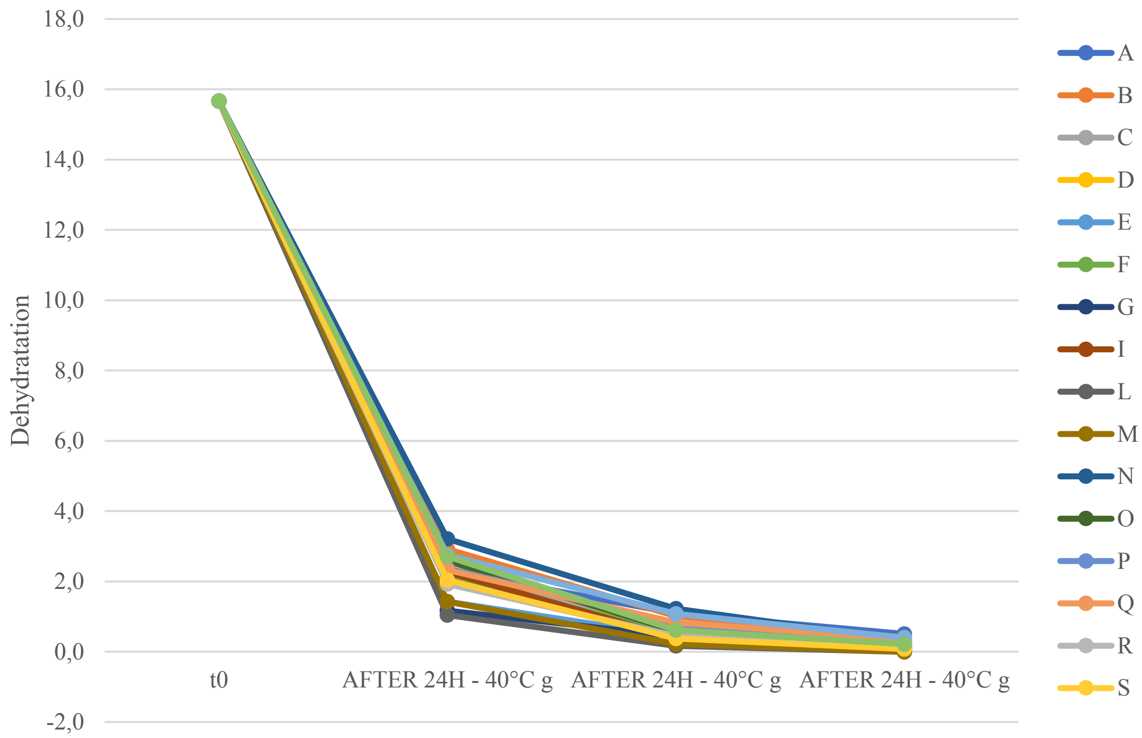


Table 6 - Dehydration curve for the fourth set

This fourth group shows a considerable decrease in tomato weight at the conclusion of the fourth day of research. These statistics assist us to understand the validity range of our model; specifically, it will only be valid within this range of tomato dehydration and moisture loss. It is critical to emphasize that the validity of an experimental model is a key factor to examine, especially when it comes to potential practical applications like the one described in this study.

Various output parameters were collected during the training sessions using Google Colab. It is essential to consider these parameters while evaluating our model. The initial set of training results was not used because we identified early on that dividing the model into the third class described as "Uncertain" would not clearly and accurately represent the model. This would lead to unwanted confusion and ambiguous indicators of recognition.

4.1 Second train

Consider the results of the second training set validation, which are summarized in Table 6 with a resolution of 640 and an infinite time of 27.7 milliseconds. Resolution, abbreviated as Res, refers to the resolution of the images used for training. YOLO, being a real-time object detection neural network, can be trained on photos of different resolutions. Higher resolutions can improve model accuracy, but they also require more processing resources. Therefore, it is customary to conduct initial training at lower or medium resolutions and then stabilize the model. "Infinite time," or "Inf time" in short, refers to the duration required for training when the model fails to converge or takes an abnormally prolonged time to reach sufficient convergence. For neural network training, a shorter "inf time" is desirable as it signifies faster convergence of the model and requires less time to attain an acceptable outcome.

	Labels	P	R	mAP50	mAP95
All	1842	0,309	0,885	0,548	0,405
H	836	0,206	0,986	0,603	0,502
S	1006	0,412	0,784	0,494	0,309

Table 7 - Output of the second train

The model has created a total of 1842 labels, consisting of 836 "Healthy" and 1006 "Spoiled" tomato classifications, which is a common feature for all training sets (Table 6). However, each set will have low Precision and Recall values.

For the second train, we achieved an overall Precision score of 30.9%. This value denotes the proportion of accurate positive predictions made by the model. Accordingly, when the model labels a tomato as either "Healthy" or "Spoiled", there is a 30.9% likelihood of it being classified correctly. In contrast, the overall Recall score of 88.5% indicates that the model can detect 88.5% of all healthy and spoiled tomatoes within the validation test images. Analyzing the data for each class (H and S), it can be inferred that the "Precision" value for healthy tomatoes, which is 20.6%, indicates a 20.6% probability that the model accurately predicted the tomato to be healthy. Similarly, a "Precision" of 41.2% for spoiled tomatoes indicates that 41.2% of the model's predictions for spoiled tomatoes are indeed spoiled. In addition, we can make comments on the "Recall" values observed for each class. The model's high performance of 98.6% "Recall" for healthy tomatoes indicates effective capture of most healthy tomatoes in validation tests. This result can be explained by the second train, which had a significant number of labeling for healthy tomatoes (4281) compared to spoiled tomatoes (344), as detailed in the "Materials and Methods" section. Accordingly, a 78.4 percent "Recall" rate for spoiled tomatoes denotes that the model captures 78.4 percent of spoiled tomatoes in the images. Nevertheless, this result implies the need for further improvement.

Of these two parameters, we can also examine the graph or curve that describes them. Figure 36 displays the "P curve" for the validation set of the second train.

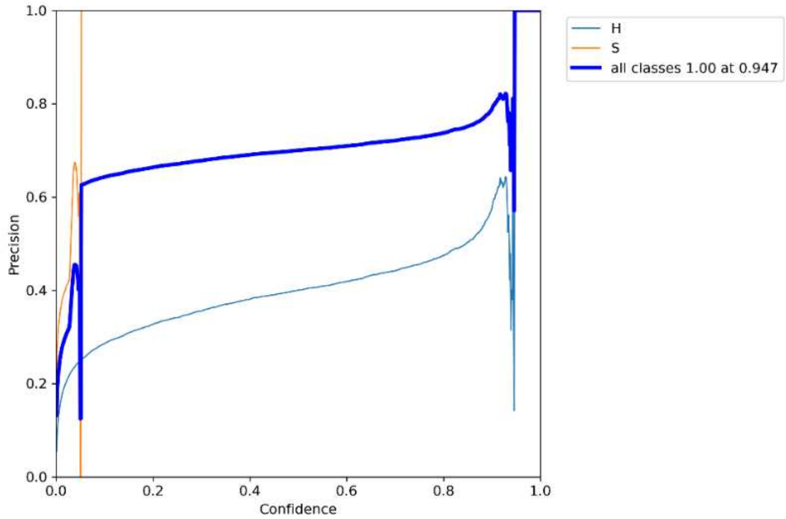


Figure 36 - P curve of the second train

The threshold values or confidence level above which an observation is positively classified, and below which it is negatively classified, are represented on the x-axis. This value range is between 0 and 1. On the other hand, the y-axis depicts the accuracy of the model, which is the metric that measures the proportion of correct positive predictions made by the model. The graph illustrates the model's challenges in sustaining total precision due to multiple peaks and dips across varying confidence levels. As the confidence level increases, the model's precision shows an upward trend. However, at threshold values, it displays peaks or declines, resulting in an overall value of 30.9%. Similarly, the "R curve" or Recall graph presented in Figure 37 can be assessed.

