StanceScorer: A Data Driven Approach to Score Badminton Player

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Abstract—In recent times, wearable devices have gained immense popularity for IoT applications, especially for sports analytics. Recent works in sports analytics primarily focuses on improving a player's performance and help devise a winning strategy based on the player's strengths and weaknesses which is also the objective of this paper. In a racquet-based sports, it is often assumed that handling the racquet majorly influences the performance of the players, however, the stance and the posture of the player are of greater importance. A perfect posture and stance allow a player to play a stroke efficiently by directing the shuttle to strategic spots. Therefore, it helps to utilize less energy and make it difficult for the opponent to return the shot and eventually score a point. Hence, we hypothesize that the performance of a player equally correlates with the stance and the efficiency of handling the racquet. In this paper, we propose to analyze the stance of the player based on the shot played. In an attempt to do so, we propose a data-driven approach to evaluate a player's performance based on the player's stance or posture. First, we employ both shallow learning and deep learning algorithms to classify the strokes which is then used to analyse the stance. Secondly, we propose a distance based methodology to compare the stance of an intermediate or a novice player with that of a professional player. Further, we learn the error between the professional player's stance with that of a participant and propose a scoring methodology. To evaluate our proposed methodology, we deploy a sensor network comprising of inertial measurement units (IMU) sensors on the dominant wrist and palm; and both the legs. We collect the data from a professional player, an intermediate player and a novice player for 12 different frequently played shots and evaluate our proposed methodology with this dataset.

Index Terms—Activity Recognition, Convolutional Neural Networks, Wearable Devices, Badminton, Sports Analytics.

I. INTRODUCTION

In recent times, human activity recognition with the power of wearable and Internet of Things (IoT) devices has paved path for interesting research directions especially in domains involving competitions. It is possible for common people to acquire and use the wearable devices and activity trackers due to the popularity, availability and affordability of such devices in the market. The popularity of such devices and the recent developments in the field of machine learning can facilitate the use of such devices in various fields such as ambulatory care, sports analytics, fitness tracking and training, work force tracking and management and many more [1]. Sports Analytics is a developing field that is gaining immense popularity globally. In almost all the sports, both the professional and

Fig. 1. (left to right) The figure demonstrates the rough body postures for different shots: Overhead Backhand Stroke, Overhead Forehand Stroke, Underarm Forehand Stroke and Underarm Backhand Stroke

amateur players rely on the analytics team to hone their skills, assess the opponents and develop winning strategies. Badminton is one such strategic and competitive sport which can be significantly improved with the help of analytics.

Badminton is a popular racket game which features in multiple global tournaments including Olympics, World Championships, Commonwealth games, Asian games and many more. The game is highly competitive where a minute error can topple the lead gained by the player. Badminton is also an intense game that typically lasts between 40 and 60 minutes. The game primarily relies on the strategical strokes, stamina and positive mindedness of the player. Strokes are the basically waving the racket and hitting the shuttle directing to the opponent's side. A successful stroke involves either altering the power of the shot or strategic placements based on the opponent's position and reflex recovery from the previous shot. Overall, both the hand movements (strokes) and footwork (stances) of the players contribute to the game winning scenario. It is essential to capture the micro-activities of the player which involves a body sensor network to understand and devise analytics of the game.

Body sensor Networks have previously been used in numerous studies such as [2], [3] where the authors proposed a sensor network to analyse the micro-activities of dance using Actigraphs [4] on extremities. There are some commercially available devices that can help track the players performance. Zepp Sensor [5] is a popular wearable for various sports such as golf, soccer and many more to track the performance of the player. Actofit sensor [6] is another commercially available
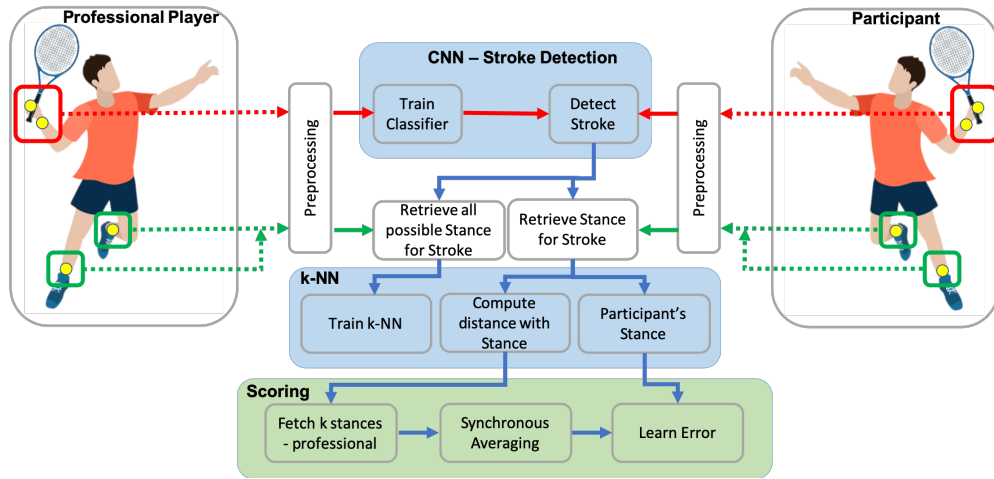
Fig. 2. Overall Architecture

