UNIVERSITÀ DEGLI STUDI DI PADOVA
Dipartimento di Ingegneria dell'Informazione

Corso di Laurea in Ingegneria Informatica

Relazione per la prova finale

Analisi comparativa e sintesi di segnali biometrici: identificazione dell'utente tramite sensori radar e IMU mediante tecniche di Machine Learning

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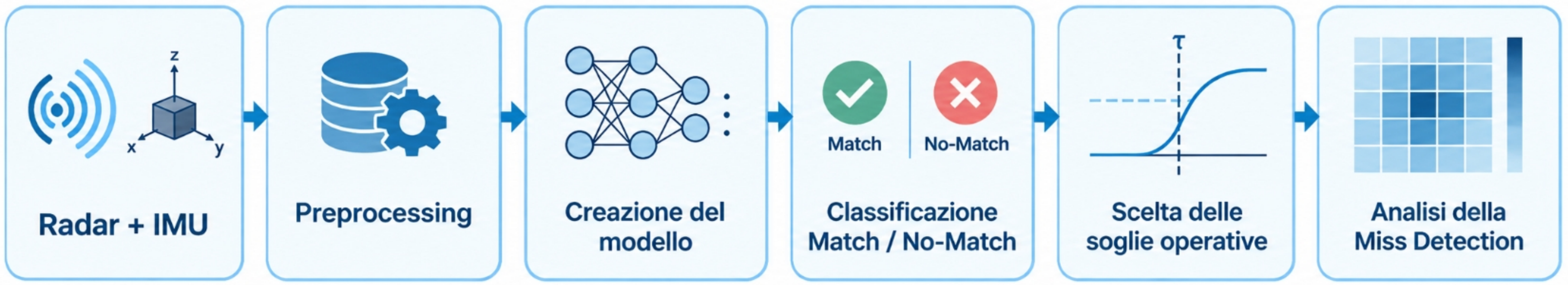
ANNO ACCADEMICO 2025/2026

Descrizione progetto

Obiettivo: sviluppare e confrontare modelli neurali in grado di valutare la coerenza tra i segnali Radar e IMU associati allo stesso movimento.

Approccio: preprocessare e allineare temporalmente i due segnali, addestrare diverse architetture di rete neurale per distinguere coppie Match / No-Match e, infine, valutare il modello selezionato in termini di False Alarm e Miss Detection.



Dataset

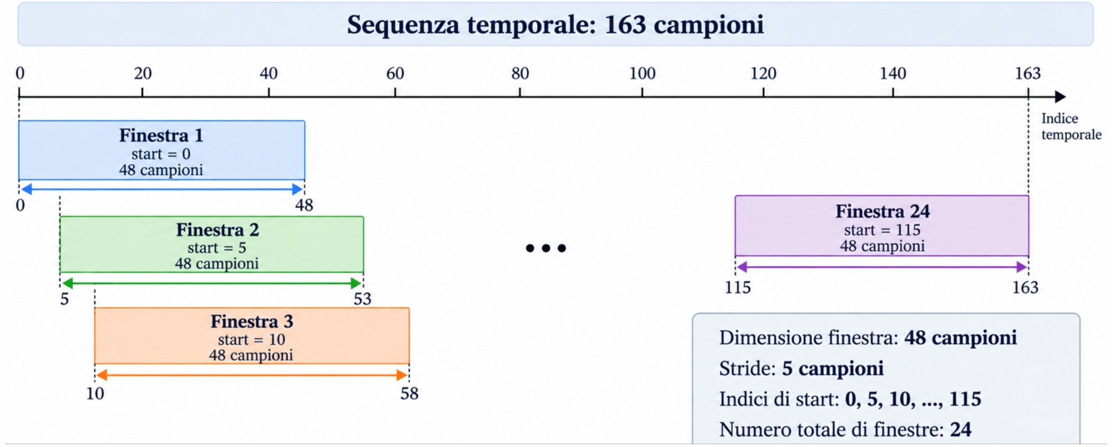
Dataset e preprocessing

Radar:

- CIR → modulo |CIR| → Z-score
- 128 x 128 x 163
  [Range bins x Frames x RDM windows]

IMU:

- Giroscopio XYZ + Accelerometro XYZ → 6 feature
- Interpolazione a 163 campioni → Z-score
- 163 x 6



Dataset split

114 registrazioni totali → 91 Train / 23 Test

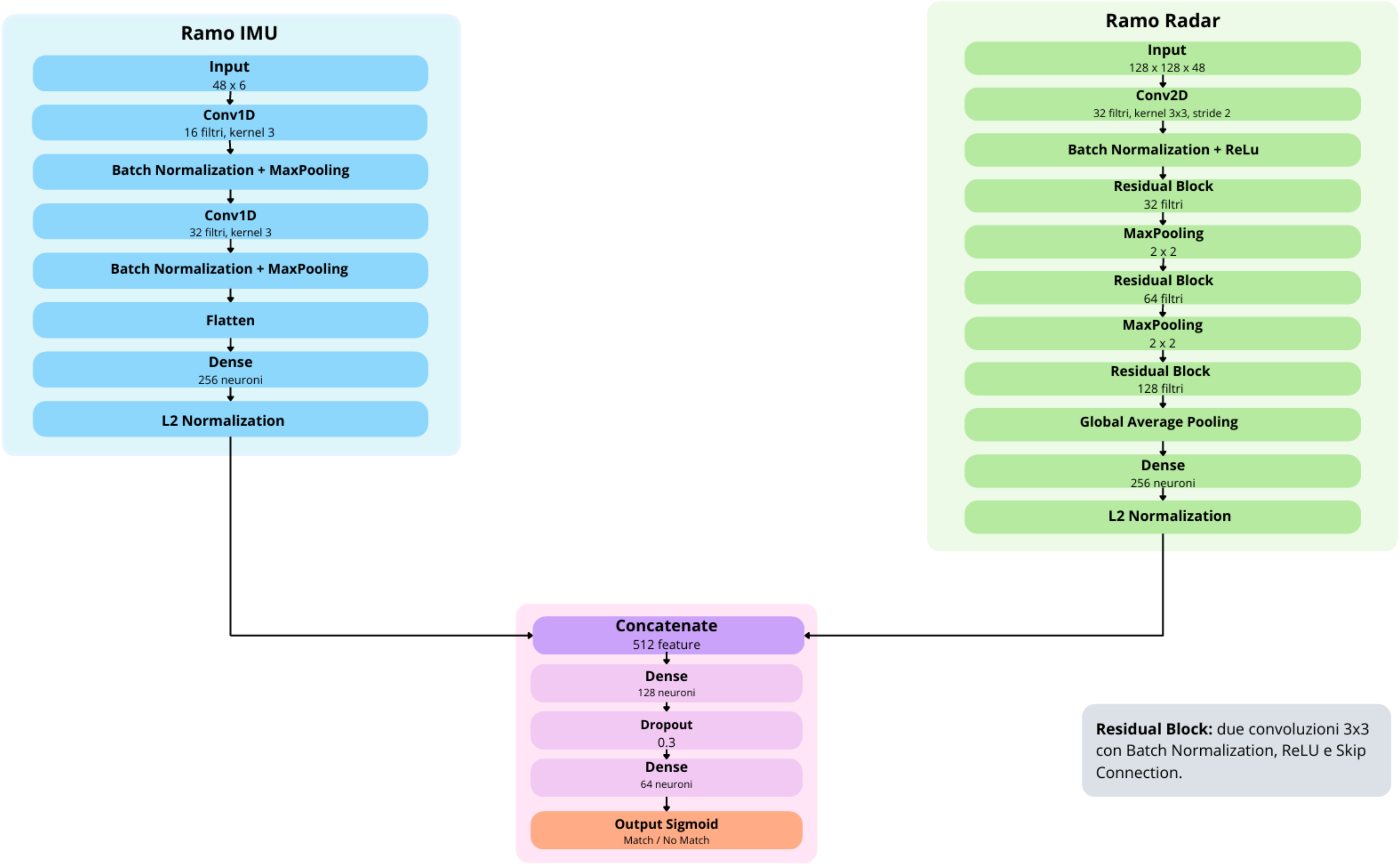
Sliding Window

Window = 48, stride = 5 → 24 finestre per registrazione
2184 Train / 552 Test

Generazione coppie

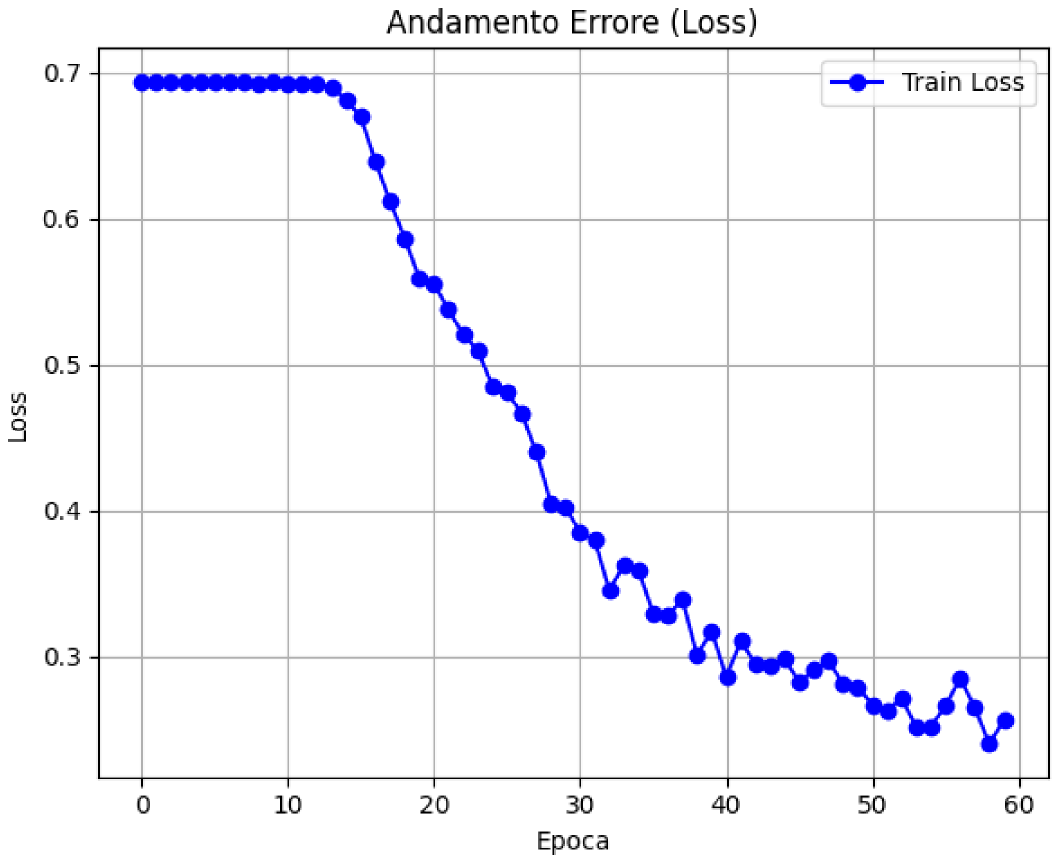
Match: IMU dalla stessa registrazione + stessa finestra
No-Match: IMU da un'altra registrazione + finestra temporale casuale

