Shoot Like Ronaldo: Predict Soccer Penalty Outcome with Wearables

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***Abstract*—A penalty shot is a crucial opportunity of scoring a goal in soccer and often becomes a game-winning factor. The goalkeeper has to guess the ball flight trajectory within a fraction of a second and typically jumps to either side of the goalpost taking (often mistakenly) cues from the kicker. These cues are postulated in goalkeeper's mind based on the kicker's posture, run-up, and angle of attack at the ball. Statistical analysis of historical data helps pundits to identify beneficial strategies in such a competitive environment but these tactical knowledge is of marginal help to a novice soccer player for improving their penalty kickout and blocking skills. Oftentimes, players are not equally skilled at successfully placing the ball around different sections of the goalpost. To empower players with a retrospective view of their performance and identifying the strong versus weak shots, and blocking capabilities, it's crucial to detect the direction, force, and trajectory of the shots. In this work, we propose a wearable sensor-based approach to detect the outcome of various goal shots from the kicker's dominant foot movement profile. We empirically assign six hot-zones inside the goal post and collect data on a real-life penalty shoot-out using economically available accelerometer sensors from four participants. We develop a deep learning approach for the shot classification and we report superior (53%) accuracy over traditional approaches (47%) in a challenging setting of recognizing different goal shots from the segmented data stream.**

***Index Terms*—Sports Analytics, Soccer Analytics, Penalty Shootout, Machine Learning, Wearables**

I. Introduction

Non-invasive data capturing capability of wearable enhances the end user to track daily life activities. Wearables are in use of monitoring the elder adults daily activities, developing smart home environments, tracking various physiological and behavioral anomaly, and many more. The non-obtrusive nature and user-friendliness of these smart devices make them appealing to the general people and encourages the community to explore various applications. Sports analytic is the recent addition to this exploration. There is a booming presence of smart devices in sport activity tracking like soccer, basketball, baseball, swimming, badminton, football and many other sports. Most often the statistical data analysis of Global Positioning System (GPS) and Inertial Measurement Unit (IMU)-based Note: always use   before any cite tracking devices [1] provide an insightful discovery of the player skill as well as the overall team strategy. For example, analysis of the total distance covered, number of high speed runs, heart rate provides helpful insight to measure the acceptable training load and players physical stability over the game. In addition, detailed analysis of smart devices help the player and coaching staff to improve their skill providing valuable feedback as well as to employ tactical strategies during the game respectively.

DONE with this para Soccer is one of the most influential games in the world with an estimated 4 billion fans and 200 soccer playing countries. Two teams comprising eleven players play the game for 90 minutes and the highest goal scoring team wins the game. While a draw is valid outcome with evenly matched goals, in the knock-out stage of most competitive soccer tournaments such as FIFA World Cup, UEFA European Championship, a game must deices a winner which often leads to a penalty shootout. Besides, during the regular 90 minutes of game-play time, an awarded penalty is an excellent opportunity to score. Due to the high impact on the winning role, this nerve wreaking event has caught the attention of professional soccer players, game theory researchers, coaches, statisticians. The analysis of historical data reveals that the team that takes the penalty at first has a 60% probability of winning the shoot out [2]. Although such analysis provides valuable insights, the data is expensive to acquire, and analysis is out of scope for a regular soccer player. Moreover, it of marginal help to a novice player to improve his/her on-field penalty shooting skills.

Several sensor-based commercial products are available that focuses on the physical and technical aspects of a soccer player [1]. APEX Athlete Series [3] is one such widely used product that made a five-year contract with the US Soccer Federation. Most of these products integrated with GPS sensor yields metrics based on the players' physical attributes such as distance covered, the number of high speed runs and very few focuses on the technical skill. MiCoach [4] from Adidas focuses on improving free kick skill, whereas DribbleUp [5] emphasizes simple to advanced dribbling skills. The ball not available anymore, also need to share more info But both of these products operate with additional requirements in terms of space, distance and does not profile penalty kick skill.