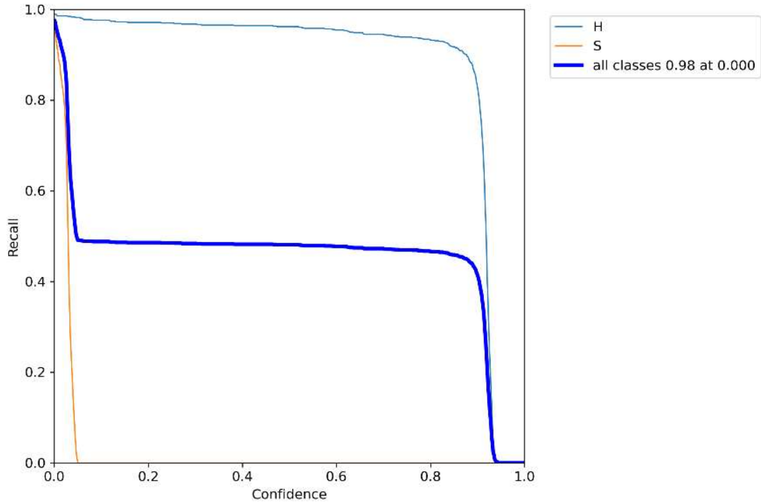


Figure 37 - R curve of the second train

The horizontal axis displays the threshold value or confidence level that distinguishes positive from negative observations. The vertical axis shows the model's sensitivity, with "Recall" indicating the proportion of true positives to the total number of true positives and false negatives. This metric measures how accurately the model identifies positive examples. The graph illustrates an irregular pattern, demonstrating a higher recall for the healthy tomato class compared to the spoiled tomato class. As confidence levels increase, both classes show a decrease in the Recall value. The decline is fast and sharp for the spoiled class while gradual but sudden for the healthy class.

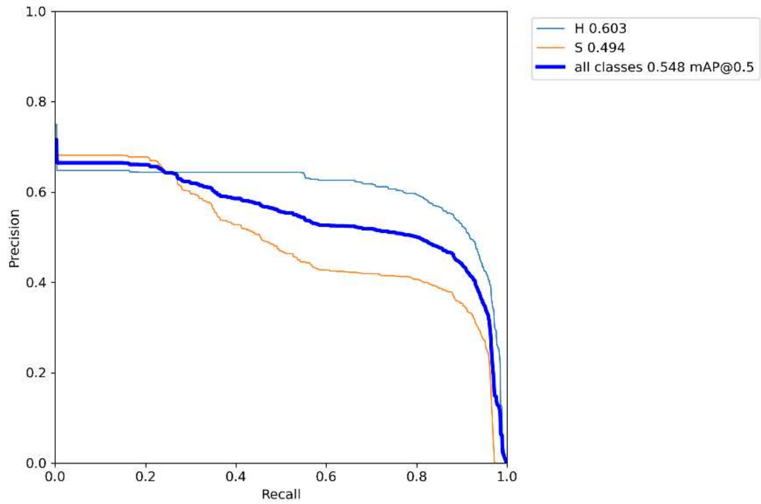


Figure 38 - PR curve of the second train

The PR (Precision-Recall) curve graph, on the other hand, is used to visualize the accuracy and recall of a classification model when the classification threshold varies. The threshold value begins at zero and steadily increases to one. The model's accuracy is represented by the y-axis. Precision is the percentage of predictions made by the model that are correct. The recall or sensitivity of the model is shown by the x-axis. A straight line from the upper left corner to the upper right corner, then falling into the lower right corner, would be a perfect PR curve. In practice, such as ours, the shape may change depending on the model's performance. Sometimes drawing a horizontal reference line (baseline) that indicates the average accuracy of the random forecasts is also useful. To determine whether the model outperforms the random predictions, compare the PR curve to the baseline. In other words, as the threshold changes, the curve demonstrates how the model balances accuracy (how accurate it is) and recall (how well it collects positive samples). Calculating the area under the PR curve (AUC-PR) is a standard approach to assess the overall performance of the PR curve. A higher AUC-PR score implies that the model is performing better. Following these criteria, we may better comprehend and confirm the model's potential for improvement.

Table 7 displays two additional metrics utilized for evaluating the performance of a classification or object detection model in computer vision issues. These metrics gauge the average accuracy (AP) at varying confidence levels for model predictions. mAP50 computes the average accuracy of model predictions by solely considering predictions with a probability or confidence greater than or equal to 50% (0.5). To calculate mAP50, the model generates predictions for each object in the image, accompanied by a confidence value. The average accuracy of the predictions is calculated by excluding those with less than 50% confidence. mAP50 is helpful in evaluating the model's ability to make predictions at a moderate confidence level. The value displayed in Table 6, which indicates a score of 0.548 for all classes, demonstrates that the model has an average accuracy of 54.8 % for predictions made with a confidence level of 50 % or higher. The provided metric value of 0.603 denotes that, on average, the model accurately predicts the "Healthy" class with a confidence of 50% or higher 60.3% of the time. In contrast, for the "Spoiled" class, the obtained value is 0.309, which indicates that the model performs with an accuracy of 30.9% in predictions made with a confidence of 50% or higher. Similarly, mAP95 is a metric that approaches mAP50, but it calculates the average accuracy by considering only forecasts with a probability or confidence greater than or equal to 95%. It is a valuable measure to evaluate the model's ability to make precise and confident predictions. In this second training session, the value of 0.405 implies that, on average, the model has a 40.5% accuracy in the predictions made with a 95% confidence level or higher for all classes. The average accuracy of the model is 50.2% for predictions made with a 95% or higher confidence level, specifically for the "Healthy" class, as indicated by the value of 0.502. In contrast, the "Spoiled" class has an average accuracy of 30.9% for the same confidence level, as shown by the value of 0.309. These values emphasize the need for improvement in the model's accuracy for both confidence levels.

Thanks to the results in Table 7 of the second validation set, we can evaluate the machine learning model's performance using an additional tool. This tool is called a Confusion Matrix, which is essentially a table that visualizes the model's ability to classify different data categories. In a confusion matrix, the rows convey the actual classes of data, while the columns convey the classes predicted by the model. The matrix segregates the model's predictions into four primary categories, as discussed in the "Materials and Methods" chapter:

<table>
<tr><td></td><td colspan="2">Class Predictions</td></tr>
<tr><td rowspan="2">Actual classes</td><td>TP</td><td>FN</td></tr>
<tr><td>FP</td><td>TN</td></tr>
</table>

Table 8 - Confusion Matrix

To compute TP, TN, FP, and FN from P and R values, an extra evaluation metric is imperative to introduce. This metric accounts for P and R and is known as the F1 score. The F1 score represents the harmonic mean of P and R, thereby considering both metrics and heavily punishing models that have exceptionally low values in either metric. A high F1 score (ranging from 0 to 1) signifies effective classification by the model, while a low score indicates poor performance. Calculated as follows:

$$F1\ score = \frac{2\ \times (Precision\ \times Recall)}{Precision + Recall}$$

This enables us to derive F1 scores for both analyzed classes. The "Healthy" class exhibits an F1 score of 0.3407, while an F1 score of 0.540 is observed for the "Spoiled" class. The following chart summarizes these results.

