Badminton stroke classification based on accelerometer data: from individual to generalized models

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***Abstract*—Activity recognition models based on wearable devices are becoming increasingly popular. However, models that are trained and tested on the same players show a large bias and are not generalizable to previously unseen players. In this paper, we tackle the badminton stroke recognition problem from this perspective, comparing the performance of individual and generalized models based on an accelerometer and a gyroscope, and identifying which components of the solution can maximize the performance of generalized models. First, we describe a simple convolutional neural network trained to classify 7 types of stroke. Second, the model is extended in a hybrid way to identify two additional classes (movement and rest). Third, data augmentation is applied on the training set. Fourth, transfer learning is applied to use data from the test player to fine-tune the generalized model and attempt to reach the performance of an individual model. These models are evaluated on a dataset collected from amateur players, both in a controlled environment and in a match simulation. The results showed a large difference between the performance of individual and generalized models; however, the latter could be improved by increasing the number of players in the training set, by data augmentation, and by transfer learning, highlighting the necessity of larger datasets in this field.**

***Index Terms*—Activity recognition, badminton, convolutional neural network, machine learning, accelerometer.**

I. INTRODUCTION

MANY sports are being subject to data collection and machine learning techniques, with the aim of improving the skills and tactics of the players or to evaluate past games. Badminton, being one of the most popular racket sports worldwide, is no exception [1], and many researchers have invested effort into several aspects of the game, such as strategy identification [2], [3], [4], [5] or player tracking [6]. In particular, stroke type recognition is one of the cornerstones of data analysis in badminton, as they are crucial to further identify strategies that might allow the players to win the game.

Previous research in badminton stroke recognition can be divided into two broad families: methods focused on video and image analysis [7], [8] and methods based on wearable sensors [9], [10]. Although the latter involve the installation of specific sensors on the racket or the players' body, they also allow a more personalized analysis of the information. Recent developments in microchip and accelerometer technology have increased the interest for this kind of approaches, as the size and weight of the sensors becomes negligible. This allows practitioners to place an accelerometer and gyroscope in the racket, a smartwatch or a wristband without any impact on the nature of the game, and at very low cost, enabling the easy collection of large quantities of personalized datasets.

It has already been established by this previous research that the differences between individual players can be significantly large, which hinders the performance of trained classification models when applied on new players [10], especially in the case of amateur players [11]. However, recent algorithmic developments such as data augmentation and transfer learning open new possibilities to enable the training of general models for badminton stroke classification.

In this paper, we address this challenge by analyzing the performance obtained by a convolutional neural network (CNN) [12] on both an individual and a generalized setting. To this goal, we gathered a dataset with 7 types of labeled strokes, plus 2 types of movement, involving 5 amateur players, using an off-the-shelf accelerometer and gyroscope. The main contributions of this paper are the following:

- We trained and analyzed the performance of an individual CNN model when training and testing on different time frames from the same player.
- We propose a hybrid model which, combined with the former, is further able to identify when players are running or resting.
- We further evaluated the generalized performance of the CNN when training and testing on different players, in combination with several data augmentation techniques aimed at improving this performance.
- We evaluated the performance of the network in a transfer learning setting, in which a few frames from the test player are used to fine-tune the trained general model, leading to significant accuracy improvements.

The paper is structured as follows. Section II presents the previous work in the field. Section III describes the proposal. Section IV details the experiments carried out and their results. Finally, Section V concludes the paper.

II. RELATED WORK

Early works in the field of movement analysis in badminton already showed that accelerometers can be used to model the arm movement in badminton swings [13], [14]. Since then,

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several publications have strived to identify different types of strokes using machine learning. These proposals can be grouped into those that use video as input, and those that require placing sensors on the players or the rackets.

Rahmad et al. [15] used the video frames of a single game[1] as input to four well-known pre-trained networks (AlexNet, GoogleNet, VggNet-16 and VggNet-19). The models were used in a binary classification setting, to detect whether the player hit the shuttle or not. An extension was also proposed to use AlexNet as a feature extractor in combination with globally extracted features, which are then fed to a Support Vector Machine (SVM); this was tested in the binary case [8] and a 5-class stroke recognition problem [16].