The constraints mentioned above and issues motivate us to develop a profiling system in penalty kick using only commodity wearables. We explored a process to detect different goal shots around the goal post, leveraging the machine learning algorithms and deep learning framework. As till now, there is no publicly available dataset on a real-life penalty kick, we collected a real-life dataset from four different participants. In summary, the followings are our contribution in this paper-

They key contributions of our paper are summarized as follows:

1) We collected a real life soccer penalty shoot out dataset

from 4 different participant in a rigorous manner.

2) Proposed a process that includes the data segmentation, feature generation and classification of six different penalty shots with a significant accuracy in terms of given complexity
3) We propose a deep learning based framework to classify the different penalty shots.

The organization of the paper is as follows - in section II, we discuss the related works in soccer analytics. In section III, we describe the overall data collection and annotation procedure. In section IV, we present the experimental results and analysis, and section V discusses the observations and future works.

II. Related Works

In this section we discuss the relevant literature works on soccer and penalty shootout.

McGarry et al. [6] reported a probability analysis of the soccer penalty shoot out outcome and identified pre-game and post-game strategies. In suggesting the line up for the penalty shoot, McGarry suggests to set the players in reverse order of their ability. Bar-Eli et al. [7] conducted studies- one on tha penal shooter and another one on the goalkeepers. Analysis of 311 penalty kicks from the top leagues and championship infers the best strategy to direct the ball is on top two corners of the goal post. Hughes el al. [8] analyzed 129 penalties from the FIFA World Cup finals, and also the finals of the European Champions League and presented these data so that to define a successful profile of optimal performance. Misirlisoy1 et al. [9] examined 361 kicks from the 37 penalty shootouts that occurred in World Cup and Euro Cup matches over a 36-year period from 1976 to 2012 and discovered that goalkeepers tend to display a clear sequential bias while choosing a diving side of the goal post. All these historical data analysis suggest different strategies and even suggests some guidelines but in terms of developing shooting skill it does very little help.

Other than historical data analysis, little work has been done in soccer and let alone in penalty shoot out. Gabriel J. Diaz from Rensselaer Polytechnic Institute performed a broad analysis of the different movement patterns of the penalty takers to predict the ball shooting direction [10]. The analysis reveals that the players placement of non-dominant foot and body posture could be the indicating factors of the possible ball direction. The analysis considered only two directions of the goal post-left or right.

The authors [11] devised a fabric pressure sensor-based smart soccer shoe to detect and analyze the interaction between the foot and the ball. Using the sensor signal collected data speculates the contact impact and the resulting angle. To detect the basic soccer skills, Inertial Measurement Units(IMU)-based wearable system are also investigated to detect the soccer kick/pass skills. Hossain et al. [12] proposed a IMU-based approach to develop a profiler for the soccer player. The authors derived various skill coefficients and profiling metrics based on different playing positions in soccer. These research works focuses on more general soccer skills but did not specifically on penalty shootout profiling.

More recently, there is a exciting surge of soccer analytics in computer vision. The proposed framework from Li et al. [13] focuses on analyzing a soccer players dribbling skill. Where as framework proposed by Sarkar et al. [14] and Theagaranjan et al. [15] focuses on generating the match statistics from the video input stream. Power et al. [16] utilized a event and player tracking data from English Premier League from 2014/15-15/16 session deriving formulas to measure the risk and rewards involved in a pass. Using the strategic features from the spatio-temporal data, Lucey et al. [17] proposed a method to predict the likelihood of chances in soccer. In terms of approach our method focuses solely on sensor based data to overcome additional constraints that video data posses for example privacy issues, convenient, data processing constraints in terms of device resources and others.

Our work is a sensor-based penalty shoot out profiling system which we develop over the real life collected data from common people.

III. Data Collection and Annotation

We collect a real-life penalty shoot out dataset and use various machine learning algorithms to develop a process that classifies different directed shots. Following the data collection, we leverage a video-based annotation over the collected data and apply a window-based segmentation technique. Fig 1 delineates the overall process for the classification task.