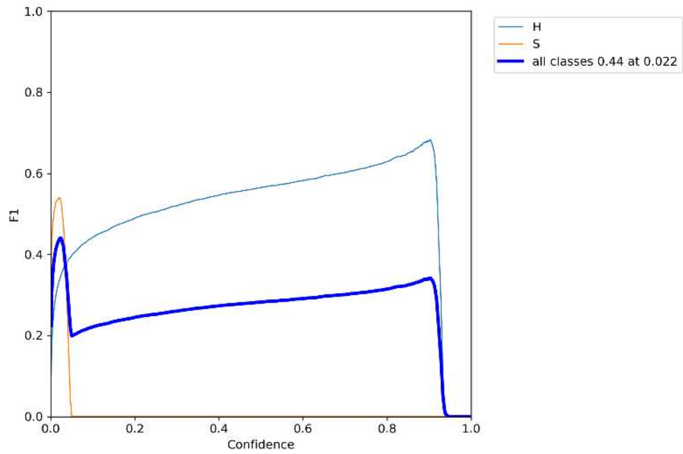


Figure 39 - F1 score curve for the second train

The chart depicts the fluctuation of F1 score with alterations in decision threshold or parameter. The x-axis represents varied decision threshold values, ranging between 0 and 1. The y-axis presents corresponding F1 score values of each parameter, also ranging between 0 and 1. The maximum point on the curve designates the ideal decision threshold value for the model to attain maximum F1 score. This is crucial since it informs us which model setup gives the optimal balance between "Precision" and "Recall." In relation to the second practice run, it is apparent that the graph lacks linear conformity, highlighting the need to assess the model's enhancement with subsequent runs.

By utilizing the F1 score values for each class and applying the "Precision" and "Recall" formulas provided below, a system with unknowns can derive the four values for the four main categories (TP, FP, TN, FN):

$$Recall = \frac{TP}{TP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

The results are presented in Table 9, where the number of labels assigned by the model during validation for the "Healthy" and "Spoiled" classes correspond to values of 836 and 1006, respectively:

	H	S
TP	38	274
FP	148	100
TN	74	306
FN	576	326

Table 9 - Value of the four main categories for the second train

Finally, the Intersection over Union (IoU) is a helpful metric for evaluating an object detection model's accuracy by measuring how well the model's predictions overlap the true object positions in an image. The IoU value ranges from 0 to 1, where 0 means no overlap between the bounding boxes and 1 indicates perfect overlap between the predicted and reference bounding boxes. As previously stated in the "Materials and Methods" chapter, a higher IoU value indicates a better match between model predictions and reference truth. The IoU formula, which employs TP, FP, and FN metrics, is as follows:

$$IoU = \frac{TP}{TP + FP + FN}$$

Substituting the previously obtained values from the confusion matrix results in an IoU value of 0.23 for the second training. This value confirms that there is a low match between the model prediction and the ground truth.

The second validation set's analysis can be concluded by examining batch examples of images labeled during the validation process. Batches refer to groups of data samples processed simultaneously by the machine learning model during training. In batch 1 image 40, all training-generated labels have been identified:

Figure 40 - Batch 1 labels second train

In image 41, which is identical to batch 1, the model's prediction labeling is visible. It accurately labeled the tomatoes with clear boundaries and correctly identified the membership classes on 3 out of 8 images. By contrast, it failed to correctly identify the membership class and bounding box for the remaining four images in the batch. For instance, in the case of the second figure at the bottom left, it made no label predictions whatsoever.

Image 41 - Batch 1 predictions second train

It can be concluded that the accuracy values of the second train are still low, as evidenced by the general values of "Recall," "Precision," and the accuracy percentages obtained with 50% or 95% confidence levels. These results enabled us to enhance the model and proceed to the third train.

4.2 Third train

Let us examine the results from the third train's set validation, summarized in Table 10 with a "Res" of 640 and an "Inf time (ms)" of 28.3.

	Labels	P	R	mAP05	mAP95
all	1842	0,857	0,929	0,947	0,805
H	836	0,851	0,929	0,937	0,803
S	1006	0,862	0,928	0,956	0,808

Table 10 - Output of the third train

The results of this model are quite promising, indicating significant success in accurately classifying tomatoes into two groups, "Healthy" and "Spoiled." The model had an accuracy of 85.1% for the "Healthy" (H) class. This indicates that when the programme predicted that a tomato was "Healthy," it was correct 85.1% of the time. Furthermore, this category's recall of 92.9% shows that it accurately identified 92.9% of all healthy tomatoes in the dataset. The accuracy for the "Spoiled" (S) class was 86.2%, which means that 86.2% of the positive predictions were right. Furthermore, the 92.8% recall indicates that the model correctly detected 92.8% of all spoiled tomatoes in the sample. These findings show that the model is very reliable in recognising spoiled tomatoes, which is critical in controlling the spread of contaminated food products.

As previously stated, we can also examine the graphical representation of these two parameters. Figure 42 displays the "P curve" for set validation of the third train.

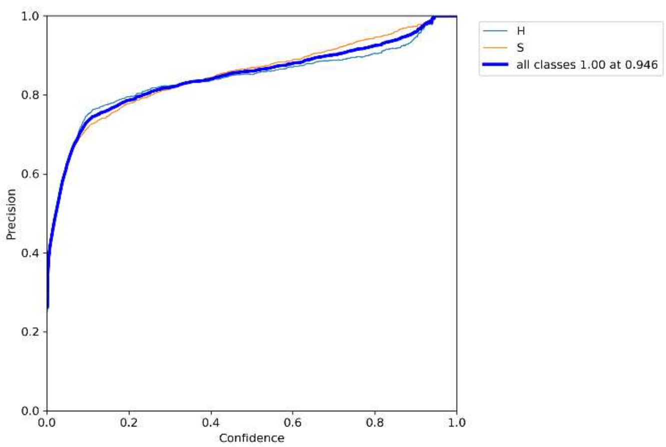


Figure 42 - P curve of the third train

The graph depicting the second train shows a more linear and homogeneous pattern compared to the third train. It is evident that as the confidence value increases, the Precision also increases. Similarly, in Image 43, one can observe the variation in recall as the threshold changes. It is observable from the graph that the model can accurately capture most of the positive examples, although it is crucial to bear in mind that increasing precision can result in decreased recall. Therefore, it is necessary to select a confident value that is rationalized concerning this matter and identify the requirements and objectives intended to be achieved with the model. For instance, one might prioritize a higher sensitivity (thus recall) and consequently sacrifice precision, or vice versa.