device that can monitor individual workout using motion tracking of the players and provides real-time feedback. [7] is a smart t-shirt that is capable of accurately measuring the heart rate of the player throughout their workout. Specifically for Badminton, the commercially available product to track the player's performance is based on 3-D motion tracking of the player [8].

Several researchers have concentrated on badminton sport specifically. The authors of [9] proposed a sensor system that captures the smash shot and studied it's correlation with the velocity of the shuttle. The velocity was measured using Two-Axis Accelerometers (ADXL321) and the sounds of the shots were recorded using Acoustic Sensor (BRT1615-06) . Another study by the authors of [10] developed a classifier model that can detect the badminton strokes. The data was collected using a Magnetic Pickup Unit (MPU 6050 sensor) and an Arduino module was used as a hub. Although the work concentrated on detecting the restricted number of strokes using the swing of the racquet, the work does not consider the movements of all the limbs. Furthermore, the dataset considered is small which causes the concern of misinterpretation of the results. In another study, the authors leveraged visual analysis to detect the players, badminton court, classify strokes and player's strategy using Hidden Markov Model. However, this study lacks explanation related to video based systems such as misclassification caused by the shadows, camera positioning, and privacy related concerns. Another important aspect of such device based and algorithm based study for sports is scoring. Scoring can be defined as a machine generated score that can help evaluate a player based on the skill compared to a professional or a rule book. In this study, we are also looking at identifying metrics that can be used for scoring a player.

In this paper, we hypothesize that a player's efficiency equally depends on the player's stance as that of the stroke played. The novelty in this paper is that we leverage a body sensor network to capture a player's movements to include the movement data from the lower limbs. Below, we summarize

our key contributions of the paper.

- We design and develop a classification model using CNN that can accurately classify the strokes played by the player. We compare the classification results for players of varied proficiency using both shallow and deep learning algorithms.
- We collect data from three players: a professional player, an intermediate player, and a novice player. Using the determined strokes of the professional player, we develop a k-NN based algorithm to model the ideal stance.
- Using the computed ideal stance from the professional player, we model the error between the ideal stance and intermediate/novice player's stance. We hypothesize that this modeled error could be used for scoring the players for their strokes and stances.

This paper is organized as follows. Section II discusses the related work and section III explains the overall architecture of this work. In section IV we discuss the proposed methodology in detail followed by the experimentation details and results in sections V and VI respectively. Finally we list the limitations of this work and enumerate the future directions in section VIII and finally concluding in section VII.

II. RELATED WORKS

In this section, we review the related literature in the following areas of sports analytics, application of machine & deep learning for micro sports activities and scoring activities.

Recently researchers have fused sports analytics, human activity recognition and the internet of things and thriving in this field. Sensors are widely used to capture the significant change in signal with respect to activities. In [11] proposed a model known as Tennis-Eye to calculate the speed of the tennis ball and proved the model is better than the state of the art. [12] proposed iBall to track the spinning and trajectory of cricket ball by embedding Inertial Motion Unit sensor inside the cricket ball. [13] developed a model to measure the acceleration of the upper and lower arm and of the racket and

acceleration showcases high correlation between ball velocity for national and international players. Several shallow machine learning and Deep Learning algorithms have been explored for Sport Analytics. [14] developed Hidden Markov Model to classify different types of badminton strokes and showcased that the model outperformed shallow machine learning algorithms: naive bayes, support vector machine, decision tree. Nowadays, researchers tend to work to understand the physics behind a particular game and by doing this, they try to postulate ideas to assist the players to improve their performances. [15] designed an e-learning model for practising the racket swings and classify similar tennis strokes. [16] proposed SVM and DTW based classification algorithms for footwork detection in fencing. We believe, for badminton, our work is one of the first to consider a body sensor network to capture data pertaining to both stance and strokes.