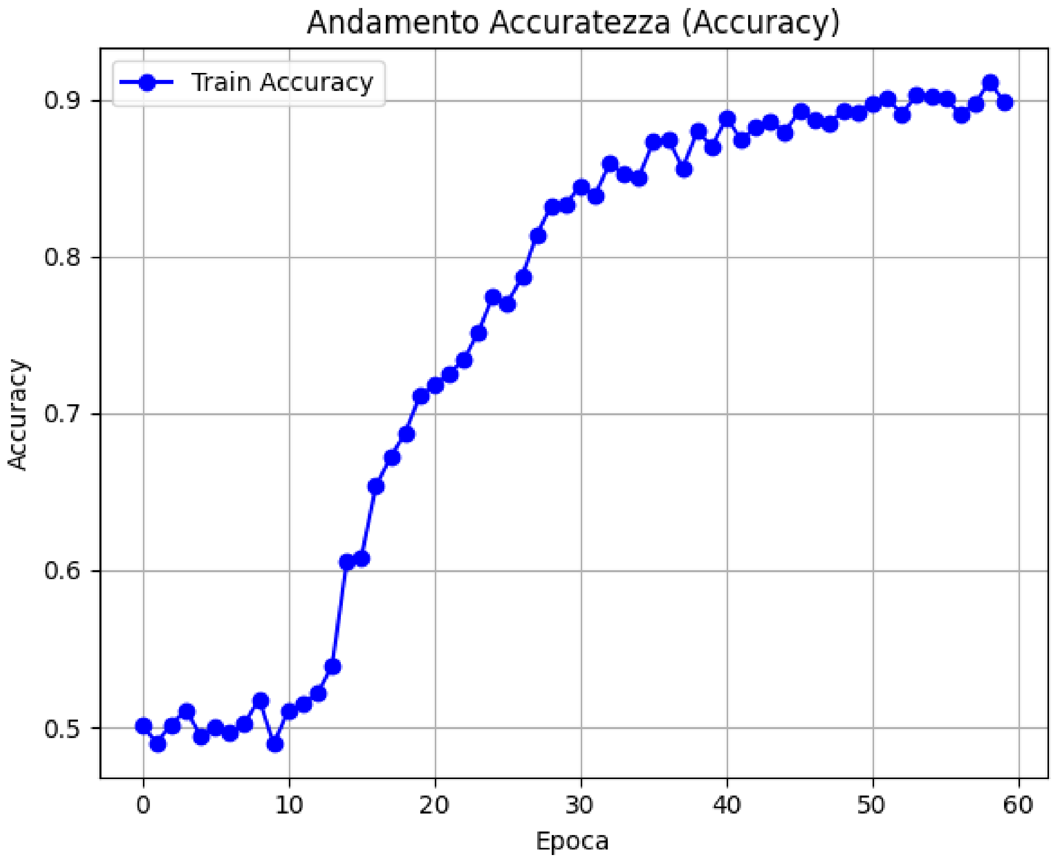
Primo modello - CNN1D + ResNet2D



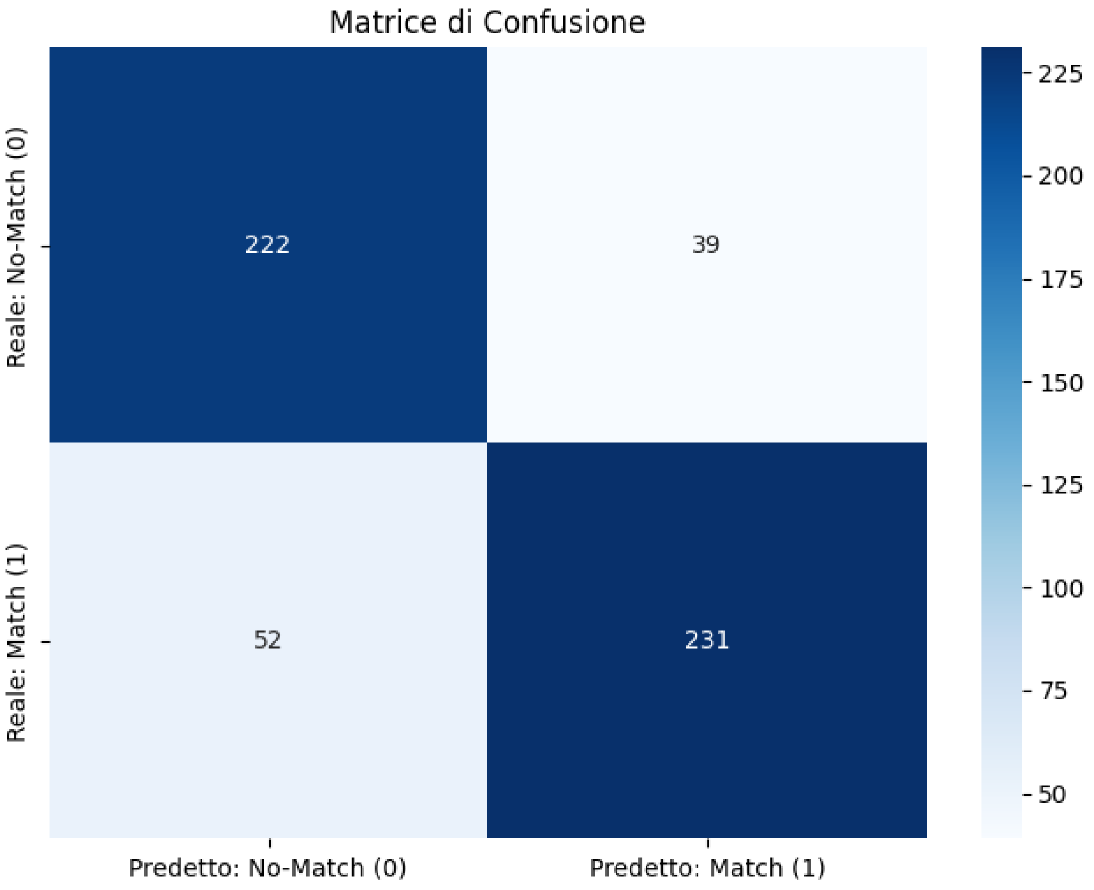
Residual Block: due convoluzioni 3x3 con Batch Normalization, ReLU e Skip Connection.