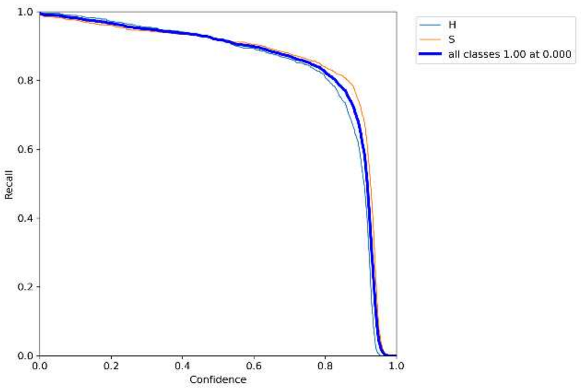


Figure 43 - R curve of the third train

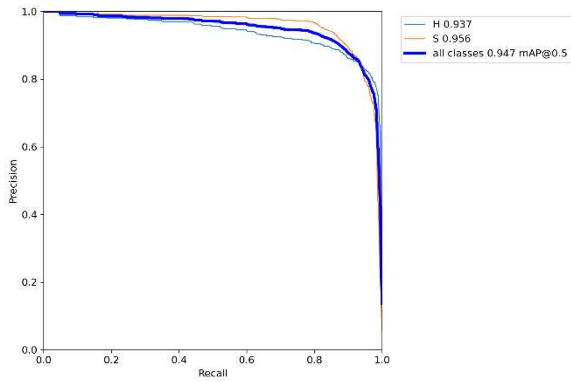


Figure 44 - PR curve of the third train

As mentioned earlier, Image 44 displays the PR curve plot, which provides a crucial visual representation of model performance when categorizing tomatoes as either 'Healthy' (H) or 'Spoiled' (S). Upon examination, we can observe that the precision for the 'Healthy' (H) category increases almost linearly with increased recall along the PR curve. The results demonstrate that the model accurately identifies most healthy tomatoes while maintaining high precision. This indicates that positive predictions for this category are consistently accurate. With respect to the 'Spoiled' (S) category, the PR curve shows a similar trend as the 'Recall' value increases, suggesting that the model is equally adept in detecting spoiled tomatoes and has high accuracy in positive predictions for this category. Overall, the PR curve results validate the model's reliability in differentiating between the two tomato classes. A hypothetical assessment of the area under the PR curve showcases that the value is notably higher in comparison to the second train, hence indicating superior performance.

Table 10 presents the third train metrics measuring the average precision (AP) at varying confidence thresholds for the model predictions. The mAP50 score of 0.947 for all categories confirms the model's high level of accuracy in detecting healthy and spoiled tomatoes, even at 50% overlap with the reference truth. The model can accurately differentiate between healthy and spoiled tomatoes even when there is a 50% overlap between its prediction and the reference truth. Additionally, the mAP95 score of 0.805 for all classes indicates that the model maintains accuracy in identifying both healthy and spoiled tomatoes even at a high level of overlap (95%) between its prediction and the reference truth. This implies that the model retains high accuracy despite significant overlap between the prediction and the reference truth, a crucial factor for detecting tomatoes under varying conditions. In summary, the model is highly reliable in distinguishing between healthy and damaged tomatoes in both moderate and extremely high overlap situations. The values of mAP50 and mAP95 support this claim. The "Healthy" class has an mAP05 value of 0.947, indicating high accuracy in detecting healthy tomatoes at a 50% overlap. The model also maintains good accuracy at a 95% overlap, with an mAP95 value of 0.805 for the "Healthy" class. The mean average precision (mAP) at 0.5 threshold for identifying spoiled tomatoes is 0.956, indicative of a high level of accuracy. Moreover, the mAP at 0.95 threshold is 0.808, implying that the model is capable of maintaining good precision even at high overlap levels.

In this third train, we can also calculate the value of the F1 score using the mathematical formula given above. This calculation yields an F1 value of 0.891, allowing us to determine the F1 score values for the two classes being analyzed. Notably, the "Healthy" class has an F1 score value of 0.888, while the "Spoiled" class has a value of 0.893. The obtained values are shown graphically below:

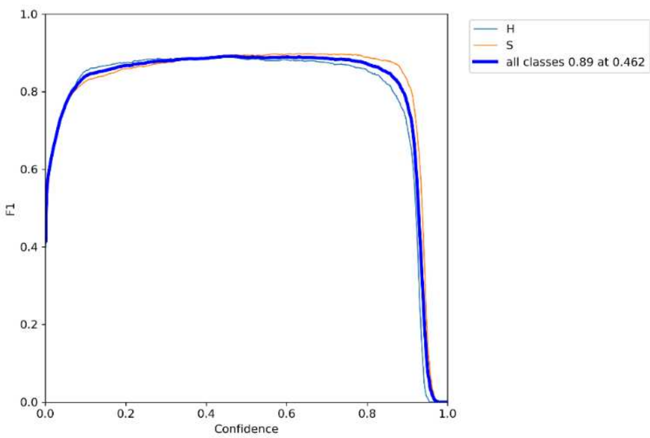


Figure 45 - F1 score curve for the third train

An overall F1 score of 0.891 is considered a good result. The F1 score of 0.888 for the "Healthy" category reveals the model's good proficiency in accurately classifying samples in the "Healthy" category, considering both precision and recall. Nonetheless, it is crucial to examine the context to ascertain the acceptability of this value and whether or not further enhancement of model performance is required for this category. The F1 score of 0.893 for the "Spoiled" category denotes the model's aptitude in accurately categorizing instances from the "Spoiled" group, incorporating both precision and recall. It is pertinent to assess the context to discern the acceptability of this value or the requirement for additional performance advancement for this classification, as with the "Healthy" category. Overall, if the F1 scores for both classes are similar, it implies that the model is balanced in its ability to classify both classes.

Thus, by knowing the F1 score values of both classes and the formulas for "Precision" and "Recall", one can derive the four values of the four main categories (TP, FP, TN, FN) through a system with unknowns.

	H	**S**
TP	407	533
FP	63	59
TN	228	372
FN	138	42

Table 11 - Value of the four main categories for the third train

As a result, the model's accuracy can be assessed by calculating the IoU value, which is an added metric. During the third training session, the obtained value was IoU = 0.81. When the IoU (Intersection over Union) value is 0.81, there is a high overlap between two bounding boxes or regions, and this value is generally considered to be very good. An IoU score of 0.81 signifies that there is an 81% overlap between the two regions, which could be two bounding boxes or any other type of region. This implies that the two regions are comparable, or that one of them is a reliable predictor of the other. Overall, an IoU score of 0.81 indicates high prediction quality and overlap between regions, implying accurate model predictions and region alignment. It's worth highlighting the noteworthy improvement over the second training.

For this third train, we can also analyse the same batch of output to try to understand how much the model has improved. The picture 46 displays all labels created during the training phase:

Figure 46 - Batch 1 labels third train

Contrarily, Image 47 depicts the model labels used for prediction. It is clear that, in contrast to the second train, bounding boxes were created for every tomato in the photos, even more than those that were identified during training. It is evident that class detection accuracy has improved as well, accurately reflecting the accuracy numbers mentioned above and acquired. Although accuracy is 94.7% with a confidence level of 50%, it can be noticed that certain inaccuracies still exist. For instance, tomatoes categorized as "Spoiled" when they are actually clearly healthy.

Figure 47 - Batch 1 predictions third train

4.3 Fourth train

This final opportunity for improvement leads us to the fourth and final train. The results of the fourth train set validation are summarized in Table 11 with a "Res" of 640 and an "Inf time (ms)" of 28.3.