In sports analytics, it is essential to derive a score in order to provide a feedback for a player's performance. Scoring methodologies have been proposed in various sports such as soccer [17]–[19]. Specifically for Badminton, [20] proposed a methodology for computing the score of the game using the badminton game streaming video. However, the score specified here refers to the score achieved by the player during the game and not the scoring used in this study for evaluating the performance of the player. We believe we are one of the first to develop a scoring method for evaluating a player's performance.

III. OVERALL ARCHITECTURE

In this section, we will present our overall architecture and briefly discuss about each component of this work. Figure 2 depicts the overview of the overall framework of the proposed work. Since badminton involves coordinated movements and both upper and lower limbs, it is essential to capture the movements of all the limbs. First, we collect the data from all the extremities for a professional player, intermediate player and a novice player. The first component of the proposed work involves using the wearables in the upper limb to train a classifier where we aim to predict the stroke played by the player. Once the stroke of the player is determined, we use the stroke information to determine the possible ways in which a player could use their lower limbs to execute the shot. To address this problem, we propose a k-NN based method to extract such possible stances. The second component of this proposed work addresses the k-NN based ideal stance learning and synchronous averaging. Finally, we compare the ideal stances learned using the professional player's data with that of an/a intermediate/novice player. We believe that the error learnt here between the professional player and intermediate/novice player can be used for scoring intermediate/novice players.

IV. PROPOSED METHODOLOGY

In this section, we discuss each component of the proposed work in detail. The first step in the pipeline was to collect the data from 3 participants of varied proficiency of Badminton. The data collection procedure is explained in section V-A.

Label	Racker Postion	Stroke	Stance
1	Forehand	Service	Subtle leg movement
2	Backhand		
3	Forehand	Clear Lob Overhead	Step back with a slight jump
4	Backhand		
5	Forehand	Clear Lob Underarm	Step sideways
6	Backhand		
7	Forehand	Net Shot Underarm	Lunge like forward steps
8	Backhand		
9	Forehand	Drop Shot Overhead	Stand and deliver or slight jump
10	Backhand		
11	Forehand	Smash Overhead	Heavy movements and jumps
12	Backhand		

Once we capture the movements of the players, we propose the CNN based stroke classification algorithm, k-NN based ideal stance learning, and error based scoring which will be described in detail in the following sections.

A. CNN based Stroke Classification

We design a deep Convolutional Neural Network (CNN) model for classifying different types of badminton strokes (shown in table I) and compared it with several shallow learning techniques such as Random Forest, Multilayer Perceptron, Decision Tree, Support Vector Machine Linear Kernel. The CNN model comprises of two components. First is the feature extraction component followed by the classification component. The feature extraction component is responsible for hierarchically extracting high level features from the data whereas the classification component which is a fully connected layer is responsible for classifying the strokes. The feature learning component of CNN comprises of the following layers. Each convolution layer comprises of the following operations in the sequence mentioned: convolution, rectilinear activation function, dropout.

B. k-NN based model for stance retrieval

To compute the ideal stance that an/a intermediate/novice player could play, we leveraged the lower limb data of the professional. We compute the euclidean distance between each instance of intermediate/novice player and the professional player. Further, we extracted k closest data instances from the professional's data for each of the data instances of intermediate/novice player. We further performed synchronous averaging of the k retrieved data instances. The notion is that performing synchronous averaging causes a filtering effect on the retrieved k stances of the professional and removes the noise, which leaves behind the core pattern of the ideal stance. During the retrieval of k stances, the labels of the professional's and the intermediate/novice player's data were matched. Finally, we hypothesize that the obtained pattern is the ideal stance for playing a particular stroke (label) as the stance was retrieved from the professional's data. A detailed algorithm of the proposed methodology is enlightened in algorithm 1.

C. Error based scoring

Following the computation of the ideal stance for each shot played by the intermediate/novice player, we compute the error metrics such as Mean Squared Error (MSE), Root Mean Squared Error ($RMSE$), Absolute Error (MAE), and Median Absolute Error ($MdAE$) [21]. The error metrics are computed as shown below.