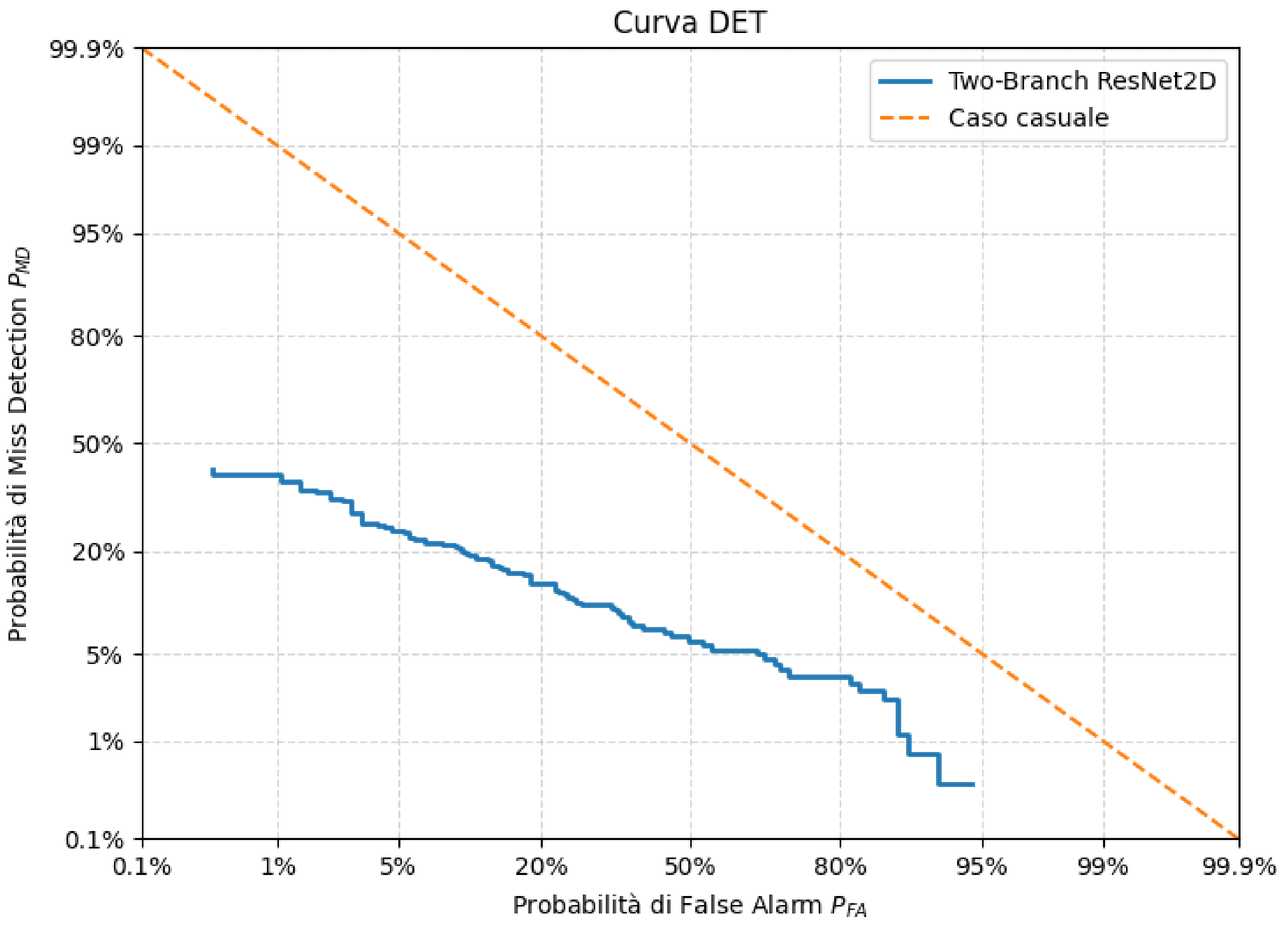
Andamento del training - ResNet2D





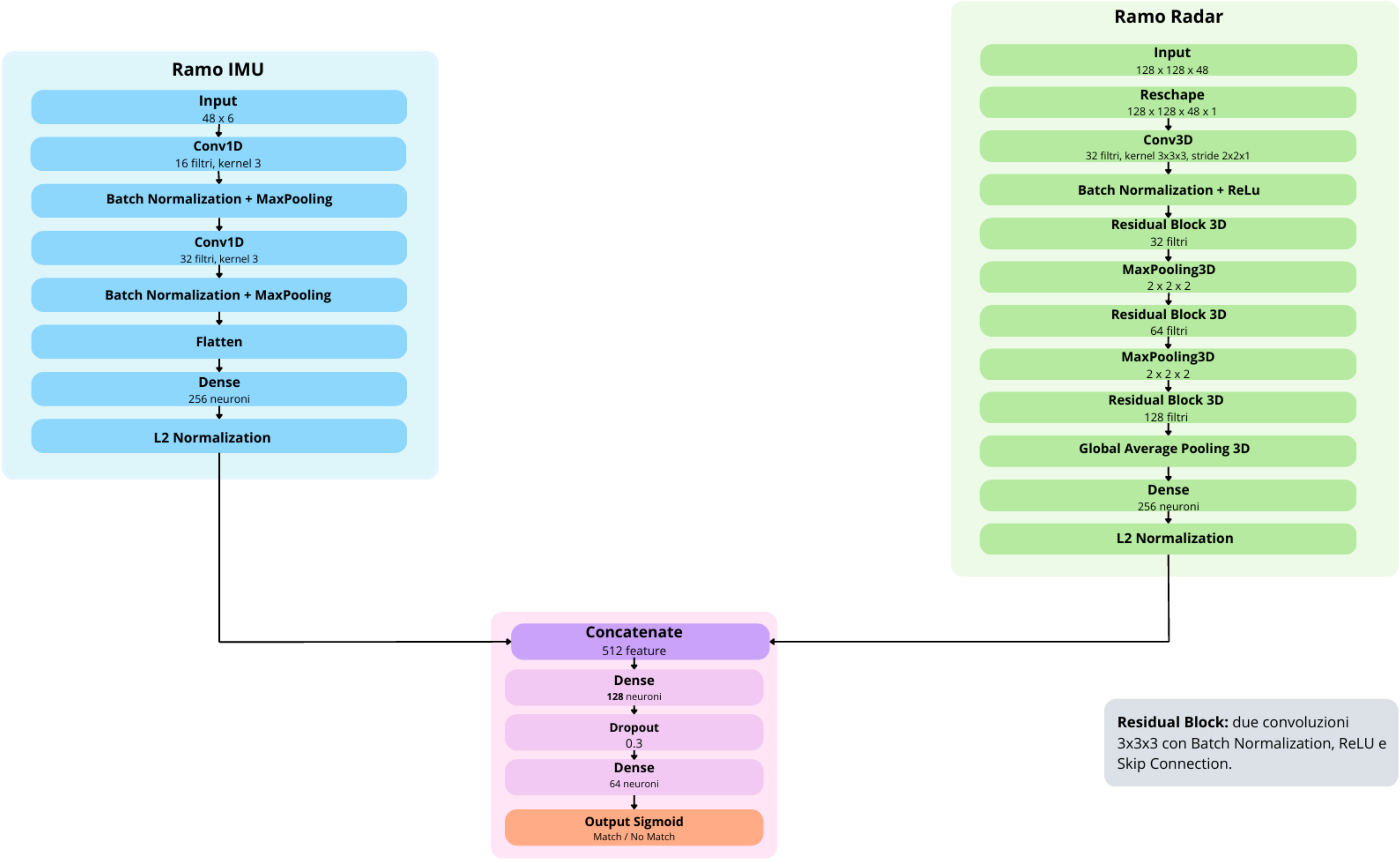
Prestazioni sul test set - ResNet2D





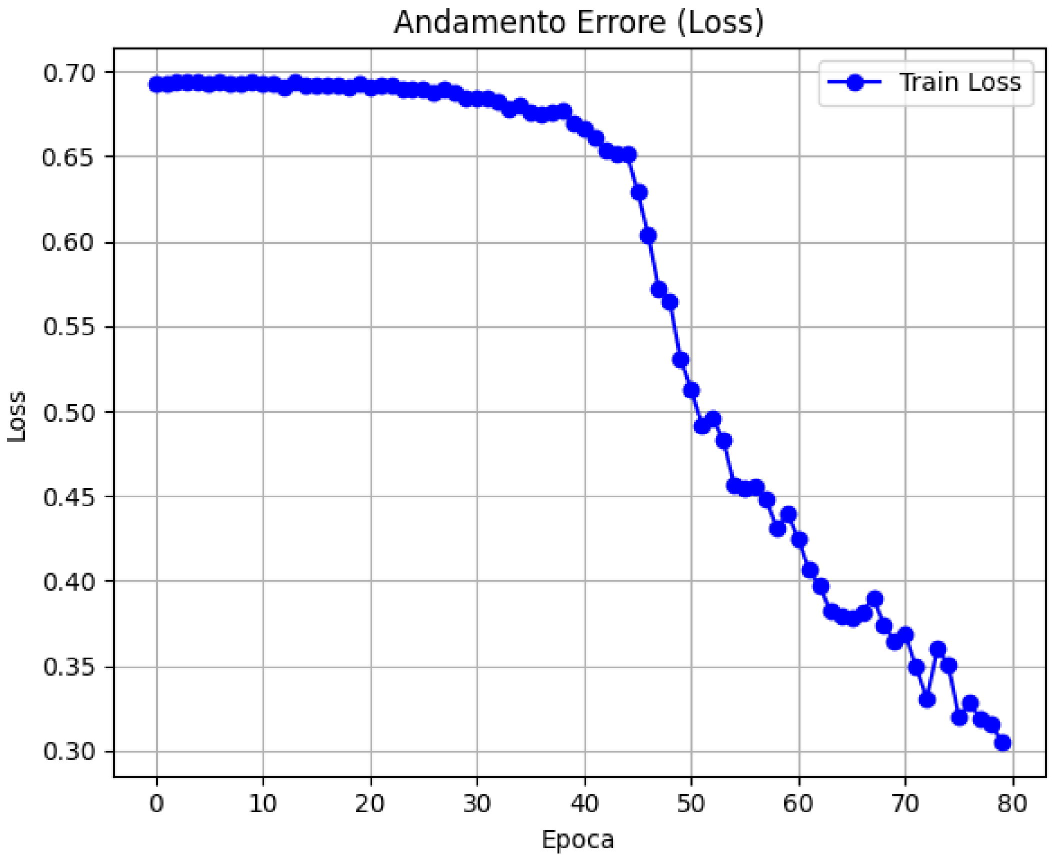
Accuracy = 83,27%

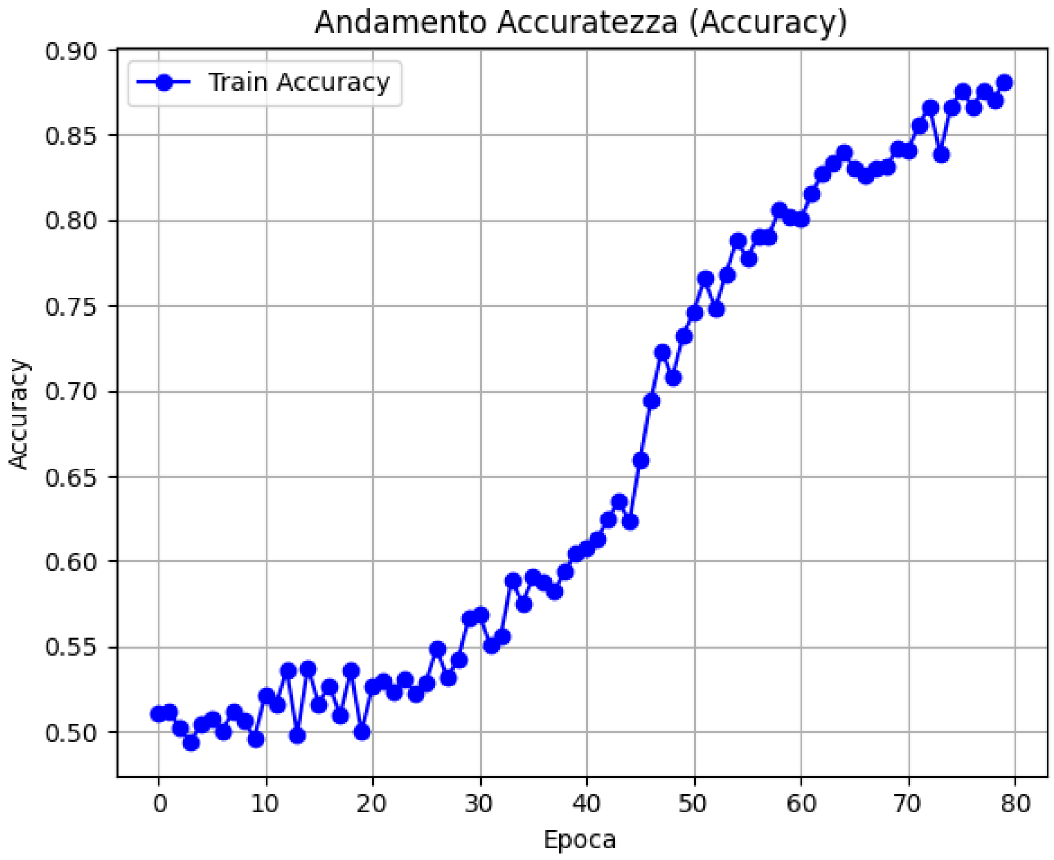
Secondo modello - CNN1D + ResNet3D



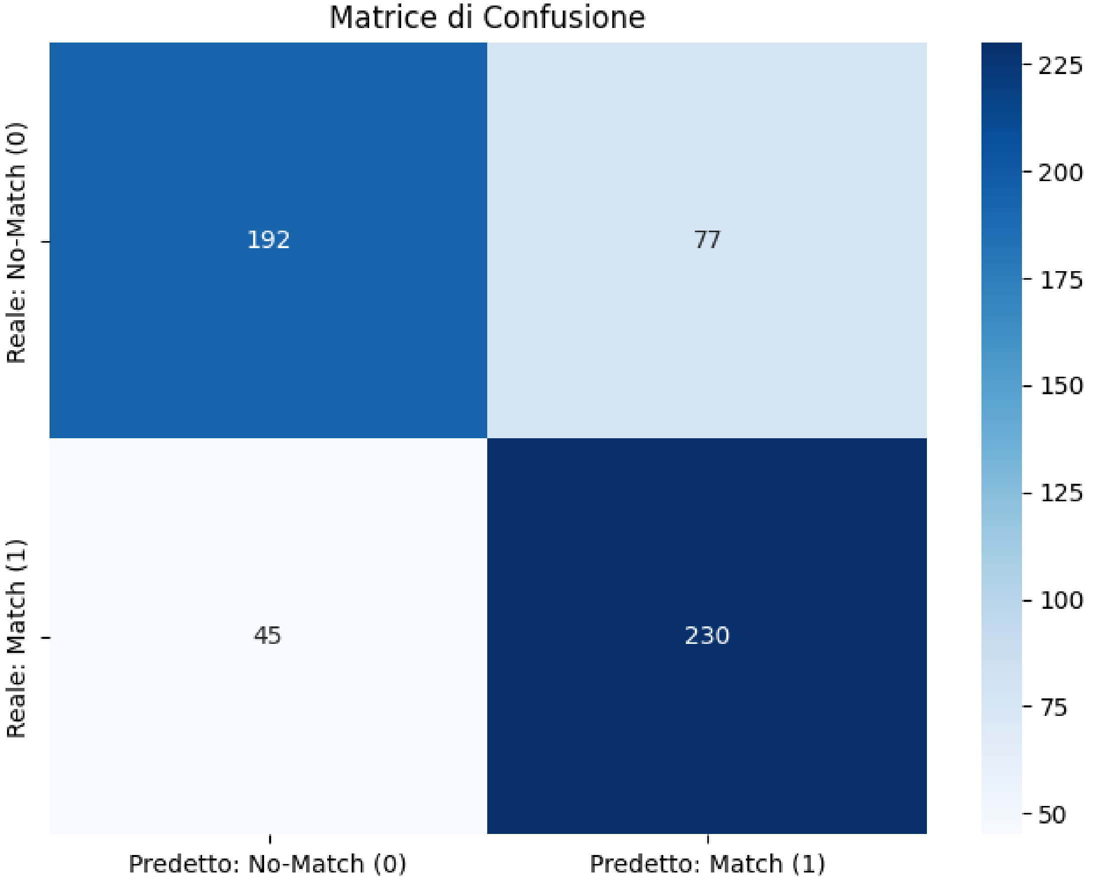
Residual Block: due convoluzioni 3x3x3 con Batch Normalization, ReLU e Skip Connection.