	Labels	P	R	mAP50	mAP95
All	1842	0,894	0,913	0,952	0,822
H	836	0,903	0,903	0,932	0,832
S	1006	0,885	0,885	0,893	0,812

Table 12 - Output of the fourth train

Based on the values, we can conclude that the model has a good accuracy of about 89.4%. This suggests that the model's positive predictions are correct 89.4% of the time. In simpler terms, when a tomato is classified as either "Healthy" or "Spoiled" by the model, there is an 89.4% chance that this prediction is accurate. Meanwhile, the model's overall "Recall" of 91.3% means that it can detect 91.3% of healthy and spoiled tomatoes in the validation test images. Analysing the data for each tomato class (H and S), it can be inferred that the precision value for healthy tomatoes, which stands at 90.3%, indicates a 90.3% likelihood that the model correctly predicted the tomato's health status. For the same reason, a "Precision" score of 88.5% for identified spoiled tomatoes indicates that 88.5% of the tomatoes classified as spoiled by the model are indeed spoiled. Additionally, we can observe the "Recall" values for each class. A "Recall" score of 90.3% for healthy tomatoes suggests that the model is highly effective at detecting most of the healthy tomatoes in the validation test images. The model's "Recall" of 88.5% for spoiled tomatoes indicates that it can identify 78.4% of the spoiled tomatoes in the images. These results suggest that the model effectively classifies "Healthy" and "Spoiled" tomatoes. The high precision of the model demonstrates that it makes few errors when making positive predictions for each class, while high recall indicates that it can correctly identify most of the positive items for each class.

Consequently, we may proceed to examine the graphs of these two parameters. Image 48 displays the "P-curve" for the set validation of the fourth train:

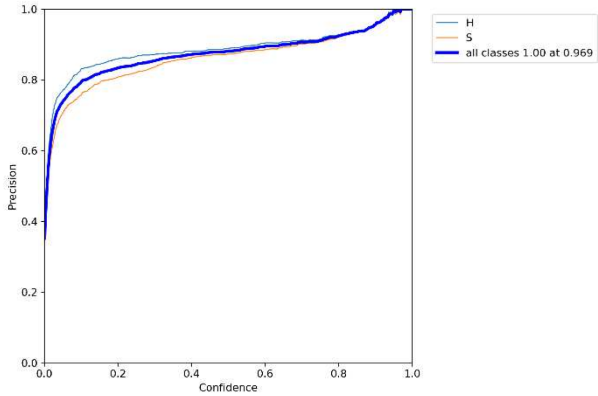


Figure 48 - P curve of the fourth train

The P Curve illustrates the model's accuracy variation across different decision thresholds. Moreover, the graph presents a comparable look to that of the third train and outlines how the confidence value's increment steadily increases Precision. The trend in precision is similar for both classes, although the "healthy" class exhibits slightly higher precision. Image 49 depicts the R curve for the "Recall" metric.

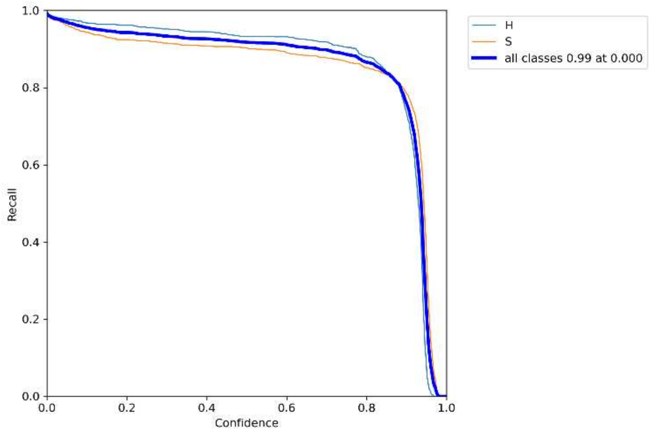


Figure 49 - R curve of the fourth train

This graph displays a comparable trend to that observed in the previous train, further confirming the good results obtained in both trains. The model shows a good recall, which represents the ability of the model to correctly identify the tomatoes that are actually classified as healthy or spoiled, with high values for both the "healthy" class (0.903) and the "spoiled" class (0.885). This suggests that the model effectively captures a majority of tomatoes from both categories, minimizing the risk of misclassifying a tomato as healthy or spoiled.

Consequently, these findings imply that the model has the capability of recognizing both healthy and spoiled tomatoes.

Finally, image 50 illustrates the graph of the PR curve:

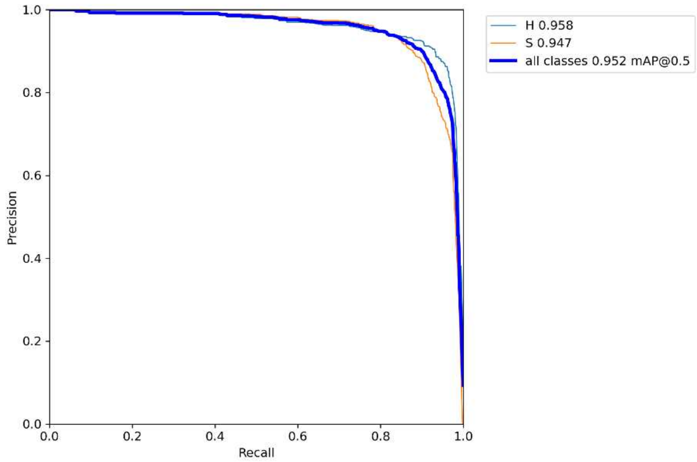


Figure 50 - PR curve of the fourth train

The trend in this image closely resembles that of the second train. Examining the overall trend of the PR curve, Precision decreases as Recall increases. This is a common trade-off in PR curves: lowering the decision threshold to increase Recall (i.e., searching for more positives) risks including false positives and reducing Precision. The PR curve reflects the model's dynamic behavior in distinguishing between healthy and spoiled tomatoes. High Precision and Recall values for both classes indicate good discriminatory capability. However, selecting the appropriate decision threshold is crucial in balancing Precision and Recall based on the specific requirements of minimizing false positives or false negatives in the application context. In the fourth train, there is a significant increase in the area under the PR curve value as compared to the second train, even though it is only visually observed.

As previously performed, another metric for evaluating the fourth train can be the average precision (AP) at various confidence thresholds for model predictions. The mAP50 metric computes the average precision of model predictions, only factoring predictions with a likelihood or confidence of at least 50 % (0.5). To calculate mAP50, the model delivers predictions for each object in the image with an affiliated confidence value. The average prediction accuracy was calculated by only considering those with a confidence level of 50% or greater. The information displayed in Table 12 indicates that the model has an average prediction accuracy of 95.2 % for predictions with a confidence level of 50 % or higher. The value of 0.932 suggests that, on average, the model accurately predicts with 93.2% confidence for the "Healthy" class with at least a 50% confidence rating. For the "Spoiled" category, however, the value reported is 0.893, indicating that the model predicts with 89.3% accuracy with at least a 50% confidence rating. Similarly, mAP95 is a metric that closely resembles mAP50, but it determines average accuracy only by considering predictions with a probability or confidence equal to or greater than 95%. It proves beneficial when evaluating the model's capability of generating highly accurate and confident forecasts. The obtained value of 0.822 in the fourth train reveals that, concerning all categories, the model achieved an average accuracy of 82.2% in predictions made with 95% confidence or above. The average accuracy of the model's predictions, with 95% confidence or higher, for the "Healthy" class is indicated by the value of 0.832, which equates to 83.2%. In contrast, for the "Spoiled" class, the model's average accuracy in predictions with 95% confidence or higher is indicated by the value of 0.812, which equates to 81.2%. The data suggests that the model achieves high accuracy in predicting the health status of tomatoes with confidence. Furthermore, there was significant progress from the second training, and a minor improvement from the third training.

