REAL TIME FENCING MOVE CLASSIFICATION AND DETECTION AT TOUCH TIME DURING A FENCING MATCH

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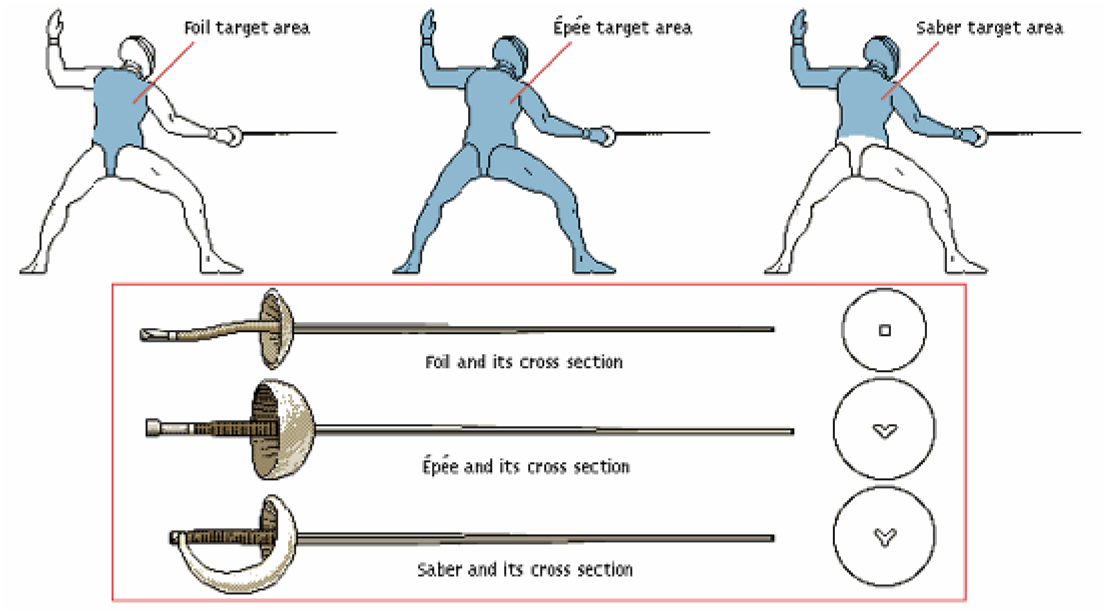
INTRODUCTION

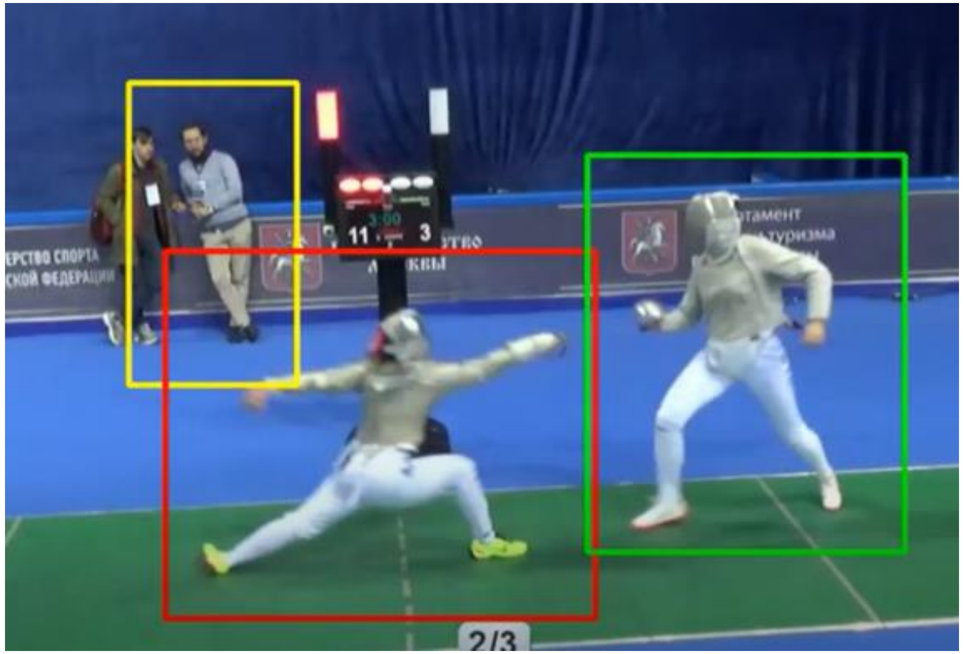
- Fencing is played by two people who are called fencers.
- The aim is to reach a certain score by performing valid moves.
- Fencing has three sword branches that are called Epée, foil and sabre.