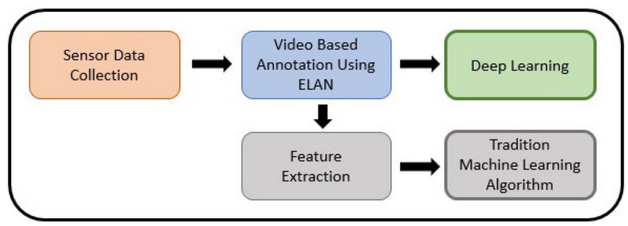

Fig. 1. Overall framework for penalty shot detection

A. Dataset Description

We collected a penalty shoot-out dataset consisting of 268 goal shots. Four graduate students aged between 24-26 years participated in the data collection process. All the participants were right foot dominant and had moderate soccer ball kicking skills. We defined the "moderate kick" skill if any participant was able to kick the ball as they wish at the four far-most corners of the goal post without any physical limitation. The participants had moderate familiarity with soccer. During the data collection process, we faced several difficulties that are worth to mention. From late August to early November was the regular game season for various college games. Different college teams had practice sessions five days in the week in different periods that narrowed down the soccer field availability time. As we maintained the standard goalpost dimension(24 X 8 FT) that restricted us to utilize other fields accommodated with goalposts. On top of these constraints, the rainy weather and schedule of the participants added the additional issues.

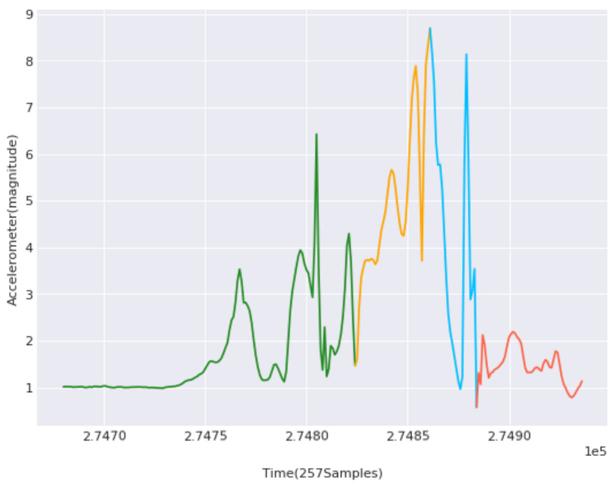

Fig. 2. Four segments of a penalty shot-Run Up(G),Preparation(O), Kick(B), Follow-Through(R)

We collected the dataset on sunny days and occasionally under gloomy weather environments.

We used a commodity device-ActiGraph [18] for the data collection. The device has a dimensions of 1.50 x 1.44 x 0.70 inches and has a very light weight of 28g. We placed the device at the inner ankle of the dominant foot with the help of thin and slim braces without causing any uncomfortable and set the sampling frequency at 100Hz. To acquire the ground-truth value and future analysis purpose, we recorded the overall data collection process using a commodity AKASO action camera(30 frame per sec) that was placed just behind the goal-post.

B. Data Collection Protocol

We defined a few protocols and during the data collection process, instructed the participants to follow to imitate the penalty shoot-out scenario as much as possible. The protocols are:

- A player can shoot the ball using different parts of the foot - ankle, toe, side-ankle, heel. To keep resemblance with the actual penalty shoot-out, the participants kick the ball using the inner ankle of their dominant foot.
- Penalty shooter can have varying run-up style and run-up lengths. But we observed one participant was using different run-up starting point while placing the ball at different regions of the goalpost as a body compensating effect. The pattern was too evident that leads us to the new protocol - the participant always maintains the same starting point and run-up angle towards the ball across all the shots.
- The device starts collecting data according to the configuration. To visually identify and track the beginning of the data collection process, we instruct the participants to jiggle their dominant foot three times before taking each shot. That would result in three sharp spikes in the collected signal and helps in data annotation process described in the next subsection.

TABLE I
DIFFERENT SEGMENTS OF A GOAL KICK

Shot Segment	Description
Run Up	The body leans forward with a foot movement towards the ball from the still position
Kick Preparation	Preparation of the non-dominant foot placement, the kicking foot backswing, and front swing
Kick	Kicking the ball and placing the kicking foot at the ground
Follow Through	First-time non-dominant foot placement just after kicking the ball

- We virtually split the goalpost into six different sections - Right Ground, Right Top, Left Ground, and Left Top, Middle Ground, and Middle Top. Each participant takes approximately 10-12 shots in each direction consecutively.