Raj et al. [17] compared several network architectures to process video and do a 6-class stroke classification. The best accuracy was achieved by a combination of CNN and Long Short Term Memory (LSTM); although other models such as a neural accumulator followed by a CNN were more computationally efficient.

Chu and Situmeang [2] proposed an entire pipeline using video input, including court detection, player tracking, stroke classification, and strategy classification. The stroke classification is done by manually snipping and labeling images from the video, which are then processed to extract the histogram of oriented gradient, which is in turn used to train an SVM classifier.

Similarly, Ramasinghe et al. [7] used videos to extract Histogram of Gradient (HOG) features and train a 4-class SVM to recognize stroke types. Their proposal was trained on a video of a player, and then tested both on the same video and on a video of a different player, respectively reaching an accuracy of 98.34% and 93.34%.

Wang et al. [9] placed an accelerometer on a racket and used AlexNet, extended with some extra preprocessing layers, to classify strokes into 10 types.

A previous study used an IMU accelerometer and a microphone placed on the racket to perform stroke classification with 6 classes [18], which led to an accuracy of 95.51% when classifying a single player, and 79.32% when training and testing on a same set of 10 players. However, the study does not consider the scenario of separating the players in the training and test set. This work was later extended [19] with a deeper analysis of the sound sensor to identify the time of each stroke, leading to small improvements in the accuracy when training the same classifiers.

Anik et al. [20] placed a sensor including accelerometer and gyroscope in the racket and derived a set of 8 features from each axis (for a total of 48 features), to then train an SVM classifier for 3 types of stroke (smash, serve, backhand). However, the size of the dataset was limited to 180 instances, and the sensor was placed in the cords of the racket, which might hinder its handling when playing a real game.

In [21], a hidden Markov model (HMM) is applied on data obtained from sensors (accelerometer and two gyroscopes) placed on the wrists and ankles of the player to detect strokes, and a second HMM is used to classify between 14 types of stroke. This system was evaluated using a dataset collected from 12 right-handed players, although the training and test set contained data from all players, which might lead to an underestimation of the error. An average accuracy of 97.96% was obtained. When using a single joint, the accuracy was greatly reduced to between 32.62% and 81.63%.

Steels et al. [10] trained a CNN based on accelerometer and gyroscope data to classify the players' actions into 7 types of strokes, plus two extra classes (standstill and running). The resulting model was then used as an ensemble, using different frame sizes as input. Their results showed that the gyroscope information significantly improved the prediction results with respect to using only the accelerometer, reaching up to 99% accuracy. However, the study was limited to two players, which were respectively used to train and test the model, which might lead the results to overfit the test player after model tuning.

Recently, Ghosh et al. [11] have proposed the use of 4 accelerometers and a CNN to classify the strokes into 12 types. This information is used as a basis for other modules of the proposal, such as score estimation.

Table I summarizes the main characteristics and accuracy achieved by the aforementioned works. Note that, in this context, 'Individual' refers to the cases in which the same player(s) were used to train and test the algorithms, whereas 'Generalized' refers to the performance when training and testing on different players.

III. PROPOSAL

A. Badminton strokes

In badminton, a first categorization of the strokes can be done according to their horizontal and vertical positioning, respectively forehand/backhand and overhand/underhand. In this work, we only consider forehand strokes, because they are easier to carry out, which means that they occur more frequently in a real game, especially when amateur players are involved.