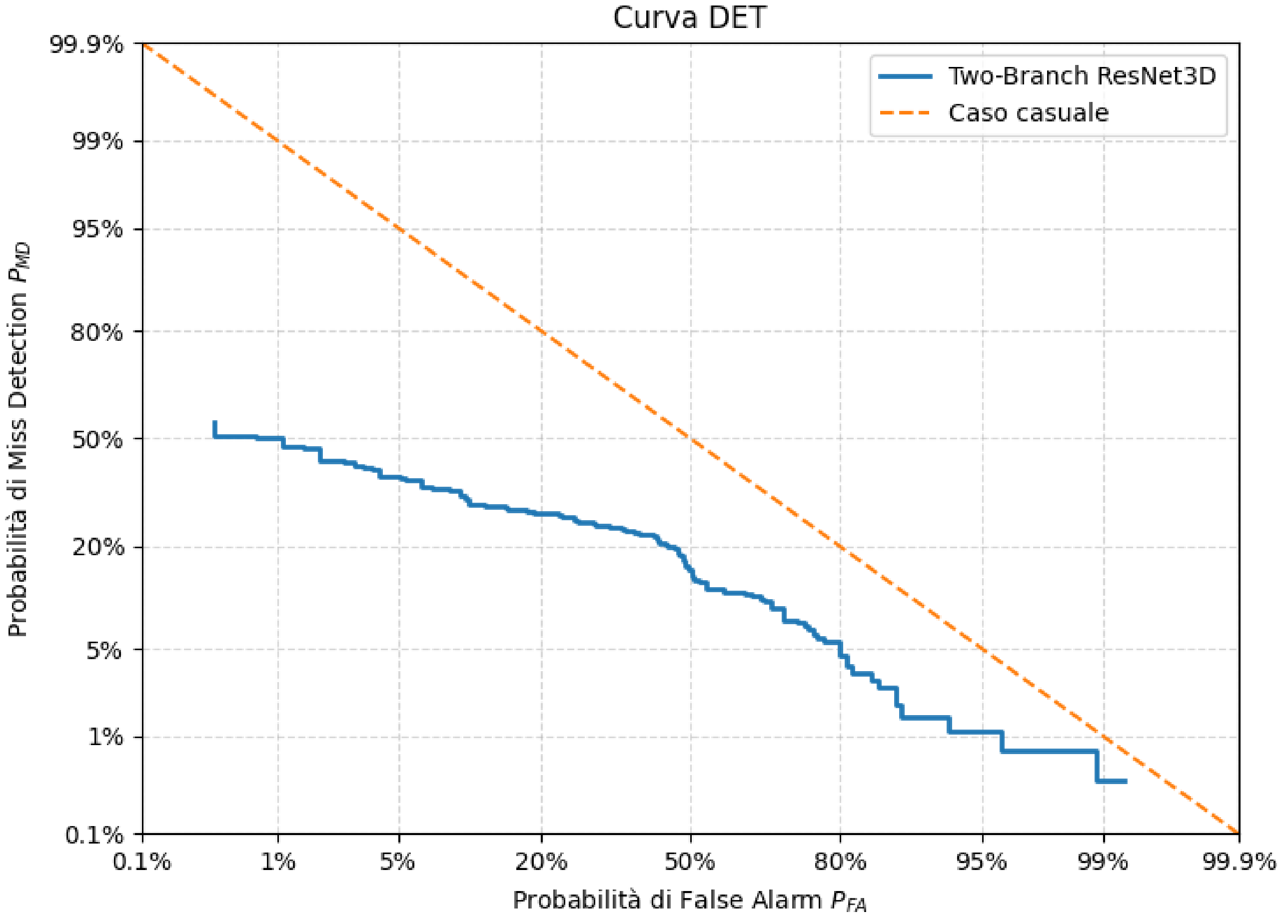
Andamento del training - ResNet3D





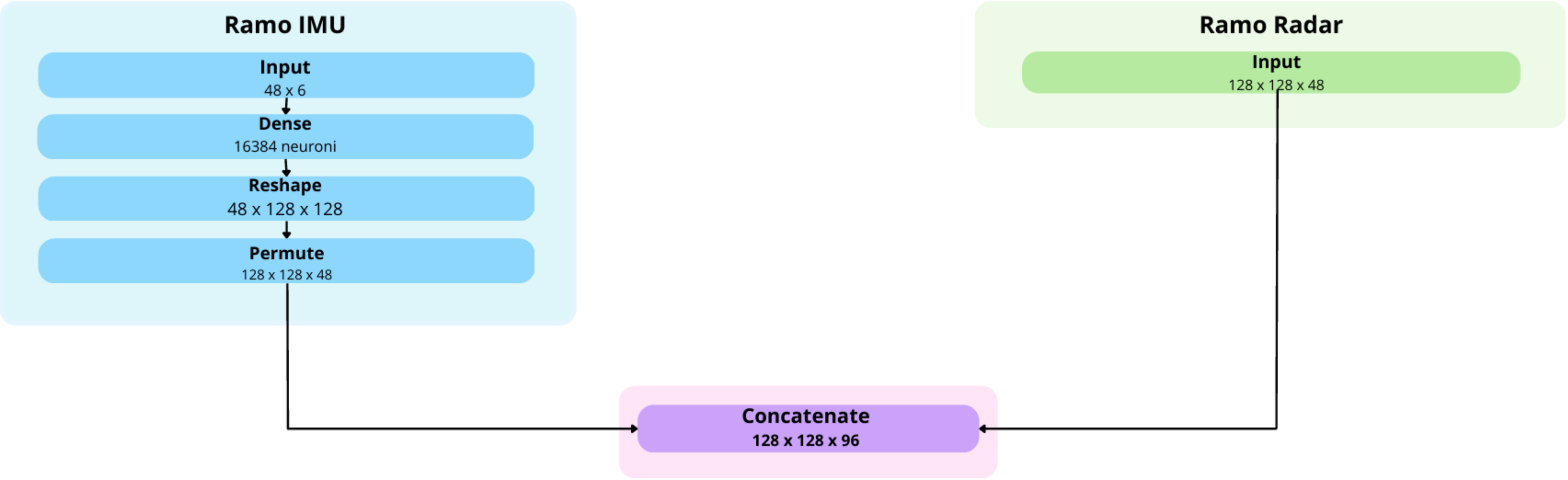
Prestazioni sul test set - ResNet3D

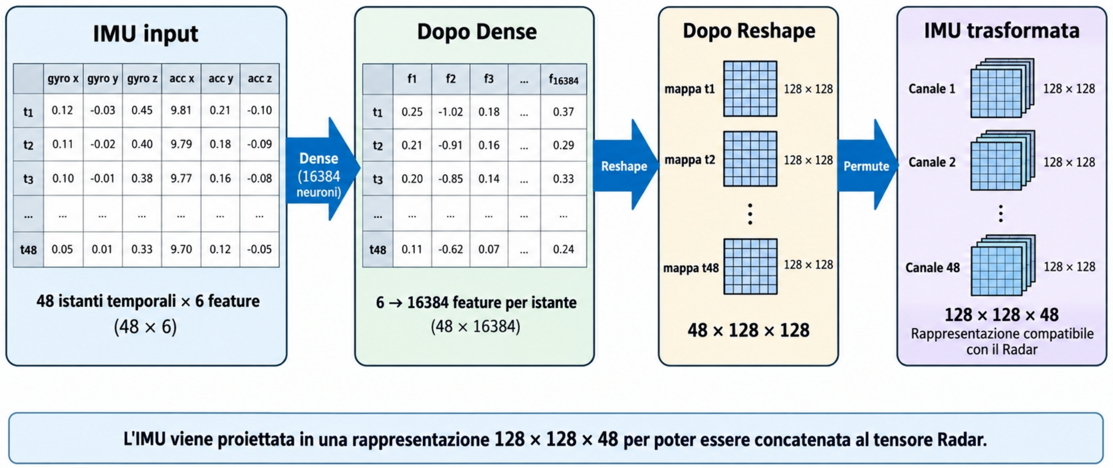


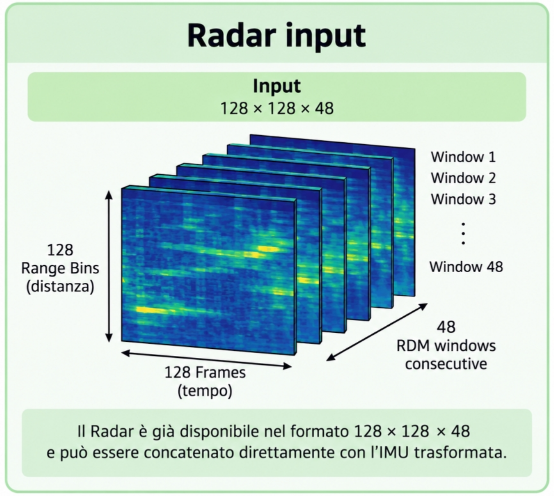


Accuracy = 77,57%

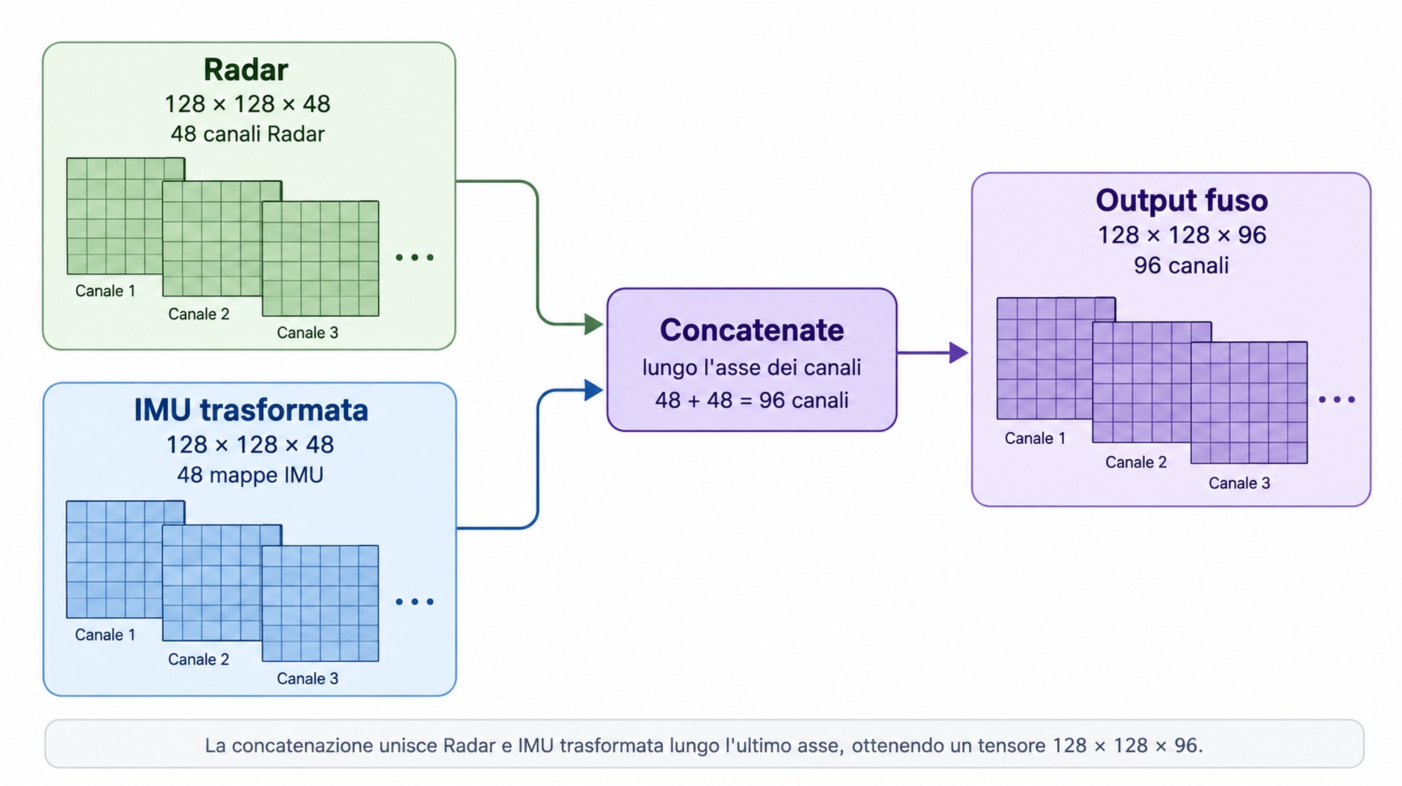