Let $X_{P-averaged}$ be the data instance of the professional after averaging the k nearest neighbours and let X_{LL} be the data instance of the intermediate/novice player corresponding to lower limbs. Then, $e_t = X_{P-averaged} - X_{LL}$.

$$\text{Mean Squared Error, } MSE = mean(e_t^2) \tag{1}$$

$$\text{Root Mean Squared Error, } RMSE = \sqrt{mean(e_t^2)} \tag{2}$$

$$\text{Mean Absolute Error, } MAE = mean(|e_t|) \tag{3}$$

$$\text{Median Squared Error, } MdAE = median(|e_t|) \tag{4}$$

Algorithm 1 Algorithm of the proposed methodology, The subscript P refers to the professional's data, LL refers to Lower Limbs

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Acquire $X_{Professional}, X_{Intermediate}, X_{Novice}$
$trainCNN(X_{Professional})$
$predictCNN(X_{Intermediate}, X_{Novice})$
for each data instance in $X_{Intermediate}/X_{Novice}$
 Extract: X_{LL}
 Compute distance (X_{LL}, X_{P-LL}) for the same shot
 $X_{P-averaged} \leftarrow$ Average of k closest data instances
 $ComputeError(X_{P-averaged}, X_{LL})$
end for

V. EXPERIMENTS

In the following section, we discuss in detail about the data collection, data preprocessing and the experimentation setup.

A. Data Collection

In this experiment, four Shimmer [22] wearable devices were used. Shimmer devices are equipped with 3 axis low noise accelerometer, 3 axis high noise accelerometer, 3 axis gyroscope and 3 axis magnetometer. We placed the 4 devices on participant's dominant wrist, dominant palm, left leg and right leg to capture the movements for each stroke. The weight of the racket was approximately 75 grams and the weight of the sensor varies from 23 to 30 grams approximately. We made sure that the players were comfortable playing the shots while wearing the sensors. The orientation of the device were maintained consistent for each participant. Figure 3 illustrates the placement of the devices deployed with its orientation. For experimentation, we collected 30 iterations of each of the 12 strokes (listed in table I) from all the 3 participants (3 males; average age: 27 years). Although the explanation of the stances in table I may look vague, all the players played the strokes and stances as a player would normally play. As playing becomes
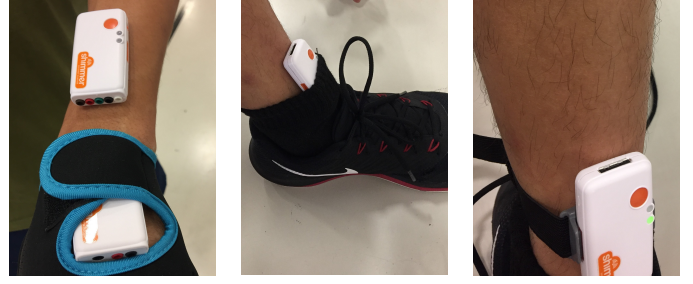

Fig. 3. Placement of the deviced during data collection

much easier compared to explaining the stances with words, we did our best to explain the stances in table I. We performed our experiment in an indoor badminton premises and strictly followed the rules of the game during the data collection process. We chose the participants based on their expertise in the game, first participant is a frequent and a professional player, the second participant is an intermediate player and last participant is a novice player. The data distribution of each class is shown in table V-C. The label for the dataset was assigned by the authors of this paper. The start time and the end time of each activity was noted down during data collection and the label was assigned based on it. In addition, to strengthen the labeling, we recorded the data collection session using a camera. In this way of assigning the labels, we feel that there may be an error at the start and end of each activity, however, since the sampling frequency was 512Hz, the error may be very minute and does not effect the classification task.

B. Data Preprocessing

For data processing, we first dropped the missing values from the raw data. Further, we normalized the 48 features and employed a sliding windowing with 50% overlap on the labeled data. We considered the 3 axis data from a Wide Range Accelerometer, Low Noise Accelerometer, Gyroscope and a digital Magnetometer from all four sensor positions as features. We examined various window sizes and we achieved the best results of window size of 64. Within each window, we employed the majority voting for data labeling for each window segment. Further, we applied a median filter for deep learning model and shallow learning techniques instead of Kalman filter because of comparatively higher computational complexity. We noticed an improvement of 2.3% to 3% for shallow learning algorithms after using median filter.