Once again, we can calculate the F1 score using the provided mathematical formula based on the available data. This yields an F1 value of 0.903 and enables us to obtain the F1 score values for both classes under analysis. For the "Healthy" class, we recorded an F1 score value of 0.903, while the "Spoiled" class scored 0.885. We observe a slight increase in the total F1 score value compared to the third set, indicating satisfactory performance of the model in classification. These values are summarized in the graph presented below:

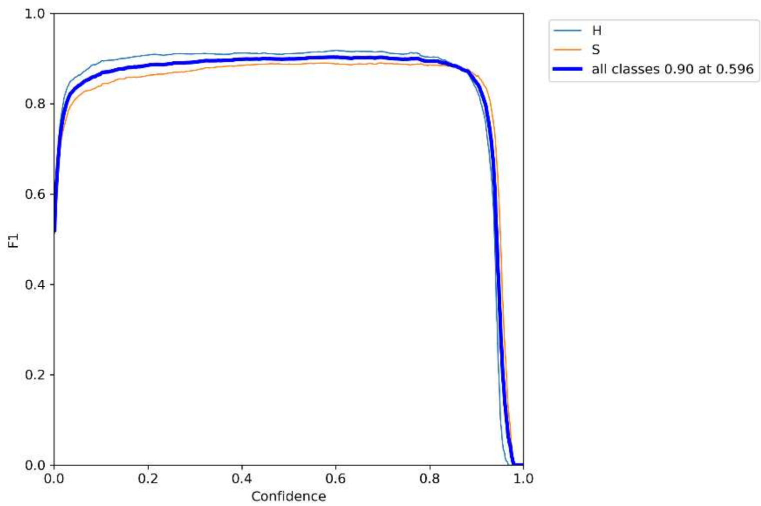


Figure 51 - F1 score curve for the fourth train

The F1-score of 0.903 signifies a remarkable balance of precision and recall in tomato classification. This result implies that the model successfully attains high precision in identifying both healthy and spoiled tomatoes while also capturing the majority of true positives in both categories. A noteworthy F1-score of 0.903 for the "Healthy" class demonstrates the model's exceptional accuracy and sensitivity in recognizing healthy tomatoes. The model exhibits dependable aptitude in precisely identifying healthy tomatoes without compromising the overall accuracy. The F1 score of 0.885 for the "Spoiled" group underscores its capacity to identify spoiled tomatoes. Once more, this value demonstrates a satisfactory equilibrium between Precision and Recall, signifying that the model can effectively categorize spoiled tomatoes without disregarding true positives. The high F1-scores imply the model's effectiveness and robustness in classifying tomatoes based on their condition. A well-trained and reliable model is indicated by the high accuracy and good ability to capture true positives in the Healthy and Spoiled classes, as shown in the graph above.

Then again, knowing the F1 values of the two classes and the formulas of "Precision" and "Recall", it is possible to derive, through a system of unknowns, the four values of the four main categories (TP, FP, TN, FN):

	H	**S**
TP	350	464
FP	30	58
TN	300	425
FN	25	59

Table 13 - Value of the four main categories for the fourth train

As a result, the value of l IoU can be calculated, which acts as an additional metric for assessing the model's accuracy. The obtained value in the fourth train is IoU = 0.83, which is slightly higher than that of the third train. The IoU value of 0.83 signifies a significant overlap between the two bounding boxes, indicating that approximately 83% of the two regions overlap.

By analyzing the images of the same output batch, we can determine if the model has improved over the third training phase. Image 52 displays all the labels that were created during the training phase:

Figure 52 - Batch 1 labels fourth train

Image 53, on the other hand, displays the model labels generated during prediction. It's evident that 7 out of 8 images precisely mirror the labels generated during the training phase. However, there remains a slight inaccuracy in the third image in the upper right corner, where the prediction model marked tomatoes as "Spoiled," even though they are healthy. While the model appeared to regress in comparison to the third train, where it successfully classified the class, the high accuracy achieved in the other batch images should still be noted.

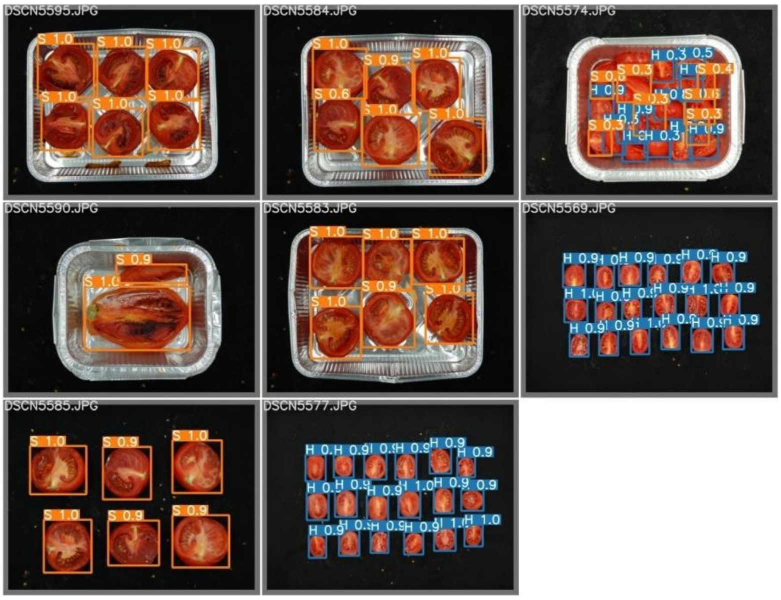


Figure 53 - Batch 1 predictions fourth train

The model has demonstrated significant advances in accuracy and reliability based on the outcomes from its last three training sessions. The interpretation of these findings should consider the context in which they were obtained. During the second, third, and fourth sessions, we increased the types of tomato species that were used and added more complexity to the identification process, moving from a "controlled" environment with a black background to a context that better simulates a production environment where tomatoes are randomly arranged in trays. Despite achieving high accuracy and a high level of confidence in the results, it is important to note that the model is susceptible to errors and cannot be considered perfect in its identification and classification of tomatoes. Nonetheless, these results demonstrate significant advancement in the model's ability to detect both healthy and spoiled tomatoes. The development of artificial intelligence for enhancing tomato sorting process in production facilities constitutes an important milestone, although there may be further improvements to be made in the future.

Additional examples of image batches are provided below to illustrate the improvement from the first to the fourth train.