Terzo modello - One Branch ResNet2D

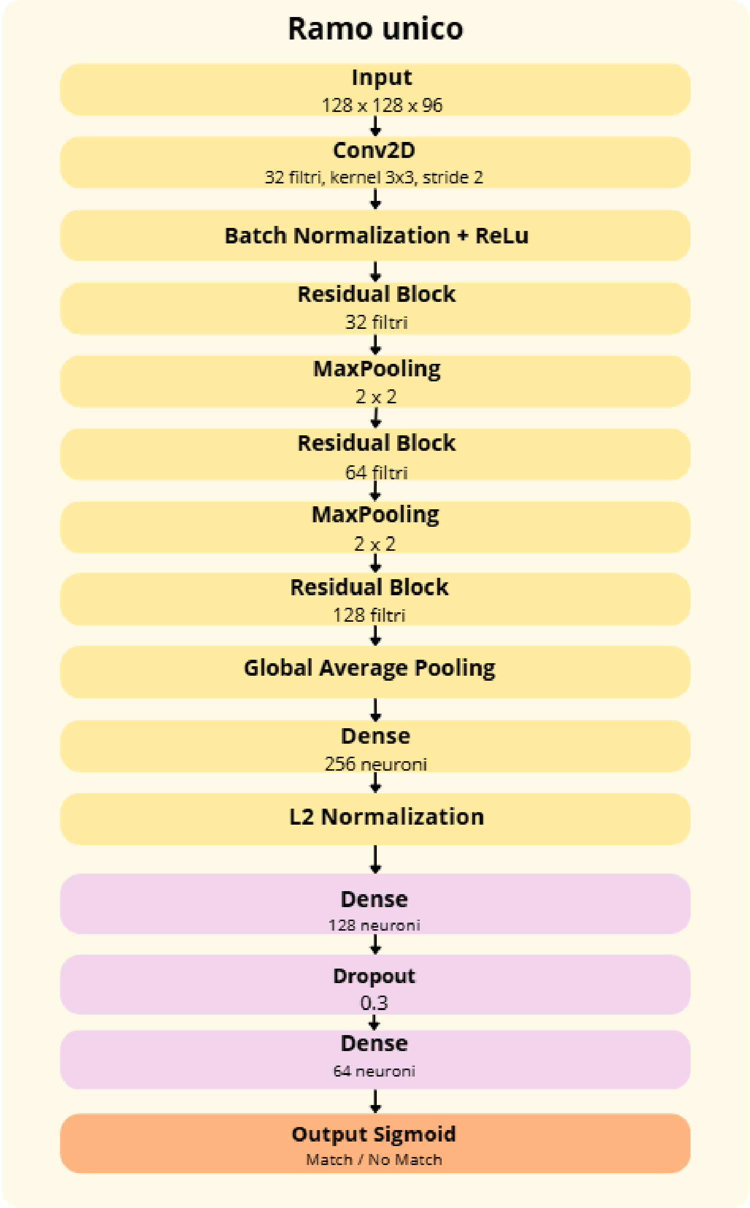




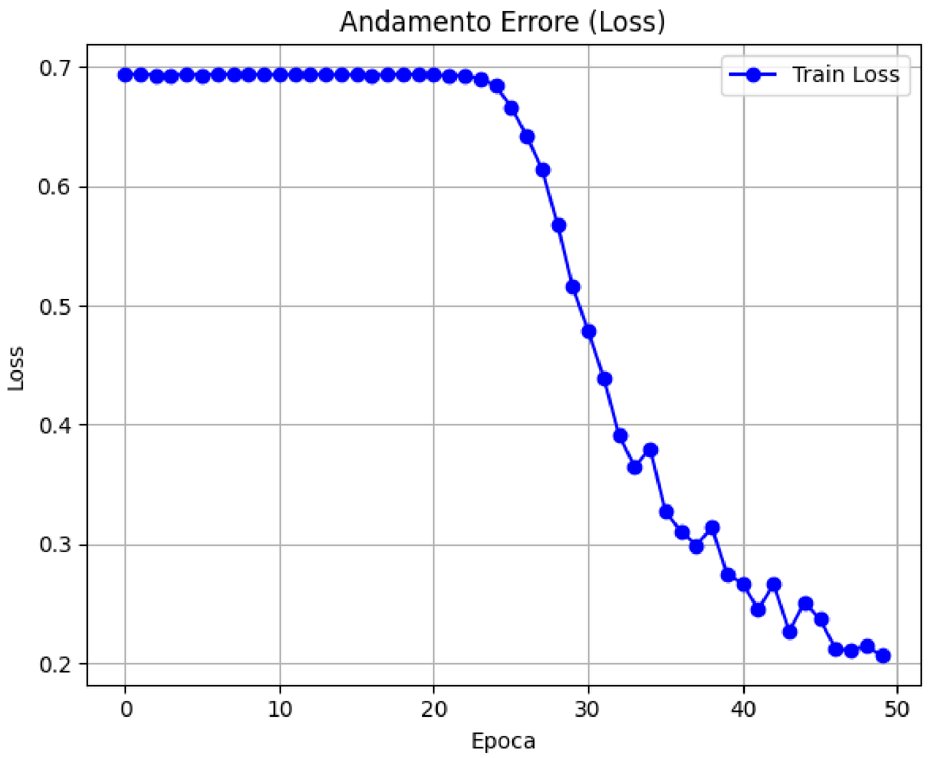


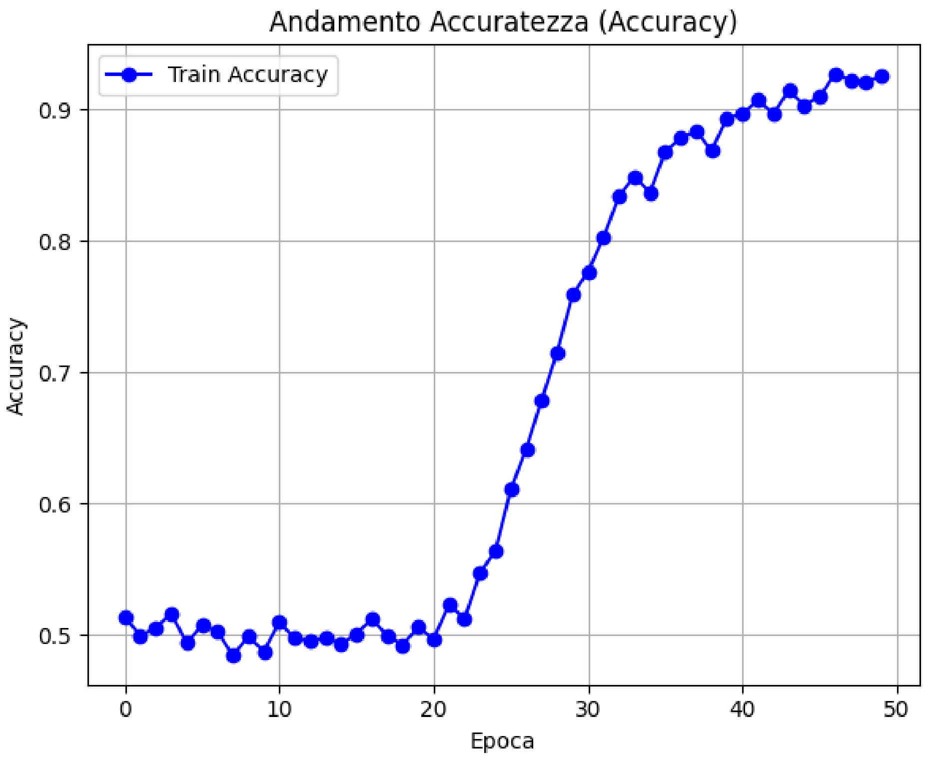
Terzo modello



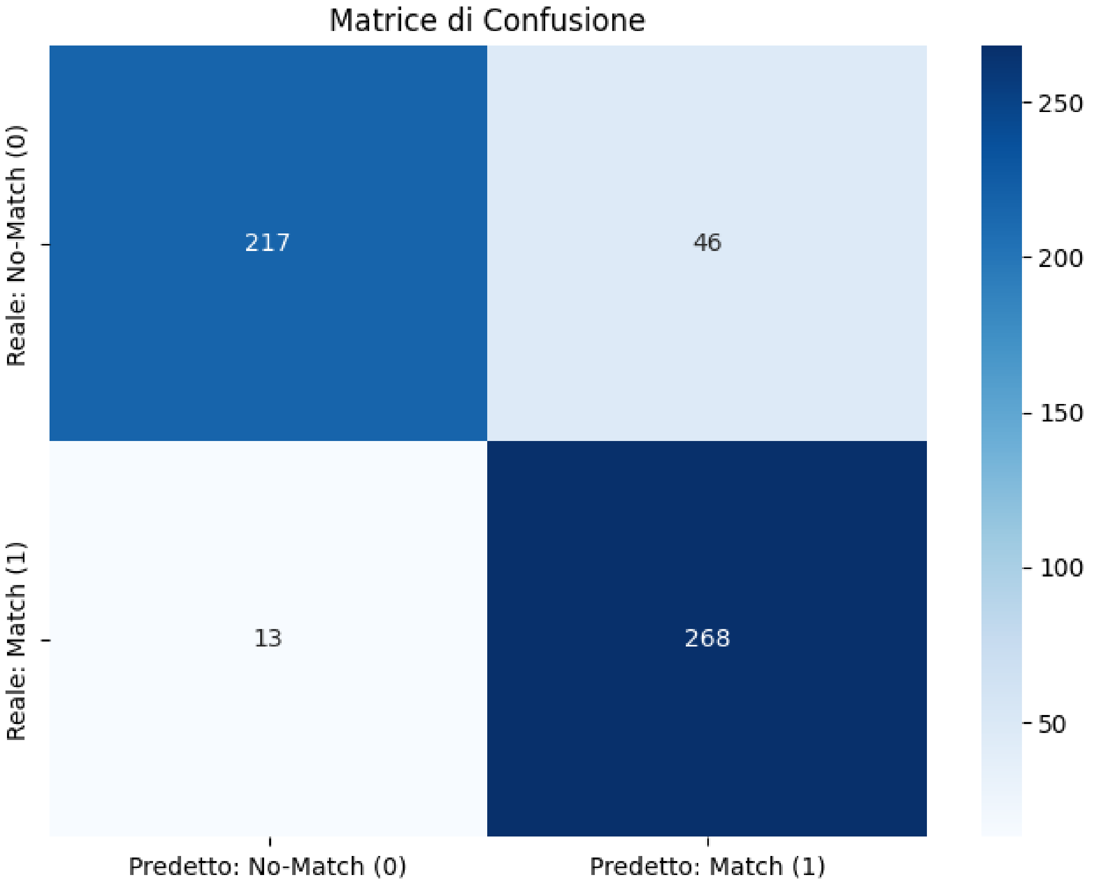


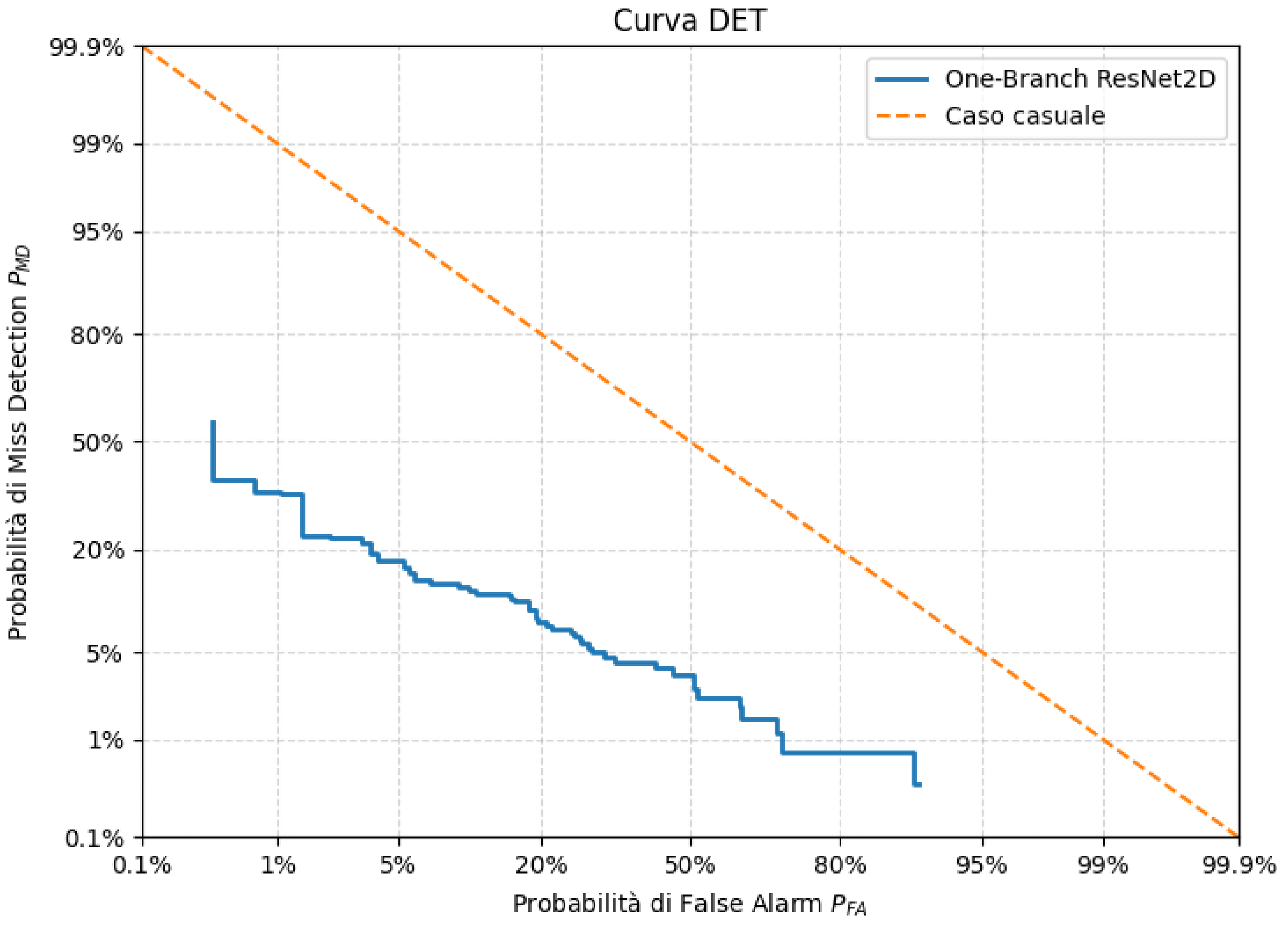
Andamento del training - One Branch ResNet2D