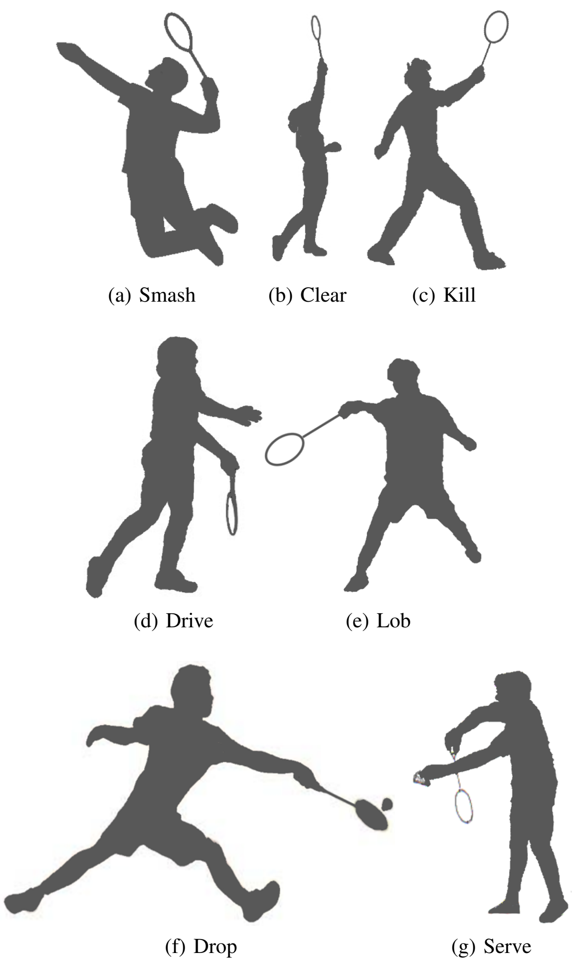
In this paper, we consider 7 types of stroke (see Figure 1), in line with previous works [10]:

- Smash: offensive overhand stroke to send the shuttle as fast as possible in a downwards straight trajectory, out of reach of the opponent.
- Clear: similar to the smash, with the difference that the shuttle is sent in an arched trajectory to the back of the court. It's a rather defensive stroke.
- Kill: overhand stroke to block the opponent's shot by sending the shuttle in a steep downwards trajectory. The kill is played at the front court with a short extension swing.
- Drive: quick, flat mid-court stroke originating from the side of the player.
- Lob: defensive shot to send the shuttle to the back of the court.
- Drop: soft stroke played next to the net, to send the shuttle in an arched trajectory as close as possible to the net in the opponent's side of the court.
- Short service: backhand stroke to start the rally, aiming to send the shuttle just behind the opponent's service line.

[1] https://www.youtube.com/watch?v=SjlJ_cV3DdA

TABLE I
RESULTS OF PREVIOUS PUBLICATIONS ON BADMINTON ACTION RECOGNITION.

Reference	Input	Model	Number of classes	Number of players	Accuracy Individual	Accuracy Generalized	F1 Score Individual	F1 Score Generalized
[11]	4 accelerometers	CNN	12	11		95.21%		95%
[15]	Video	CNN	2	2	87.5%			
[8]	Video	CNN+SVM	2	-	98.7%			
[16]	Video	CNN+SVM	5	-	82.0%			
[17]	Video	CNN+LSTM	6	-	88.6%			
[18]	IMU + acoustic	SVM (Poly)	6	10	95.91%	79.32%	95.90%	
[19]	IMU + acoustic	SVM (Poly)	6	10	96.5%	84%	95.01%	
[20]	Accelerometer+Gyroscope	SVM	3	-	88.89%		88.67%	
[21]	4 $\times$ Accelerometer+Gyroscope	HMM	14	12	96.97%			
[9]	Accelerometer	Preprocessing+CNN	10	-	98.65%			
[7]	Video (HOG)	SVM (Linear)	4	1	98.34%	93.34%		
[2]	Video (HOG, automatic features)	SVM	5	6	70%			
[2]	Video (HOG, manual features)	SVM	5	6	83.33%			
[10]	Accelerometer	Ensemble of CNN	9	2		86%		
[10]	Accelerometer+Gyroscope	Ensemble of CNN	9	2		99%		99%



(a) Smash (b) Clear (c) Kill

(d) Drive (e) Lob

(f) Drop (g) Serve

Fig. 1. Badminton strokes (images from [10])

B. Sensors

We used an Axivity AX6 sensor to gather the data, which contains a 6-axes movement sensor composed of an accelerometer and a gyroscope, which respectively measure linear acceleration and angular speed with a high precision. The raw data is collected by the sensor in an internal flash memory. The sensor measures $23 \times 32.5 \times 8.9$ mm and weights 11 grams, which makes it ideal to measure movements with minimal or no impact on the activity being performed.