C. Experimentation setup

The experiments were conducted on a Linux server. The server housed a Intel i7-6850K CPU, 4x NVIDIA GeForce GTX 1080Ti GPUs and 64GB RAM. All the codes pertaining to data preprocessing, shallow learning and deep learning algorithms were implemented with Python. Especially for deep learning, Keras libraries were used. The number of data instances for the professional, intermediate and novice players were 45556, 22095, 23779 respectively. We used a training and testing split of 80-20 % for shallow learning. For deep

TABLE II
DISTRIBUTION OF CLASS LABEL

Class Label	Percentage	Class Label	Percentage
Class 1	12.2%	Class 7	11.5%
Class 2	7.7%	Class 8	8.9%
Class 3	4.7%	Class 9	8.3%
Class 4	7.3%	Class 10	6.1%
Class 5	6.4%	Class 11	12.2%
Class 6	7.3%	Class 12	11.3%

TABLE IV
ACCURACY FOR STROKE CLASSIFICATION USING CNN

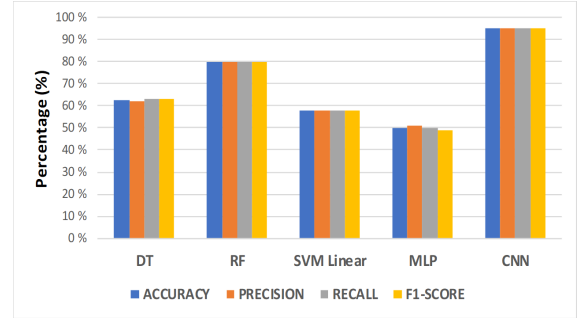| Combinations	Train Accuracy	Validation Accuracy	Testing Accuracy
All Participants	92.50 %	86.20 %	86.27 %
Professional and Intermediate	92.61%	83.98%	83.97%
Intermediate and Novice	97.41%	93.16%	93.66%
Professional and Novice	93.75 %	87.71 %	88.02 %

Fig. 4. Comparison of shallow learning and deep learning for stroke classification

learning, we used a 60-20-20 % split for training, testing and validation.

TABLE III
HYPER-PARAMETERS OF CNN MODEL

Hyper-parameters	Values
No. of maximum convolution layers	3
No. of filters in convolution layers	256, 128, 64
Convolution filter dimension	15x1,15x1,9x1
No. of maximum fully connected layers	1
No. of neurons in fully connected layers	256
Batch size	400
Dropout rate	0.85
Max number of epochs	150

VI. RESULTS AND DISCUSSIONS

In this section, we discuss all the results obtained in the proposed methodology. For the detection of strokes, the accuracies, F1 score, precision, and recall using shallow learning algorithms such as Decision Trees (DT), Random Forest (RF), Support Vector Machine (SVM), Multi Layer Perceptron (MLP) are reported in fig. 4. The classification results for deep learning algorithm, CNN is reported in table IV. The best results were obtained with the hyperparameters listed in table III. In table IV, we can note that we achieved the highest accuracy with intermediate and novice player's data. This is due to the fact that both novice and intermediate players have played the shots in a similar fashion and when compared to that of the professional player, they differed. Due to this difference, we can see a drop in the accuracy when all the players' data were considered. Overall, Deep learning has an improvement of approximately 7% when all the participants' data were considered compared to shallow learning algorithms. However, in the future, when we collect the data from many more participants, we believe that the improvement in the accuracy will be much more prominent.

Figures 5, 6 and 7 represents the histogram of various errors computed using equations 1-4 for $k = 25$. We tried different values of k ranging from 5 to 25 with an interval of 5 and report the best results obtained in this paper. In fig. 6, the probability of a higher error to occur is much less for the intermediate player than the novice player. The shot considered here is a clear lob overhead shot which is a very common shot and easy to play comparatively. In figure 5, the shot considered is the backhand service. It is interesting to note that the histograms of both players look more or less similar. The reason for such a case is because the backhand service is considered a difficult shot to play for both novice and intermediate player. Another interesting intuition observed was the opposite

to the intuition observed in previous two cases. In fig. 7, we can observe that the occurrence of lower error is higher for novice player than the intermediate player. The reason behind such a phenomena is interesting because when the data was collected from the professional player, the professional player did not move around to perform the Backhand overhead drop shot. A similar trend was noticed in the performance of the novice player. However, the intermediate player moved around a lot for backhand overhead drop shot. This can clearly be seen in the error histogram plots. This further strengthens our hypothesis that the error metrics used in this study are a good representative of scoring a player based on the stance.