Prestazioni sul test set - One Branch ResNet2D

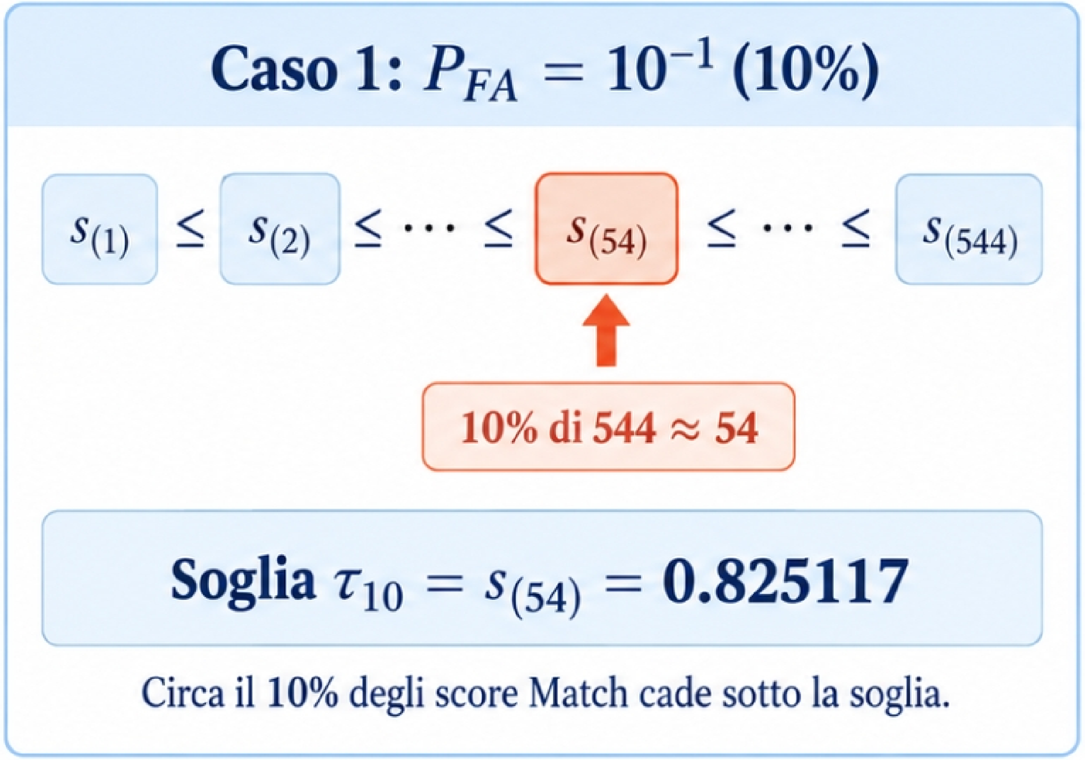


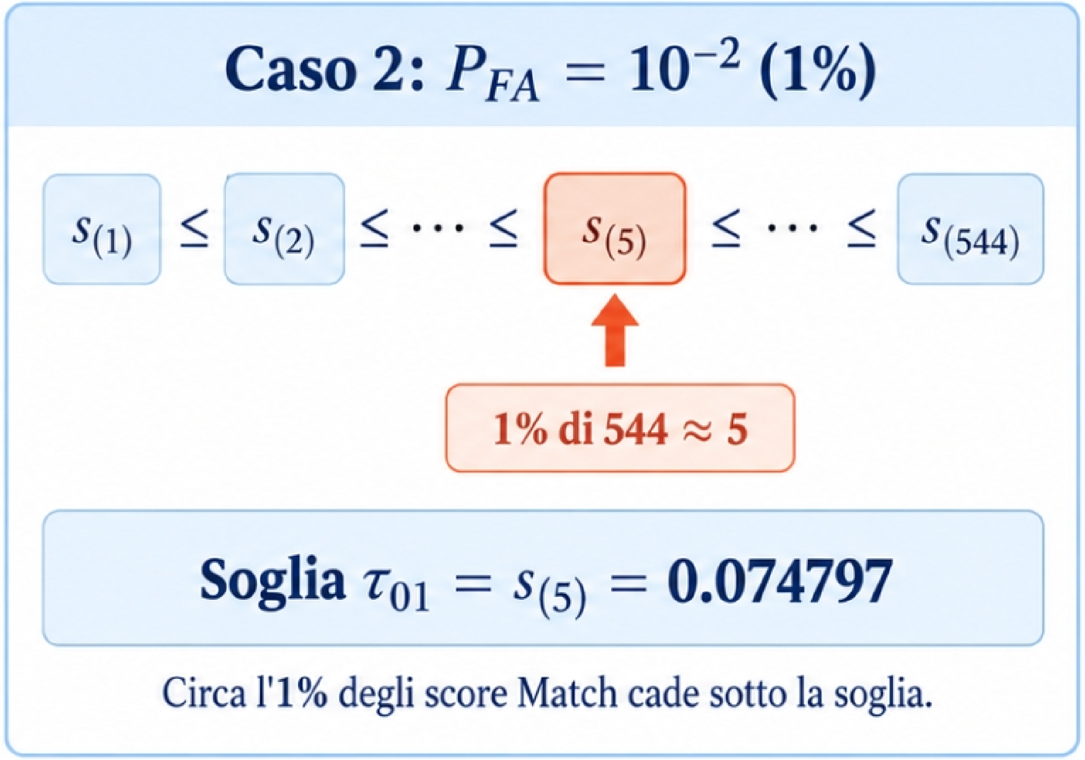


Accuracy = 89,15%

Definizione delle soglie

Dopo il confronto tra i modelli, selezioniamo il modello One-Branch.
Fissate due probabilità di falso allarme, $P_{FA} = 10^{-1}$ e $P_{FA} = 10^{-2}$ ricaviamo le soglie decisionali da utilizzare successivamente per il calcolo della Miss Detection.





Costruzione delle tabelle di Miss Detection

Fissate le soglie decisionali, si analizza il comportamento del modello su coppie Radar–IMU appartenenti a soggetti diversi e successivamente su coppie dello stesso soggetto.
Si calcola dunque la Miss Detection, cioè la percentuale di attacchi erroneamente accettati.

Struttura della **tabella**:

- Righe → 10 condizioni Radar
- Colonne → 10 condizioni IMU
- Le condizioni derivano da 2 velocità x 5 pose = 10

Costruzione di una **cella**:

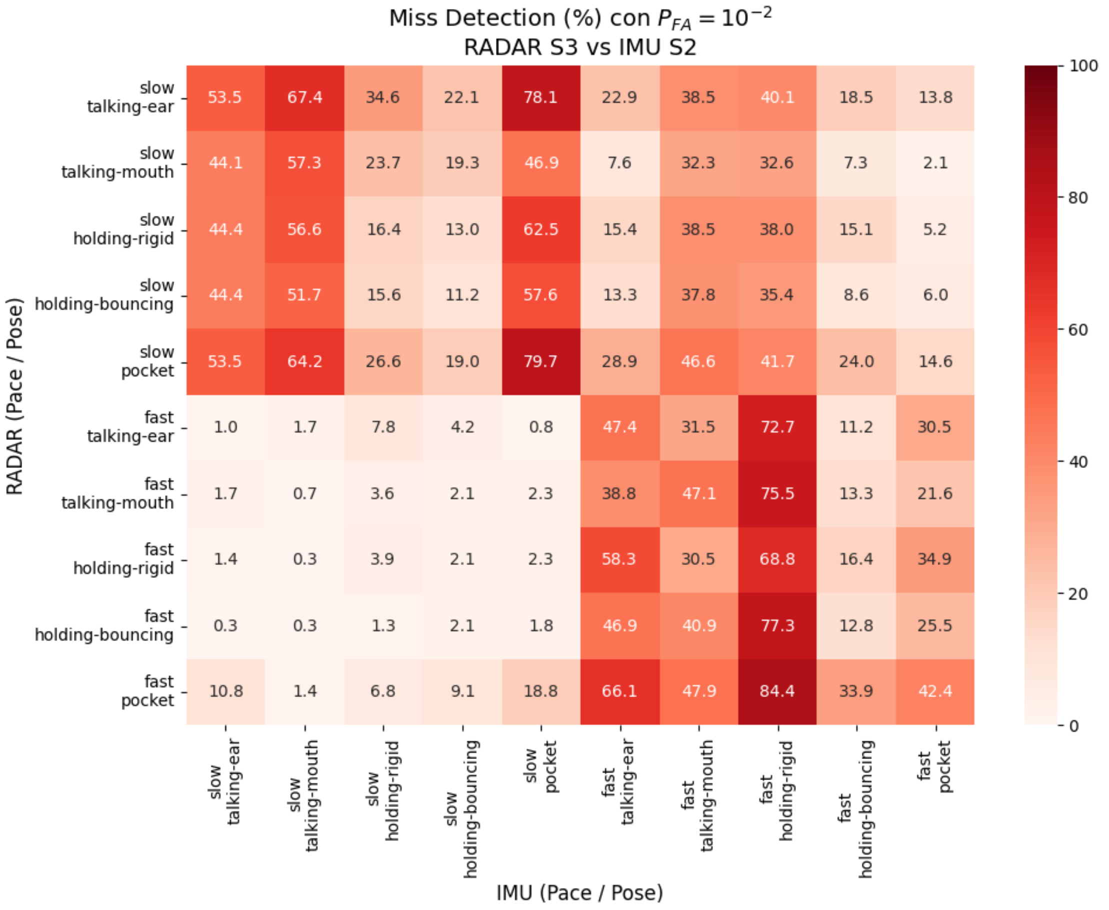
- Si fissano una condizione Radar e una IMU
- Si prendono tutte le registrazioni disponibili delle due condizioni
- Si esegue il prodotto cartesiano tra le registrazioni Radar e IMU
- Si confrontano 24 finestre temporali corrispondenti

Decisione:

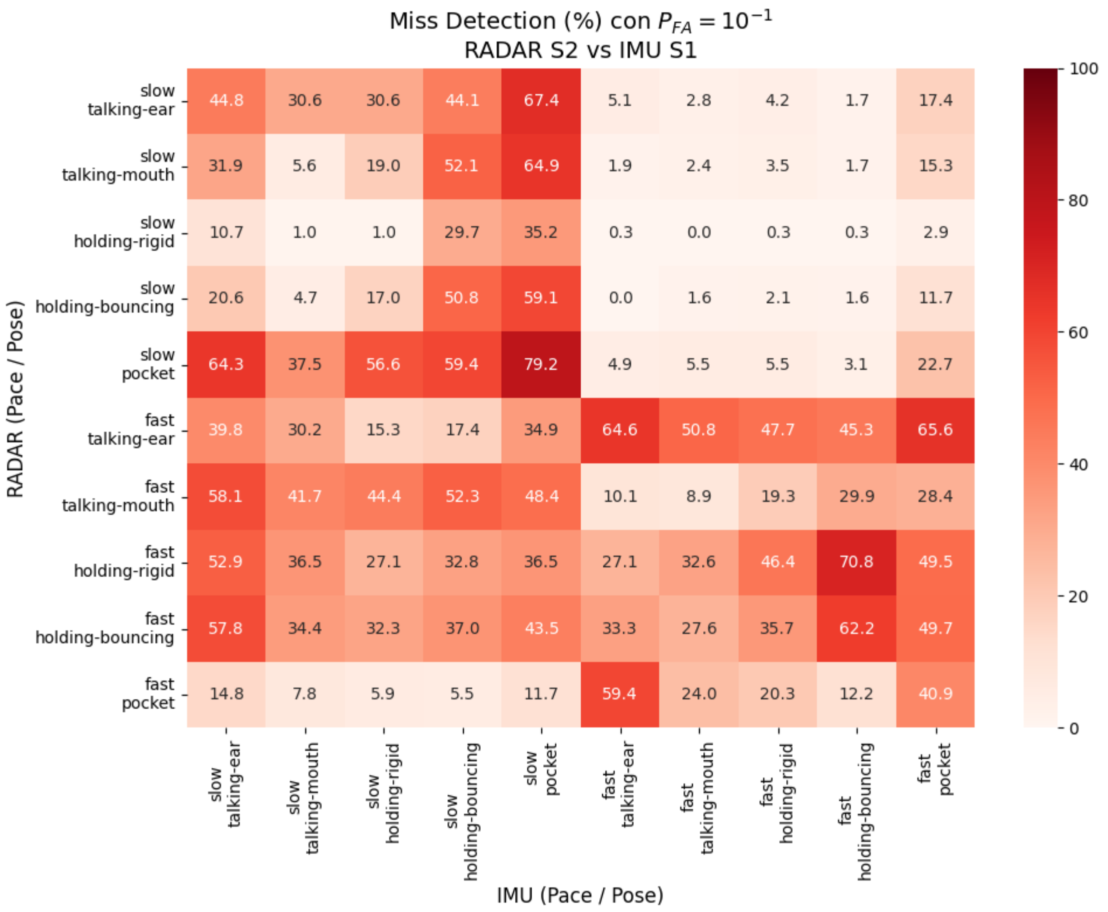
$$score \geq \tau \Rightarrow \text{attacco accettato} \Rightarrow \text{Miss Detection}$$
$$score < \tau \Rightarrow \text{allarme corretto}$$