C. Data collection

We collected data from 5 amateur players, whose characteristics are shown in Table II. Each player was asked to repeat the same movement for each type of stroke for 4 minutes, without opponent and without shuttle, with 1 minute break between stroke types. This design aims to reduce the noise of the measurements, making the labeling easier, and reducing the time needed to collect the data. For each stroke, 1 minute of movement is separated as a validation set. The accelerometer was set to collect data at a frequency of 50 Hz.

TABLE II
OVERVIEW OF THE PLAYERS

Player	Age	Height (cm)	Weight (kg)	Hand	Previous experience
P1	21	175	68	Left	No
P2	53	172	65	Right	No
P3	25	168	65	Left	Yes (tennis)
P4	23	179	65	Left	No
P5	21	168	53	Right	Yes (badminton)

In order to test the models in a more realistic and less controlled environment, extra data was captured from 3 of the players (P1, P3 and P5). They were asked to simulate a real game (without opponent nor shuttle), performing the 7 types of stroke after each other in arbitrary order, and including movement across the court and periods of standing still, which makes for a total of 9 classes. The procedure was carried out for 3 minutes for each player, which yielded an average of 35 actions.

D. Preprocessing

The signal was first preprocessed to segment the different strokes in the series and to remove part of the noise. Noise removal in this type of data is particularly critical, because the peaks of the acceleration series are particularly valuable to distinguish the classes. Therefore, for this work, the following noise removal procedure was carried out specifically for each class. For each class, four parameters are specified: the typical duration of the stroke t, the duration between the start of the stroke and the peak acceleration t_s, the maximum acceleration peak a_{peak}, and the dominant axis $r \in \{x, y, z\}$. First, the time series of axis r is explored and all the peaks larger than a_{peak} are identified. Then, for each of these peaks occurring at time t_{peak} the window of the stroke is established in the time interval $[t_{peak} - t_s, t_{peak} - t_s + t]$.

In addition to this preprocessing, for the generalization experiments we also applied data augmentation on the training set to increase its size and variability, aiming to improve the training of the neural network. Several types of data augmentation techniques specific to accelerometer data were applied in combination:

- Jittering: adding Gaussian noise to the signal. In our experiments, we used a mean of $0g$ and standard deviation of $0.2g$.
- Scaling: multiplying the entire series by a constant factor k, which in our case was normal random number with mean $1g$ and standard deviation $0.2g$.
- Time warping [22]: the distortion of the signal is a continuous function dependent on time, so that some periods are compressed and others are dilated. We used a cubic spline with 4 knots and standard deviation of 0.2, independent for each axis.
- Permutation: segmenting the time series into fragments of equal size that are randomly permuted.

Finally, before being fed to the model, the data is split into frames of equal length. In this case, a frame length of 40 was chosen, in accordance with previous work [10], which at a frequency of 50 Hz is equivalent to 0.8 seconds.

E. CNN and hybrid model

The model chosen to classify the strokes is a standard convolutional neural network, with the architecture and parameters specified in Table III. The Adam optimizer was used with a batch size of 64 and 100 epochs.

TABLE III
CNN ARCHITECTURE.

Type	Size	Activation	Parameters
Conv2D	$2 \times 2 \times 16$	ReLU	
Batch normalization			
Dropout			probability = 0.2
Conv2D	$2 \times 2 \times 32$	ReLU	
Dropout			probability = 0.1
Dense	64	ReLU	L2 reg. weight = 0.01
Dense	7 or 3	SoftMax	

In order to model a classifier that can identify all types of strokes, along with the movement or rest state of the player, a hybrid approach was followed. Therefore, two identical networks were trained, with the sole difference of the last layer, which encodes either 3 classes (the state of the player: stroke, movement or rest) or 7 classes (the stroke types). First, the 3-class model is applied on an input. Then, if the input is predicted to be a stroke, the 7-class model is apply to determine the specific stroke type.