BACKGROUND AND RESEARCH JUSTIFICATION

- The players act fast while trying to reach their opponents.
- Their fastness poses a problem for referees and trainers to decide which fencer should:

1. get the score
2. track their moves to get insight

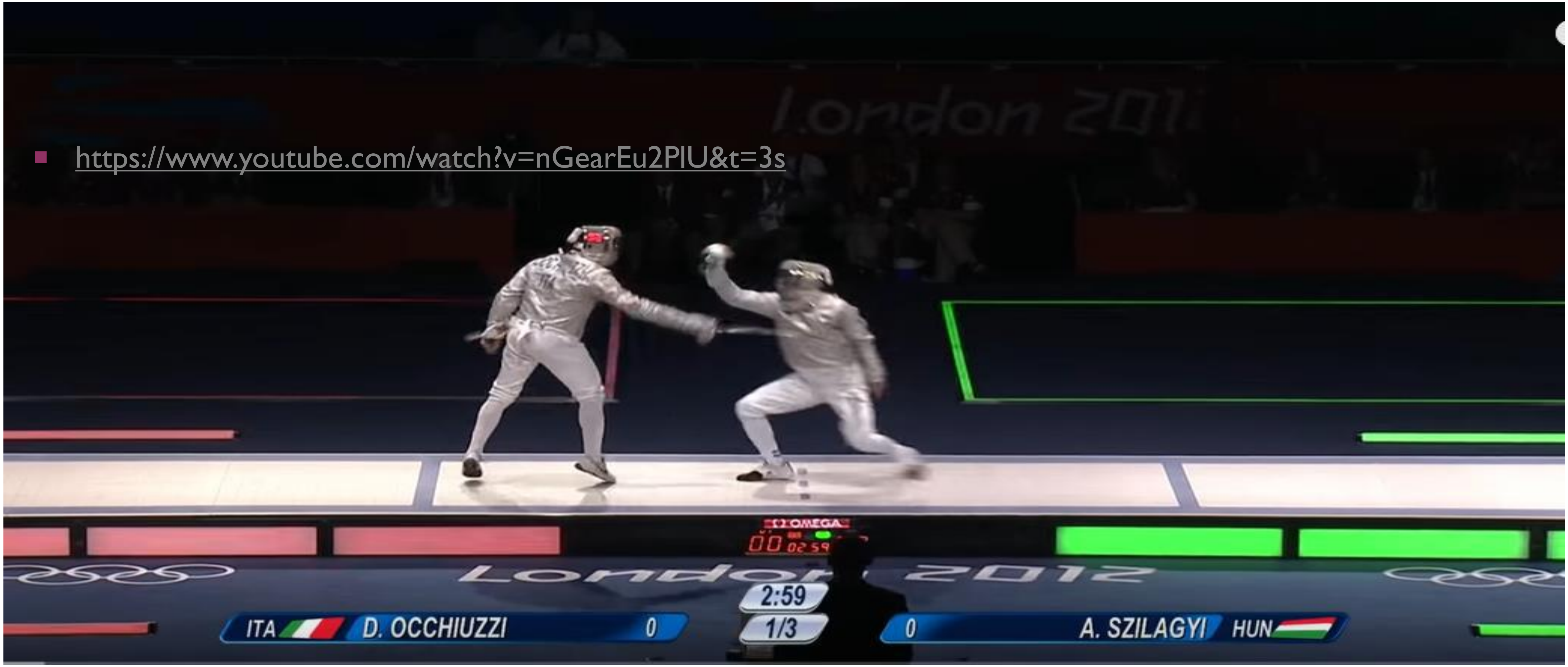


Therefore, the we want to:

- ❑ **Automate detection**
- ❑ **fencing move classification**
- ❑ **to reduce human referee error!**

AN EXAMPLE

- https://www.youtube.com/watch?v=nGearEu2PIU&t=3s



THE CHOSEN MOVES

Lunge

Preparation to attack

Counter-Attack

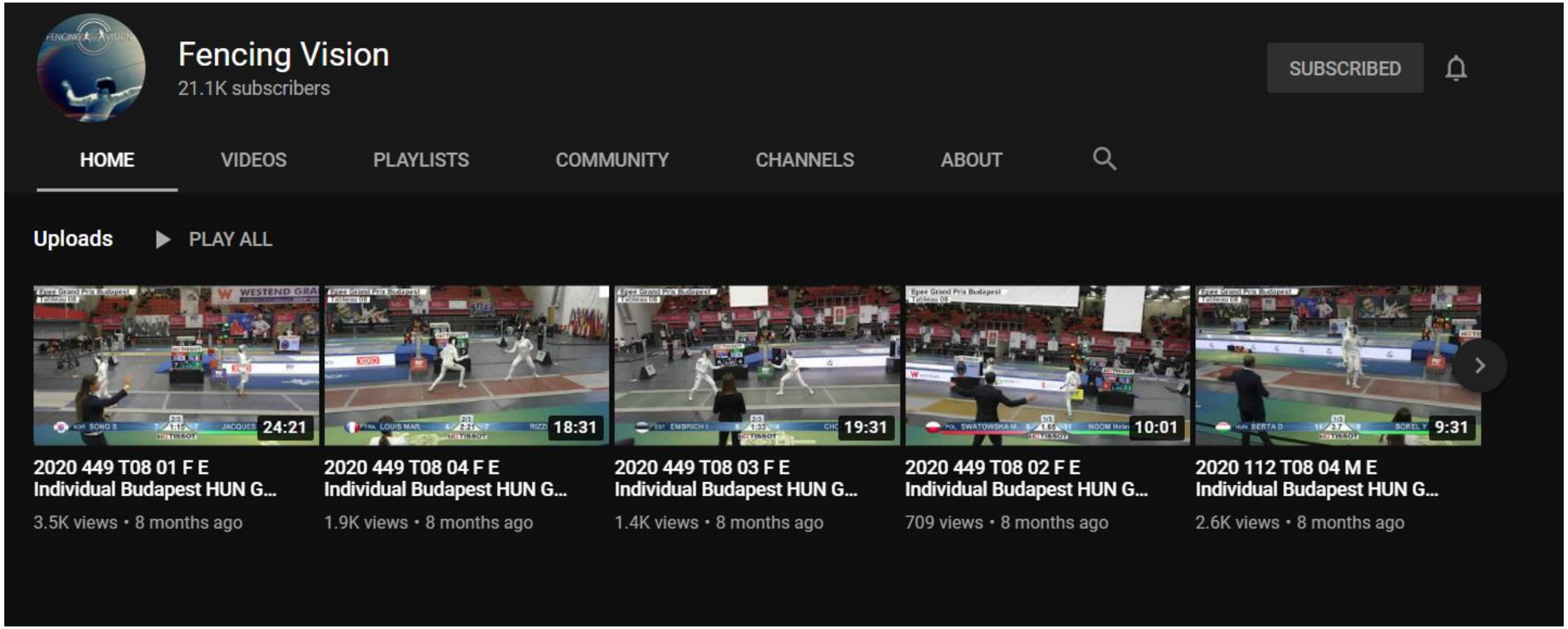
FALSE POSITIVE PREVENTION MEASURES

Refereee

Not a Valid Move

USED DATASET

- Fencing Vision Youtube
- https://www.youtube.com/channel/UCA40s4GODjkaJ9JeM0fBcdg