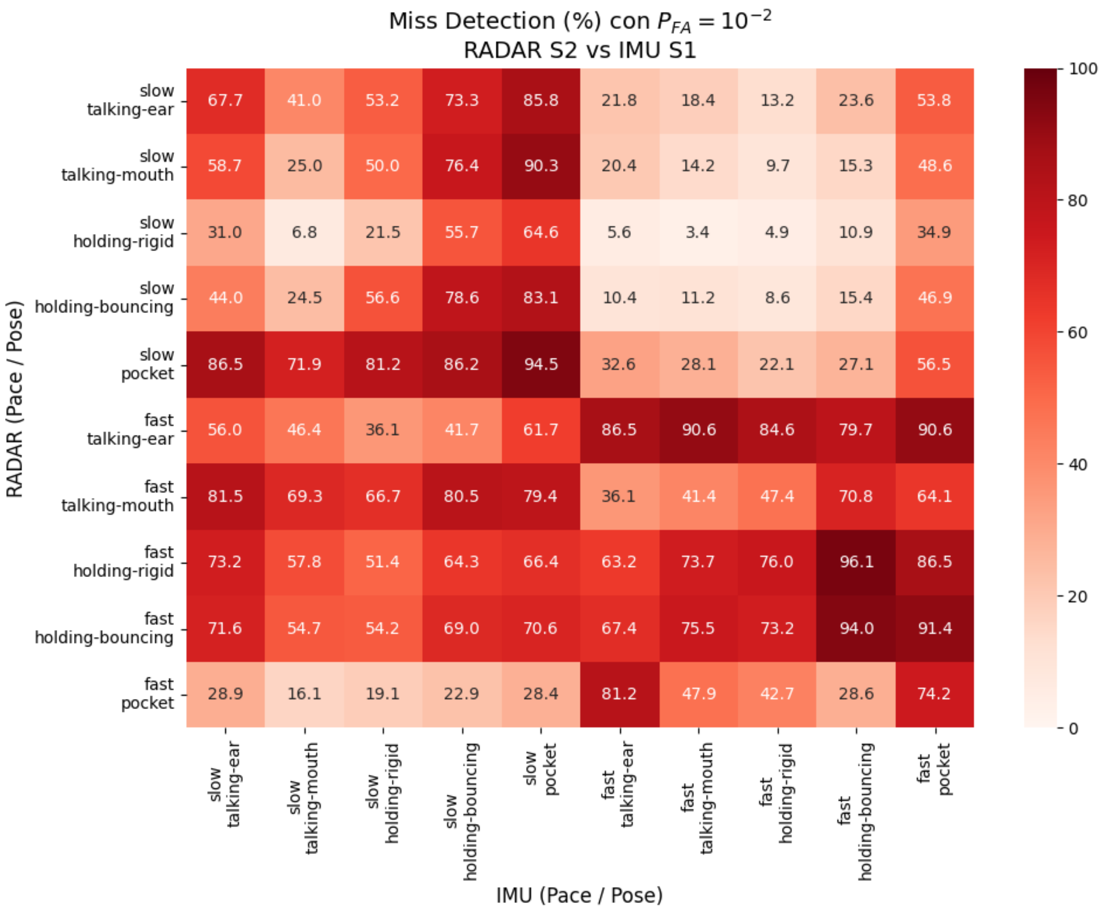
$$\text{Miss Detection } [\%] = \frac{N(score \geq \tau)}{N_{tot}} \times 100$$