F. Transfer learning

As mentioned previously, in this work we evaluate the difference between individual models, which are trained and tested on the same player, and generalized models, which are trained on a set of players and tested on previously unseen players. We also explore an intermediate possibility: using a generalized model as a baseline, and fine-tuning it with only a few frames from the new player. For this, we use the same CNN described in Section III-E, with all layers frozen except the last one, which is re-trained during this fine-tuning process. In the experiments, we vary the amount of frames using for this fine-tuning between 0 and 10.

IV. EXPERIMENTS AND RESULTS

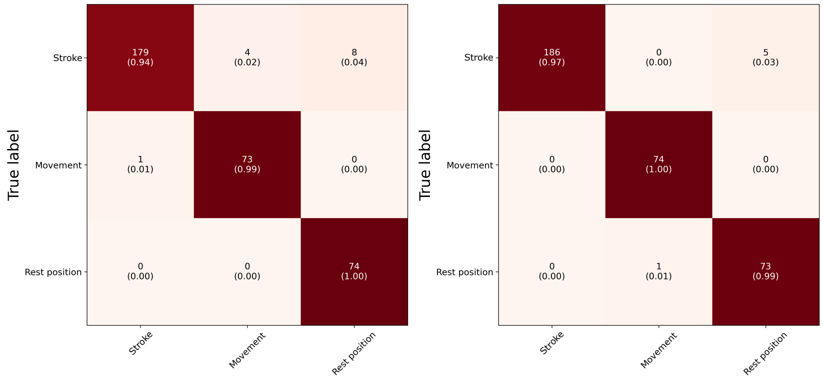
As described in Section III-C and Table II, for this study we collected data from 5 different players and labeled them with 7 stroke types. For each player and each stroke, 1 minute of data (approximately 25 %) was held out as test set. In each case, two models were trained: only using the accelerometer input, and using both accelerometer and gyroscope. Then, three sets of experiments were carried out: individual experiments, consisting of training and testing on the same player (Section IV-A), experiments on the hybrid model (Section IV-B), and generalization experiments, consisting of training and testing on different players (Section IV-C).

A. Individual

Table IV shows the test accuracy obtained for each player, using either the accelerometer, or both sensors, and without applying any data augmentation nor transfer learning. Furthermore, the last column shows the accuracy obtained in the match simulation dataset described in Section III-C, albeit only taking into account the 7 stroke classes and discarding the movement and rest classes, to keep the results comparable to those of the controlled environment. It is clear in the table that adding the gyroscope improves the accuracy of the model; also, there is a certain variability among the accuracy obtained for different players. Some (such as P1 and P5) seem to be easier to classify. It can also be seen that the match simulation data is more challenging, as there is a significant drop of the accuracy in all cases. It is noteworthy to point out that all the serve and kill strokes of player P3 were mistakenly classified as the most similar ones in the dataset: drive and smash, respectively. This highlights how the movements of a player can change slightly between a fully controlled environment and a game simulation, hindering the results of a classifier trained exclusively on data from the controlled environment.