Figure 54 - Batch 2 labels

Figure 55 - Batch 2 predictions first train

Figure 56 - Batch 2 predictions second train

Figure 57 - Batch 2 predictions third train

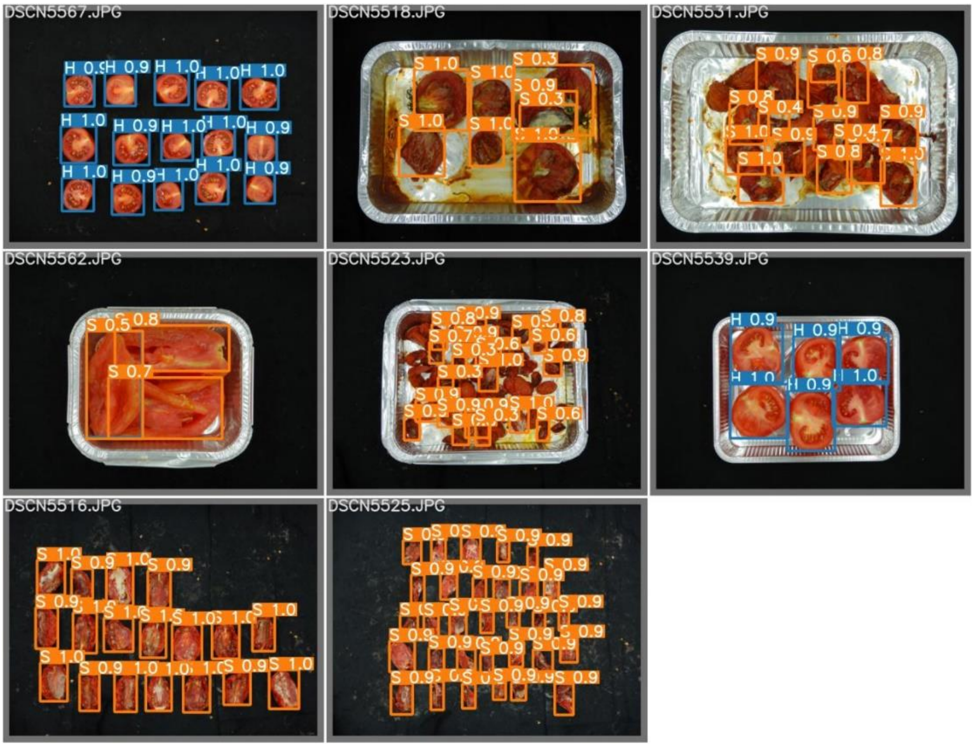


Figure 58 - Batch 2 predictions fourth train

Chapter 5 – Discussion

Analysing the results from various training models is crucial in assessing the overall effectiveness of the approach in identifying "Healthy" and "Spoiled" tomatoes. Significantly different results were obtained from the three trainings, namely the second, third, and fourth, reflecting the evolution of model performance. Initially, during the second training, the model struggled to produce accurate and clear predictions, resulting in an overall accuracy of only 30.9%. The model required improvement, which was achieved during the third training. The performance of the model witnessed a substantial increase, with an overall accuracy of 85.1%, indicating its ability to accurately distinguish between "Healthy" and "Spoiled" tomatoes. Additionally, Recall significantly improved, reaching 92.9% for the "Healthy" class and 92.8% for the "Spoiled" class. The findings imply that the third training session improved the model's identification accuracy. Subsequently, during the fourth training session, the model continued to show significant enhancement. The overall accuracy increased to 89.4%, with a recall rate of 91.3%. These results verify the continuous improvement of the model's performance in distinguishing between "Healthy" and "Spoiled" tomatoes.

During the course of the model's trials and various trainings, multiple metrics were analysed to evaluate overall performance, as outlined in the "Results" section. Generally, these metrics offer a more detailed understanding of the model's capability to classify "Healthy" and "Spoiled" tomatoes in various contexts and with different confidence thresholds.

For instance, when drawing final conclusions about the mAP50 and mAP95 metrics, it can be stated that during the second training session, a mAP50 value of 0.548 was achieved. This value indicates an average accuracy of 54.8% in predictions with 50% or higher confidence. In the third training session, this value remarkably improved to a mAP50 of 0.947, denoting an average accuracy of 94.7%. Additionally, the mAP95 metric experienced a significant improvement, increasing from 0.405 to 0.805 from the second to the third training session. The model's performance was further enhanced after the fourth training, exhibiting an exceptional mAP50 of 0.952 and a mAP95 of 0.822. These outcomes indicate commendable accuracy in average predictions with high confidence levels, affirming the model's improved ability to make precise and confident predictions. With regards to the F1 scores, we observed values of 0.3407 for the "Healthy" class and 0.540 for the "Spoiled" class during the second training. The overall F1 score increased from 0.891 in the third training to 0.903 in the fourth, highlighting a noticeable improvement. The results demonstrate a noteworthy advancement in the model's aptitude to equalize precision and recall. Moreover, the Intersection over Union (IoU) presents substantial growth in model performance. During the second training, we attained an IoU of 0.23, disclosing a minimal overlap between model predictions and ground truth. However, during the third training, the Intersection over Union (IoU) rose to 0.81. In the following training session, the value further increased to 0.83, indicating a marked improvement in the model's predictive accuracy.

Overall, the data suggests a gradual enhancement in model performance throughout the different trainings as we can see in the Table 14. Specifically, the third and fourth sessions yielded noteworthy advancements compared to the second, providing strong evidence supporting the effectiveness of the method.