VII. CONCLUSION

In this study, we successfully implemented a CNN based methodology for badminton stroke detection and achieved an improvement of approximately 7% using the data corresponding to the upper limbs. Leveraging the classified label information, we designed a k-NN based method to learn the ideal stance from the professional, and further use it to learn the error between the professional player's ideal stance and intermediate/novice player's stance. We have also identified the error metrics that can be used as a scoring metric for the game of Badminton for stance. Through the histogram plots, we strengthen our hypothesis that the error metrics are a good representation of scoring the strokes and stances of the game of Badminton.

VIII. LIMITATIONS AND SCOPE FOR FUTURE WORKS

The primary focus of this study is to study the stances and strokes and device a scoring methodology. However, this work does not address the other aspects that could effect a player's performance such as the player's height, strength, swing speed, racket style, and many more. In addition, this work does not address cross-user variation in playing the sport
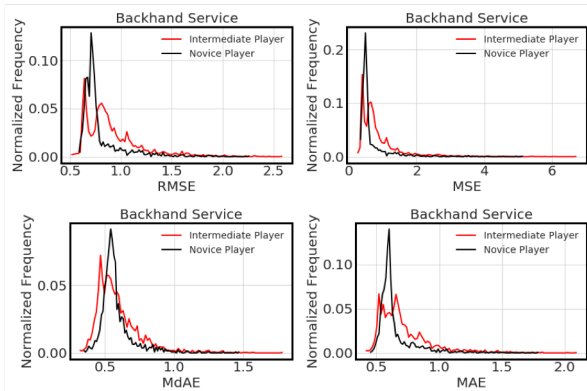
Fig. 5. Comparison of intermediate player and novice player based on error for Backhand Service.
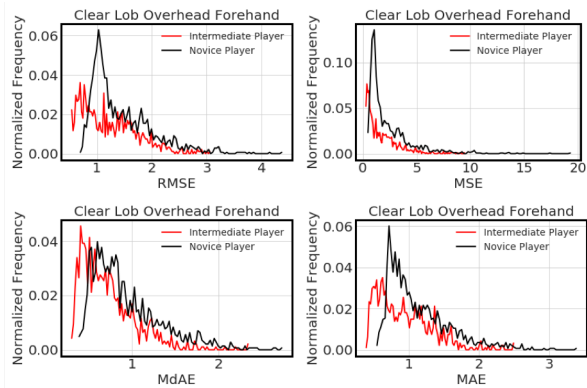

Fig. 6. Comparison of intermediate player and novice player based on error for Forehand Clear Lob.

Fig. 7. Comparison of intermediate player and novice player based on error for Backhand Drop Shot.

and the device related heterogeneity that may arise due to the variety of wearable devices available for purchase. In the future, we would like to address these issues. Further, in this paper, we proved our hypothesis that the error can be a good representative for scoring a player's performance. However, an exact score was not computed in this paper. In the future, we would like to propose an algorithm to predict an actual score about the stroke and the stance in real-time deployed on a resource constrained device.

IX. Acknowledgement

References

[1] S. Ramasamy Ramamurthy and N. Roy, "Recent trends in machine learning for human activity recognition—a survey," *WIREs Data Mining Knowl Discov*, vol. 8, no. 4, p. e1254, 2018.

[2] A. Z. M. Faridee, S. R. Ramamurthy, H. Hossain, and N. Roy, "Happyfeet: Recognizing and assessing dance on the floor," in *Proceedings of the 19th International Workshop on Mobile Computing Systems & Applications*. ACM, 2018, pp. 49–54.