PIPELINE IN MOTION

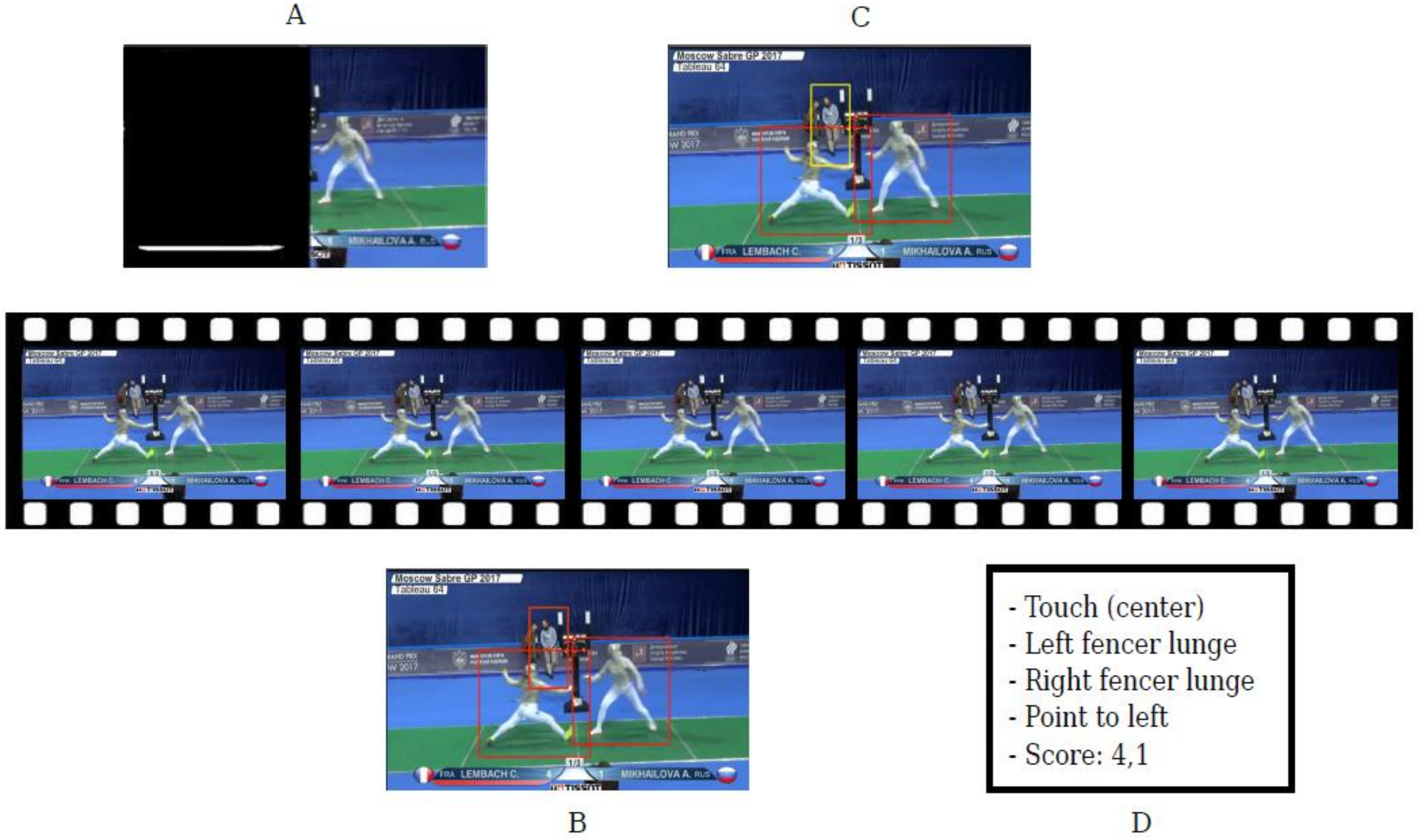


Fig. 2. Move classification of a single round. Initially the notification of contact is extracted from colour information in the video overlay feed. YOLOv3 estimates object proposals, and our residual architecture estimates the move and keeps track of the final scores. Further details in Section III.