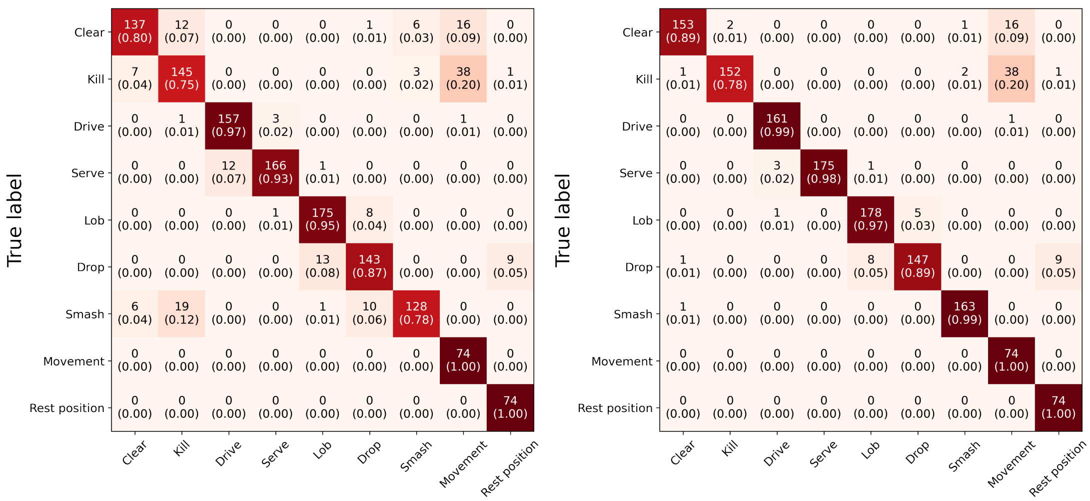
TABLE IV
TEST ACCURACY OF THE CNN FOR INDIVIDUAL STROKE CLASSIFICATION

Player	Acc.	Acc. & gyro.	Match simulation (only acc.)
P1	96.73%	98.98%	77.27%
P2	89.08%	92.02%	
P3	93.02%	96.28%	63.70%
P4	90.53%	94.24%	
P5	95.63%	98.02%	88.18%
Average	93.00%	95.91%	76.38%



(a) Accelerometer (b) Accelerometer & gyroscope

Fig. 2. Confusion matrix for 3-class network



(a) Accelerometer (b) Accelerometer & gyroscope

Fig. 3. Confusion matrix of hybrid model

B. Hybrid model on all players

In a first approach, we trained the same CNN with only 3 classes: stroke, movement, and rest. In this case, a single model was trained for all players, respecting the same training/test partition done for the rest of the experiments. The results obtained can be seen in Figure 2, for an average of 96.40% accuracy with only accelerometer, and 98.09% also using the gyroscope.

When the output of this 3-class model is combined with that of the 7-class model, we obtain the 9-class confusion matrices shown in Figure 3, which yield an average accuracy of 87.65% and 93.35% for with the accelerometer, respectively with and without the gyroscope.

Naturally, the performance of the 9-class problem is lower than that of the 7-class problem and 3-class problem separately. We also observer that the inclusion of the gyroscope data still increases the accuracy of the models in all cases.

C. Generalized

In this section, we describe the results obtained when the data from different players was used to train and test the models. Four sets of experiments were carried out: baseline, with data augmentation, with transfer learning, and an additional set of experiments to compare between different frame sizes.

Figure 4 shows the accuracy obtained for stroke classification when using each player as test, as a function of the number of players used for the training and the sensor used as input. We can see that there is still a significant difference between players, but in general terms the accuracy improves along with the size and diversity of the training set. In opposite to the conclusions drawn from the individual models, in this case the gyroscope data doesn't systematically improve the accuracy; in some cases, the models trained only on accelerometer data yielded similar or better results than when using both sensors. This can be attributed to an overfitting of the training set, which becomes much more clear in a generalized setting (i.e. when the test player isn't present in the training set of the models) than in an individual setting.

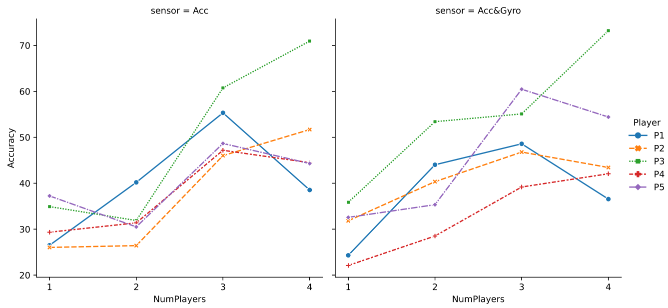


Fig. 4. Accuracy obtained using each player as test, as a function of the number of players used for the training.

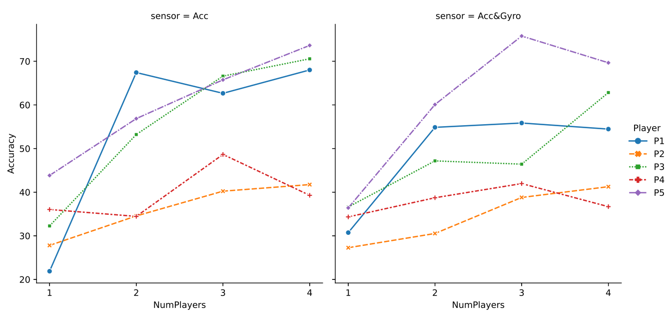


Fig. 5. Accuracy obtained using each player as test, as a function of the number of players used for the training, when using data augmentation.