Radar soggetto 3 vs IMU soggetto 2

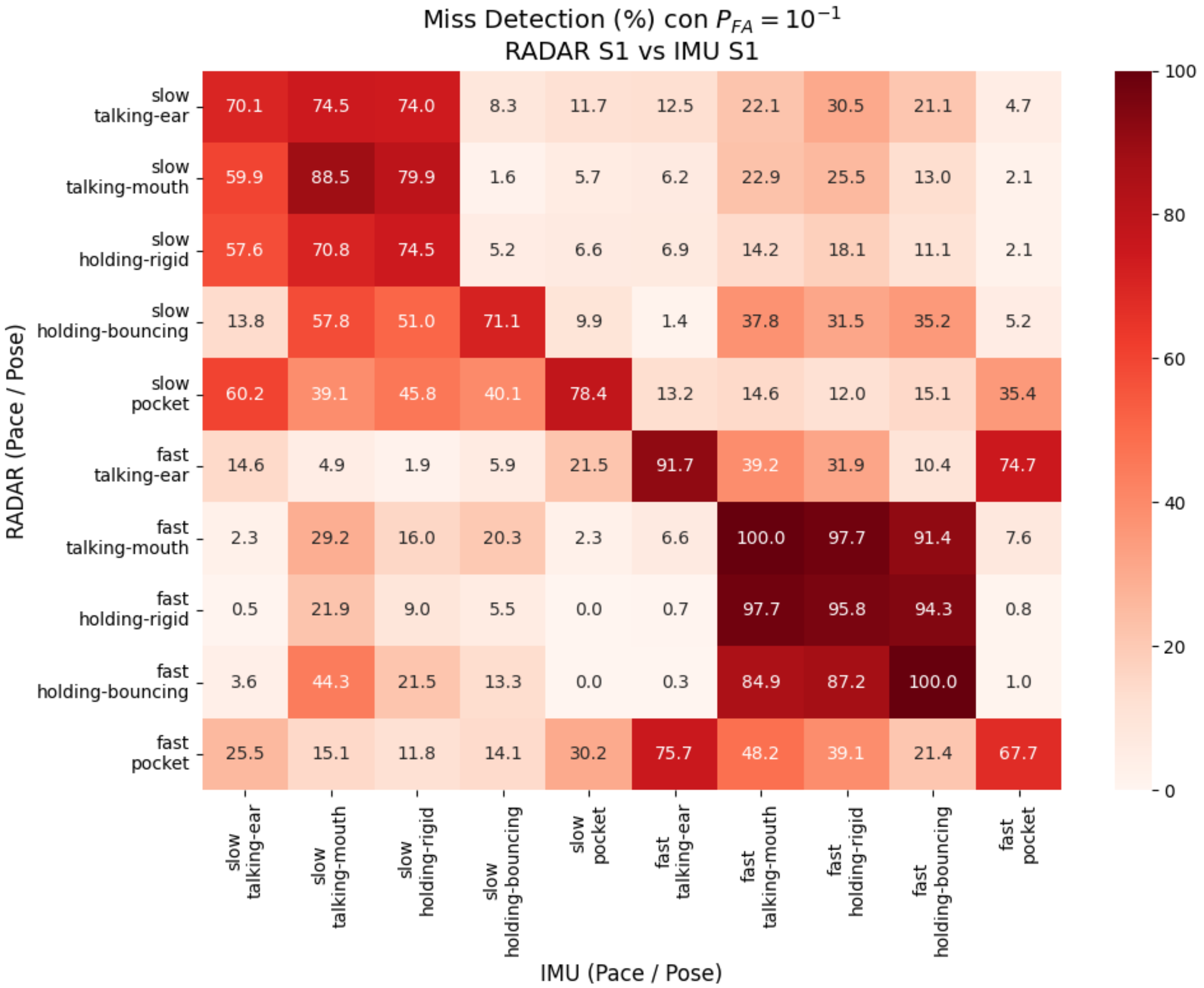


Radar soggetto 2 vs IMU soggetto 1

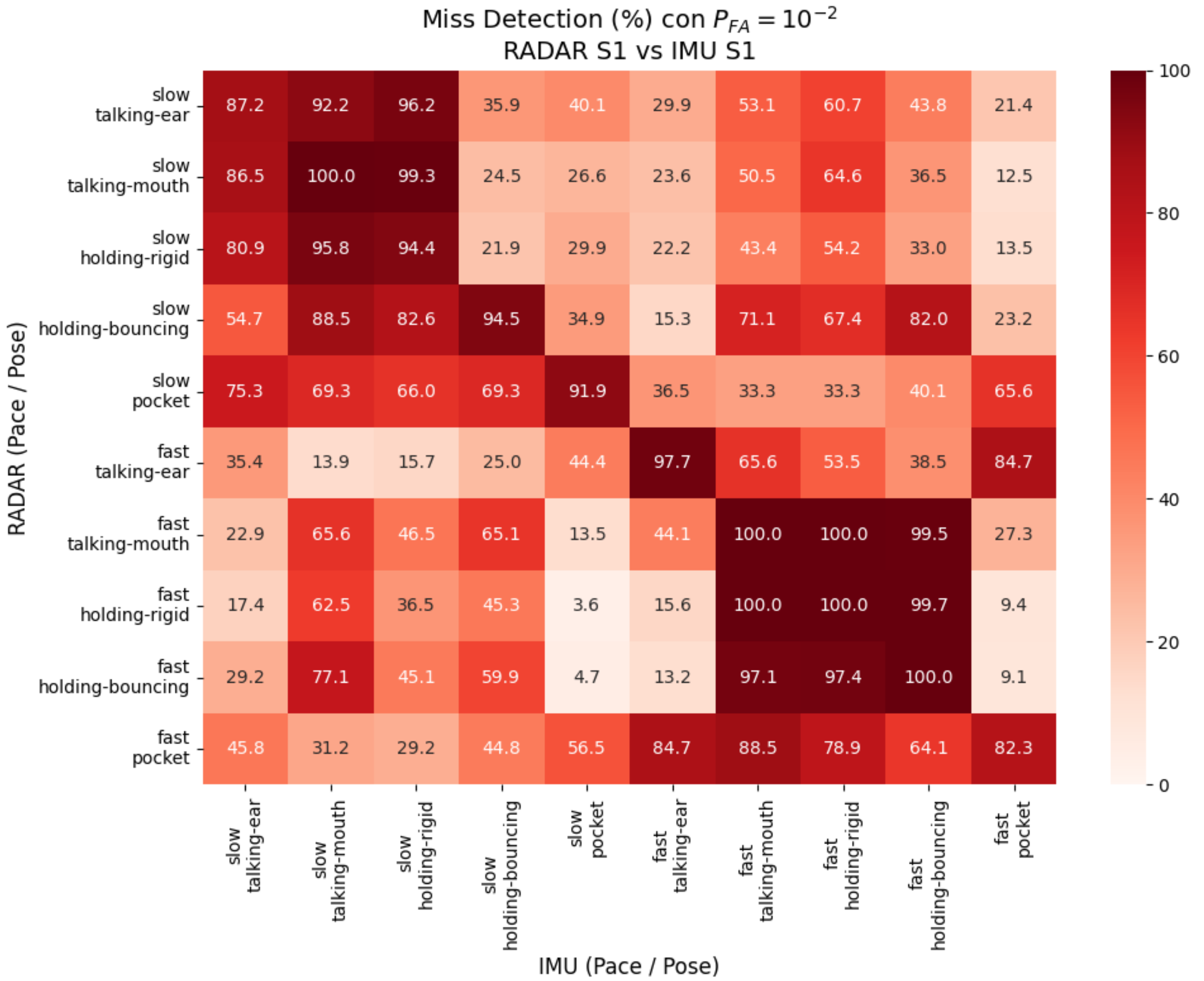




Soggetto 1

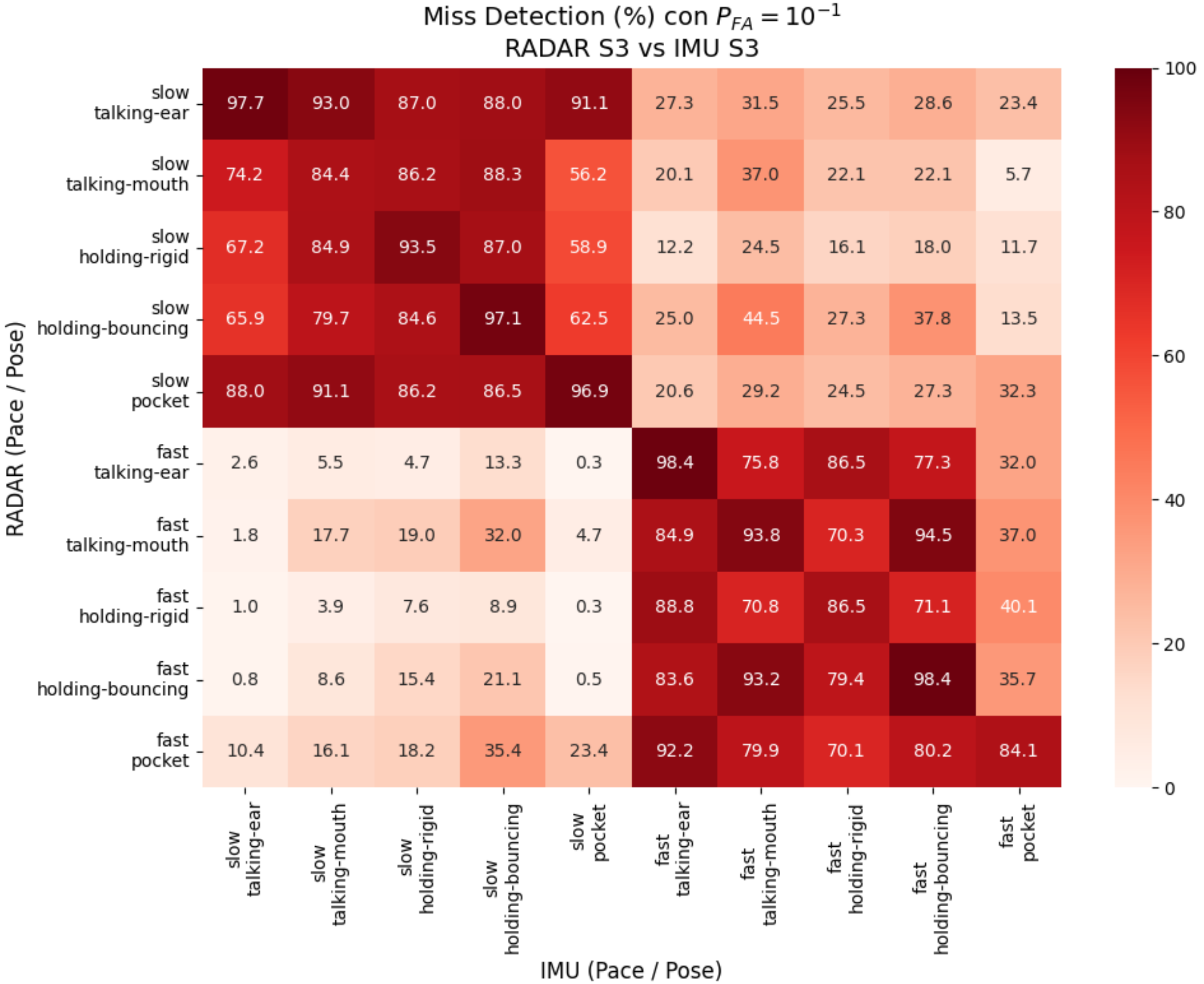


Miss Detection (%) con $P_{FA} = 10^{-1}$
RADAR S1 vs IMU S1
RADAR (Pace / Pose)
IMU (Pace / Pose)
slow talking-ear: 70.1 74.5 74.0 8.3 11.7 12.5 22.1 30.5 21.1 4.7
slow talking-mouth: 59.9 88.5 79.9 1.6 5.7 6.2 22.9 25.5 13.0 2.1
slow holding-rigid: 57.6 70.8 74.5 5.2 6.6 6.9 14.2 18.1 11.1 2.1
slow holding-bouncing: 13.8 57.8 51.0 71.1 9.9 1.4 37.8 31.5 35.2 5.2
slow pocket: 60.2 39.1 45.8 40.1 78.4 13.2 14.6 12.0 15.1 35.4
fast talking-ear: 14.6 4.9 1.9 5.9 21.5 91.7 39.2 31.9 10.4 74.7
fast talking-mouth: 2.3 29.2 16.0 20.3 2.3 6.6 100.0 97.7 91.4 7.6
fast holding-rigid: 0.5 21.9 9.0 5.5 0.0 0.7 97.7 95.8 94.3 0.8
fast holding-bouncing: 3.6 44.3 21.5 13.3 0.0 0.3 84.9 87.2 100.0 1.0
fast pocket: 25.5 15.1 11.8 14.1 30.2 75.7 48.2 39.1 21.4 67.7
slow talking-ear, slow talking-mouth, slow holding-rigid, slow holding-bouncing, slow pocket, fast talking-ear, fast talking-mouth, fast holding-rigid, fast holding-bouncing, fast pocket
0 20 40 60 80 100

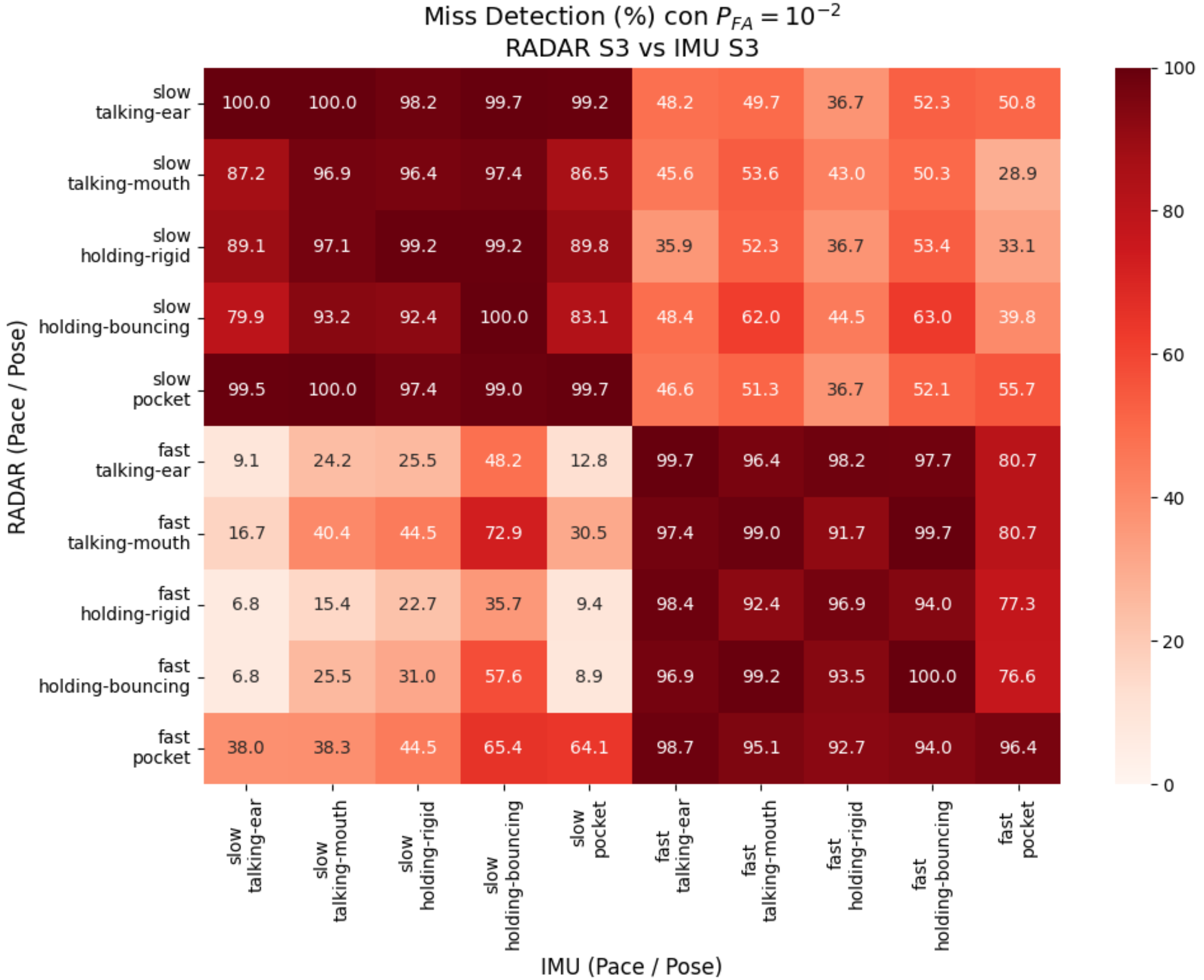


Miss Detection (%) con $P_{FA} = 10^{-2}$
RADAR S1 vs IMU S1
RADAR (Pace / Pose)
IMU (Pace / Pose)
slow talking-ear: 87.2 92.2 96.2 35.9 40.1 29.9 53.1 60.7 43.8 21.4
slow talking-mouth: 86.5 100.0 99.3 24.5 26.6 23.6 50.5 64.6 36.5 12.5
slow holding-rigid: 80.9 95.8 94.4 21.9 29.9 22.2 43.4 54.2 33.0 13.5
slow holding-bouncing: 54.7 88.5 82.6 94.5 34.9 15.3 71.1 67.4 82.0 23.2
slow pocket: 75.3 69.3 66.0 69.3 91.9 36.5 33.3 33.3 40.1 65.6
fast talking-ear: 35.4 13.9 15.7 25.0 44.4 97.7 65.6 53.5 38.5 84.7
fast talking-mouth: 22.9 65.6 46.5 65.1 13.5 44.1 100.0 100.0 99.5 27.3
fast holding-rigid: 17.4 62.5 36.5 45.3 3.6 15.6 100.0 100.0 99.7 9.4
fast holding-bouncing: 29.2 77.1 45.1 59.9 4.7 13.2 97.1 97.4 100.0 9.1
fast pocket: 45.8 31.2 29.2 44.8 56.5 84.7 88.5 78.9 64.1 82.3
slow talking-ear, slow talking-mouth, slow holding-rigid, slow holding-bouncing, slow pocket, fast talking-ear, fast talking-mouth, fast holding-rigid, fast holding-bouncing, fast pocket
0 20 40 60 80 100

Soggetto 3



Miss Detection (%) con $P_{FA} = 10^{-1}$
RADAR S3 vs IMU S3
RADAR (Pace / Pose)
IMU (Pace / Pose)
slow talking-ear
slow talking-mouth
slow holding-rigid
slow holding-bouncing
slow pocket
fast talking-ear
fast talking-mouth
fast holding-rigid
fast holding-bouncing
fast pocket
97.7 93.0 87.0 88.0 91.1 27.3 31.5 25.5 28.6 23.4
74.2 84.4 86.2 88.3 56.2 20.1 37.0 22.1 22.1 5.7
67.2 84.9 93.5 87.0 58.9 12.2 24.5 16.1 18.0 11.7
65.9 79.7 84.6 97.1 62.5 25.0 44.5 27.3 37.8 13.5
88.0 91.1 86.2 86.5 96.9 20.6 29.2 24.5 27.3 32.3
2.6 5.5 4.7 13.3 0.3 98.4 75.8 86.5 77.3 32.0
1.8 17.7 19.0 32.0 4.7 84.9 93.8 70.3 94.5 37.0
1.0 3.9 7.6 8.9 0.3 88.8 70.8 86.5 71.1 40.1
0.8 8.6 15.4 21.1 0.5 83.6 93.2 79.4 98.4 35.7
10.4 16.1 18.2 35.4 23.4 92.2 79.9 70.1 80.2 84.1
0 20 40 60 80 100



Miss Detection (%) con $P_{FA} = 10^{-2}$
RADAR S3 vs IMU S3
RADAR (Pace / Pose)
IMU (Pace / Pose)
slow talking-ear
slow talking-mouth
slow holding-rigid
slow holding-bouncing
slow pocket
fast talking-ear
fast talking-mouth
fast holding-rigid
fast holding-bouncing
fast pocket
100.0 100.0 98.2 99.7 99.2 48.2 49.7 36.7 52.3 50.8
87.2 96.9 96.4 97.4 86.5 45.6 53.6 43.0 50.3 28.9
89.1 97.1 99.2 99.2 89.8 35.9 52.3 36.7 53.4 33.1
79.9 93.2 92.4 100.0 83.1 48.4 62.0 44.5 63.0 39.8
99.5 100.0 97.4 99.0 99.7 46.6 51.3 36.7 52.1 55.7
9.1 24.2 25.5 48.2 12.8 99.7 96.4 98.2 97.7 80.7
16.7 40.4 44.5 72.9 30.5 97.4 99.0 91.7 99.7 80.7
6.8 15.4 22.7 35.7 9.4 98.4 92.4 96.9 94.0 77.3
6.8 25.5 31.0 57.6 8.9 96.9 99.2 93.5 100.0 76.6
38.0 38.3 44.5 65.4 64.1 98.7 95.1 92.7 94.0 96.4
0 20 40 60 80 100

Conclusioni

- I modelli hanno appreso una relazione tra i segnali Radar e IMU
- Nei confronti tra soggetti diversi il modello riesce in alcuni casi a riconoscere l’incoerenza tra i due segnali
- La capacità di discriminazione non è però uniforme

Grazie per l’attenzione