DEMO

- https://youtu.be/nQ16GX-F0Gw

ARCHITECTURE PIPELINE

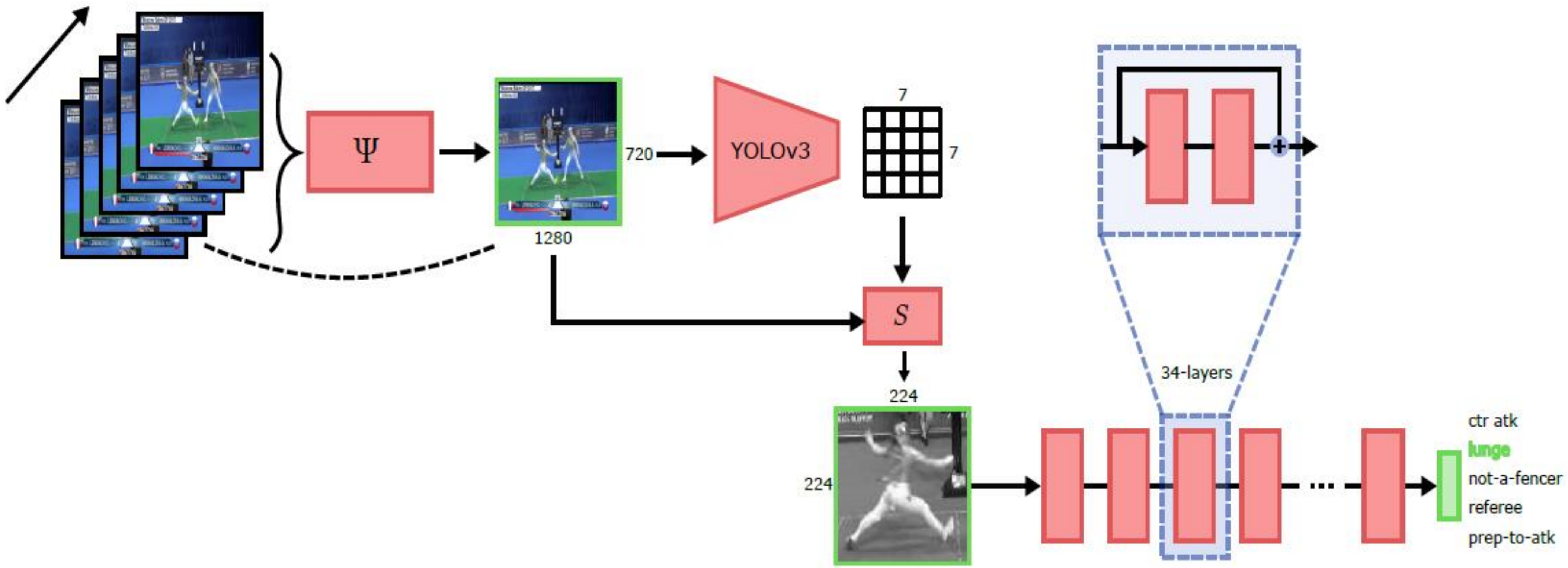


Fig. 1. The proposed architecture initially extracts contact frames using the colour function Ψ, then detects and crops players before the final classification using a residual architecture.

CONTRIBUTIONS

B. Contributions

With the objective of building an accessible fencing move analysis system, this paper makes the following contributions:

1) We design and propose a modular architecture that is able to detect and classify fencer moves at touch time with 83.0% accuracy on unseen tournament footage.
2) We provide some preliminary fencing analysis using results obtained of our system, in particular we surprisingly find that both winners and losers generally have similar distributions of moves, although more analysis is needed to be definitive on this.
3) We found the combination of YOLOv3 and ResNet-34, using an auxiliary image processing function to retrieve the fencing circuit signal, to be effective in this computer vision application setting.