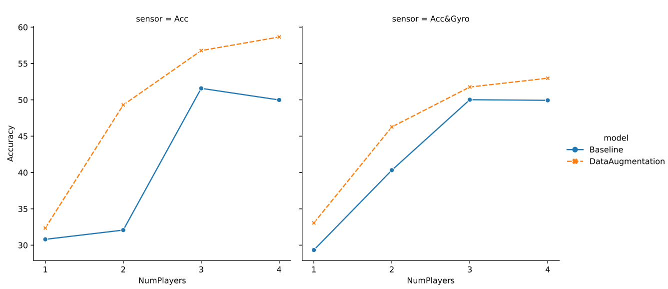


Fig. 6. Average accuracy for all players.

Similarly, Figure 5 shows the accuracy after applying data augmentation. The same patterns as before can be seen: the accuracy improves with the number of players in the training set, but the addition of the gyroscope does not increase it. Figure 6 shows the average accuracy obtained across all players. It is clear that the gyroscope does not add much value to the results, especially in the case with data augmentation. Also, data augmentation clearly improves the baseline results, by increasing the size and variability of the training set with realistic noise. This hints that the results of this study could be further improved by collecting a large dataset from many diverse players, performing the strokes under different conditions.

Figure 7 shows the accuracy obtained with the transfer learning approach, which involves training a model on the 4 other players in the dataset, and fine-tuning it using a small amount of frames from the test player. This approach closes the bridge between the individual and the generalized models, and it is clear that the improvement in accuracy is very large. With only 10 frames for the fine-tuning, the performance of these models gets much closer to that of the individual models shown in Table IV. We can also see in the figure that the accuracy drop when adding the gyroscope data becomes smaller than when using purely generalized models.

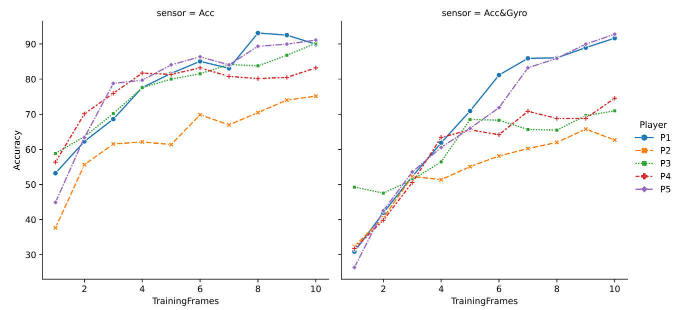


Fig. 7. Accuracy when using transfer learning.

V. Conclusion

In this paper, we have proposed the use of CNN, data augmentation and transfer learning to deal with the challenges posed by generalized badminton stroke recognition using accelerometer and gyroscope data. Using a dataset gathered from 5 amateur players, both individual and generalized models have been tested to classify 7 types of stroke and 2 types of movement.

The results showed that the difference between players can be very large, stressing the need for generalized models. These showed how an increased number of players in the training set can yield better results, up to a limit. Furthermore, the applied data augmentation improved the baseline results, highlighting that larger datasets collected from different players under different conditions would probably allow the proposed models to obtain better results. Finally, the transfer learning proposed to incorporate new players into the model showed a great improvement of the classification accuracy, allowing it to largely breach the gap with individual models by only using a few frames from the test player.

As for the sensors used in the study, it was clear that the addition of the gyroscope to the accelerometer only improved the results for the individual models. When dealing with generalized models, the gyroscope data caused an overfitting of the models to the behavior of the players in the training set, hindering the application of these models on previously unseen players. However, when using transfer learning, this impact was greatly reduced, and the combination of accelerometer and gyroscope produced similar results to those obtained using exclusively the accelerometer.

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