[3] A. Z. Md Faridee, S. R. Ramamurthy, and N. Roy, "Happyfeet: Challenges in building an automated dance recognition and assessment tool," *GetMobile: Mobile Computing and Communications*, vol. 22, no. 3, pp. 10–16, 2019.
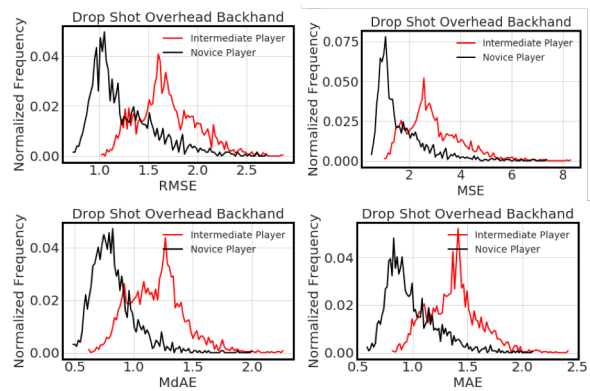
[4] Actigraphcorp, 2019. [Online]. Available: https://www.actigraphcorp.com/

[5] Zepp, 2019. [Online]. Available: https://www.zepp.com/en-us/

[6] Actofit, 2019. [Online]. Available: https://actofit.com/

[7] Sensoria, 2019. [Online]. Available: https://www.sensoriafitness.com/

[8] Coollang-Asia, 2019. [Online]. Available: https://www.coollang-asia.com/badminton-sensor

[9] C. T. Kiang, C. K. Yoong, and A. Spowage, "Local sensor system for badminton smash analysis," in *2009 IEEE Instrumentation and Measurement Technology Conference*. IEEE, 2009, pp. 883–888.

[10] M. A. I. Anik, M. Hassan, H. Mahmud, and M. K. Hasan, "Activity recognition of a badminton game through accelerometer and gyroscope," in *2016 19th International Conference on Computer and Information Technology (ICCIT)*. IEEE, 2016, pp. 213–217.

[11] H. Zhao, S. Wang, G. Zhou, and W. Jung, "Tenniseye: tennis ball speed estimation using a racket-mounted motion sensor," in *Proceedings of the 18th International Conference on Information Processing in Sensor Networks*. ACM, 2019, pp. 241–252.

[12] M. Gowda, A. Dhekne, S. Shen, R. R. Choudhury, L. Yang, S. Golwalkar, and A. Essanian, "Bringing iot to sports analytics," in *14th {USENIX} Symposium on Networked Systems Design and Implementation ({NSDI} 17)*, 2017, pp. 499–513.

[13] T. Jaitner and W. Gawin, "Analysis of badminton smash with a mobile measure device based on accelerometry," in *ISBS*, 2007.

[14] Z. Wang, M. Guo, and C. Zhao, "Badminton stroke recognition based on body sensor networks," *IEEE Transactions on Human-Machine Systems*, vol. 46, no. 5, pp. 769–775, 2016.

[15] A.-M. Sevcenco, K. F. Li, and K. Takano, "Collection and classification of tennis swings using a virtual racket," in *2012 Fourth International Conference on Intelligent Networking and Collaborative Systems*. IEEE, 2012, pp. 47–54.

[16] F. Malawski and B. Kwolek, "Classification of basic footwork in fencing using accelerometer," in *2016 Signal Processing: Algorithms, Architectures, Arrangements, and Applications (SPA)*. IEEE, 2016, pp. 51–55.

[17] H. S. Hossain, M. A. A. H. Khan, and N. Roy, "Soccermate: A personal soccer attribute profiler using wearables," in *2017 IEEE PerCom Workshops*. IEEE, 2017, pp. 164–169.

[18] L. Pappalardo, P. Cintia, P. Ferragina, E. Massucco, D. Pedreschi, and F. Giannotti, "Playerank: data-driven performance evaluation and player ranking in soccer via a machine learning approach," *ACM Transactions on Intelligent Systems and Technology (TIST)*, vol. 10, no. 5, p. 59, 2019.

[19] T. Fernando, X. Wei, C. Fookes, S. Sridharan, and P. Lucey, "Discovering methods of scoring in soccer using tracking data," in *KDD Workshop on Large-Scale Sports Analytics*, 2015.

[20] A. Ghosh, S. Singh, and C. Jawahar, "Towards structured analysis of broadcast badminton videos," in *2018 IEEE Winter Conference on Applications of Computer Vision (WACV)*. IEEE, 2018, pp. 296–304.

[21] B. B. Nair, M. Patturajan, and et al., "Predicting the bse sensex: Performance comparison of adaptive linear element, feed forward and time delay neural networks," in *2012 International Conference on Power, Signals, Controls and Computation*. IEEE, 2012, pp. 1–5.

[22] ShimmerSensing, 2019. [Online]. Available: http://www.shimmersensing.com/