RESULTS

TABLE I

TEST ACCURACY ON UNSEEN TOURNAMENT VENUES. WE SHOW THE MEANS AND STANDARD DEVIATIONS BEST TEST ACCURACY FOR THE MODEL TRAINED TEN TIMES, AND THE SINGLE BEST TEST ACCURACY.

Model/Color	Mean/Std test acc	Best test acc
ResNet-18 RGB	$79.7\% \pm 1.8\%$	84%
ResNet-34 RGB	$81.6\% \pm 2.4\%$	86%
ResNet-34 HSV	$77.2\% \pm 3.0\%$	81%
ResNet-34 Gray	$\mathbf{83.0\% \pm 1.3\%}$	**86%**
ResNet-34 Edge	$77.8\% \pm 1.5\%$	81%

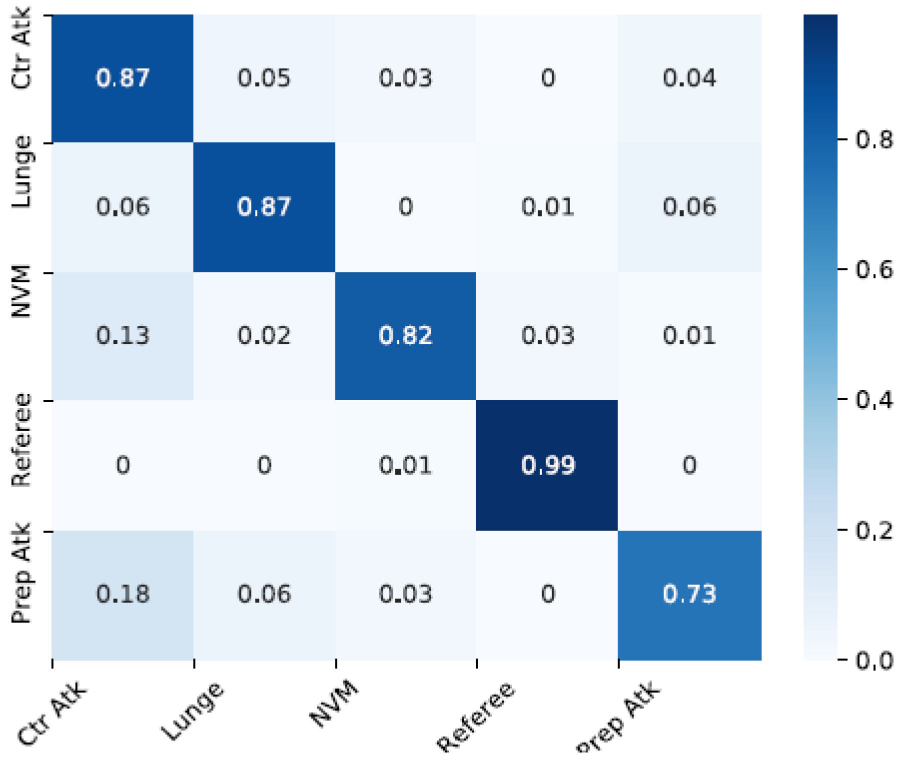


Fig. 10. Confusion Matrix for the best performing model, ResNet-34 Gray, on the Test Dataset. 'NVM' is the 'Not A Valid Move' class.

OBTAINED STATISTICS

Winner			Loser		
Counter-attack	Lunge	Preparation-to-attack	Counter-attack	Lunge	Preparation-to-attack
1237	2592	236	832	1729	184
30.4%	63.8%	5.8%	30.3%	63.0%	6.7%

Table 2: Fencing move distribution for winner and loser

Counter-Attack	Lunge	Preparation-to-Attack
5464	10935	1219
31.0%	62.1%	6.9%

Table 4: Frequency of Fencing Moves in the touch time

OBTAINED STATISTICS

Left	Center	Right
1078	6311	710
13.3%	77.9%	8.8%

Table 3: Locations of the piste that touch has been made

AVAILABILITY

- The model and our dataset are publicly available at:
- https://github.com/CodLiver/RT-Fencing
- released under the MIT licence.
- Mail: cem.ekin.sunal@gmail.com