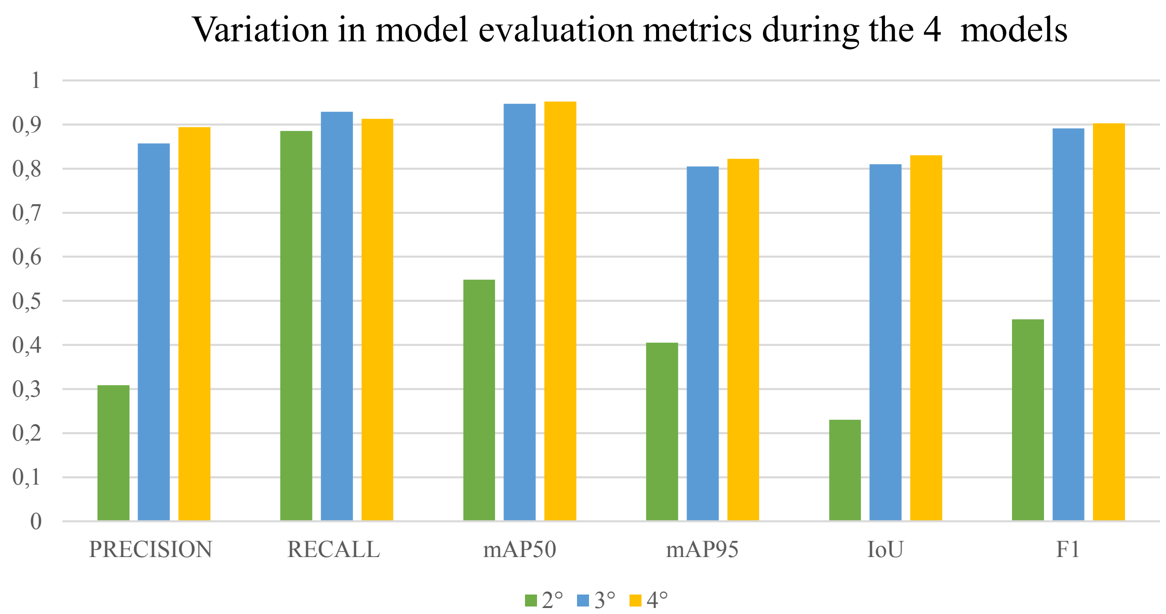


Table 14 - Variation in model evaluation during the 4 models

Finally, the results from the dehydration curves not only confirm the variation in water content within the tomatoes, but also indicate a crucial aspect in their interpretation. These results establish a range of validity for our experimental model, meaning it will only be accurate and reliable within this specific range of dehydration and moisture content for the tomatoes. This aspect is particularly significant when evaluating the potential practical applications of the findings, especially in the food industry. Our experimentation and model instruction have revealed that the efficacy of our methodology is heavily reliant on the operational surroundings and the state of the tomatoes we are attempting to identify. It is vital to stress that our model is exclusively valid within the specific parameters and conditions pursuant to its training. We began with a controlled environment featuring a black background for the second training, followed by the third and fourth sessions that involved randomly arranged tomatoes in trays alongside the controlled environment. This variation from the controlled environment facilitated testing the model's adaptability to more practical production scenarios. Significantly, the augmented complexity also arose from the secondary training due to the introduction of a wider variety of tomato species, with distinct shapes and sizes. Notably, despite this complication, the model has demonstrated effective adaptation to these challenges and a steady enhancement of its performance. In conclusion, it is essential to acknowledge the constraints imposed on this model by tomato size and varieties, extent of dehydration, and usage context, given that the validity of an experimental model represents a critical parameter to be considered, as it can directly impact the applicability of the results that were obtained.

A concluding discussion can analyse the errors of the model, specifically the False Positives and False Negatives. For error analysis, Images 59 and 60 serve as a reference point as they demonstrate error-free labelling. Image 59 depicts labelling of healthy tomatoes, whereas image 60 shows spoiled tomatoes.

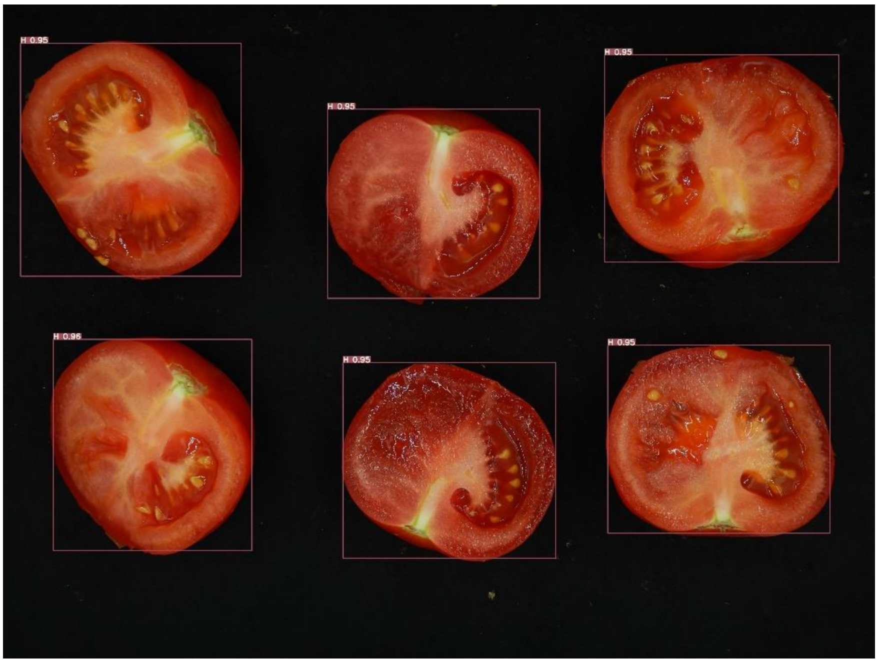


Figure 59 - Labelling of healthy tomatoes

Figure 60 - Labelling of spoiled tomatoes

In image 61, we observe a false negative error in which the model failed to detect the intended tomato. Specifically, the third tomato in the first row was not detected.

Figure 61 - Example of false negative

We can now analyze instances of false positives. Image 62 displays healthy tomatoes wrongly categorized as spoiled and spoiled tomatoes inaccurately labeled as healthy. Image 63 shows all but one healthy tomato labeled as spoiled. In contrast, image 64 reveals the labeling of one healthy tomato that had visible mold on the upper left side. To conclude, image 65 shows the model incorrectly identifying two healthy tomatoes as spoiled.

Figure 62 - Example 1 of false positive

Figure 63 - Example 2 of false positive

Figure 64 - Example 3 of false positive

Figure 65 - Example 4 of false positive

If we analyze these errors, we can conclude that the model was understandably confused due to several factors. Firstly, photos 63 and 64 are very dark, which can lead to confusion and mistakes by the model. Secondly, recognition of the mold in this test was significantly influenced by the light color it possessed. Hence, any variation in the red color on the surface of the tomato may result in misinterpretation by the model. Most likely, algorithm confusion occurred in images 62 and 65 due to the reflection of water content in the tomatoes. Similarly, in image 63, the petiole attachments may have been misidentified as mold for the same reason. Hence, the errors in this model can mostly be attributed to the image collection conditions of the dataset. Once the root causes of the algorithm error are identified and analyzed, the training picture conditions can be improved for future performance enhancement.

Nevertheless, the outcomes demonstrate notable advancements in the model's ability to detect "Healthy" and "Spoiled" tomatoes across different training sessions. Despite the error, these developments mark a critical milestone in applying artificial intelligence to enhance the process of tomato selection in manufacturing contexts. The findings are encouraging and imply that this method may have practical implications in tomato production and other related domains. However, it is imperative to conduct further analysis and enhance the model's performance to tackle future hurdles and increase the accuracy of its forecasts.

Chapter 6 – Conclusion

In conclusion, this study investigated the use of artificial intelligence to detect mold in tomatoes during the drying process. The primary aim was to address the problem of waste and loss in the food industry caused by the presence of mold, which makes tomatoes unfit for human consumption. The YOLOv7 object detection algorithm was utilized to train artificial intelligence models on a vast image dataset illustrating healthy and spoiled tomatoes.

Results from multiple training sessions demonstrate a progressive enhancement in the model's capacity to discriminate between "healthy" and " spoiled" tomatoes. The overall accuracy increased from 30.9% initially to 89.4% after the fourth session. Furthermore, metrics such as mAP50 and mAP95 showed a considerable boost in prediction accuracy with a high degree of confidence. Ultimately, F1 scores and Intersection over Union (IoU) asserted the model's ability to maintain a balance between precision and recall.

Artificial intelligence, once trained, functions at an extraordinary speed in executing its tasks. Unlike a human worker, the model can analyze thousands of images within seconds. Therefore, it can detect mold in tomatoes promptly, which is critical for preventing contamination and ensuring product quality in a real-time production environment. Artificial intelligence maintains high performance under our control and direction, while humans may be subject to fatigue or errors. Nevertheless, it is crucial to note that the model operates under specific constraints, such as tomato size, degree of drying, and context of use. Therefore, the application of the obtained results relies on the training conditions and control variables. Furthermore, the model's validity is restricted to a particular range of tomato drying and moisture content. However, it can be conveniently modified and trained to suit diverse tomato types or production conditions.

The progress made in this paper is a crucial advancement towards employing artificial intelligence in tomato cultivation and other related areas. This technology has the potential to aid in minimizing food waste, enhancing product quality, and improving industrial processes' speed and efficiency. Additional research will be necessary to tackle any remaining challenges and optimize the model's effectiveness. The incorporation of this technology into HACCP plans in the food industry may advance quality, food safety, and sustainability in food production for future generations. The potential for artificial intelligence in this area is promising, with the pathway already laid out.

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