C. Data Annotation

Due to the configuration heterogeneity between the sensor and video data, we synchronize data sources using the annotation tool ELAN [19]. ELAN provides two operating modes - Device synchronization and annotation mode. Using the "Synchronization Mode" and leveraging three spikes from the very beginning shot, we synchronize the data first. Following the data synchronization, we use the "Annotation Mode" for the annotation.

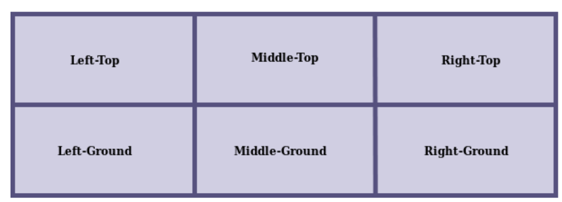

Fig. 3. Visual representation of a goalpost with six different splits

During annotation, we maintain certain rules for labeling all the participant data. We split each shoot into four segments-Run up, Kick preparation, Actual kick, and Follow through. As players tend to follow different run-up styles, lengths, and follow-through, which eventually lead to different body posture, we do not consider these movements in the annotation. In the annotation process, except for the "run-up" segment, we label the rest segments with the same label. We use six labels representing the six regions of the goalpost. Please refer to Fig 3.

IV. EXPERIMENTS AND RESULTS

In this section, we describe the detailed dataset segmentation approach over the labeled data. We discuss the performance of the various machine learning algorithms and compare the results with the performance of the proposed deep learning framework.

A. Data Processing

We select the shots that are intended and correctly directed, and we did not consider the missed penalty shots from the annotated dataset. We calculate statistical features over the labeled segmented data using rolling window technique. Calculated features are - mean, variance, standard deviation, magnitude mean, mean magnitude, co-variance, average power. We experiment with different rolling window size with different overlap ratio and find a rolling window size 20 or higher with an overlapping percentage of 50% produces a better dataset to use in the machine learning algorithms.

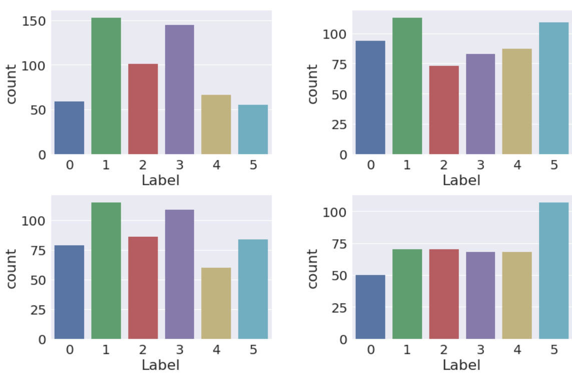

Fig. 4. Labeled instance distribution from four participants.

B. Results

1) Classification Performance: We apply several machine learning(ML) algorithms with 5-fold cross validation over the resulting dataset. Although we use accuracy as a performance measurement metric but also report precision, recall. Different parameters for the ML algorithms are finetunned to achieve the maximum accuracy and Table 1 details these settings. For the experimentation process we use SciKit-learn [20] python library.

The applied algorithms are - Random Forest(RF), Decision Tree(DT), Support Vector Machine(SVM), and Multi-linear Perceptron(MLP). In RF, we use a forest of maximum depth-25. In case of DT, we "gini" criterion with max depth of 25. "RBF" kernel is used in SVM with a gamma value of 17. Whereas the settings for MLP are 2 hidden layer with each layer containing 32 components, a learning rate of 0.00005, and "tanh" activation function. Table 1

TABLE II
ALGORITHM PERFORMANCE

Algorithm	Accuracy	Precision	Recall	F1
Random Forest	45.79	0.45	0.45	0.45
Decision Tree	33.81	0.33	0.33	0.33
SVM	47.98	0.48	0.47	0.47
MLP	31.72	0.30	0.29	0.29

Among the algorithms the SVM performs better than the other algorithms. A closer look at the confusion matrix reveals that the algorithms found comparatively easier on

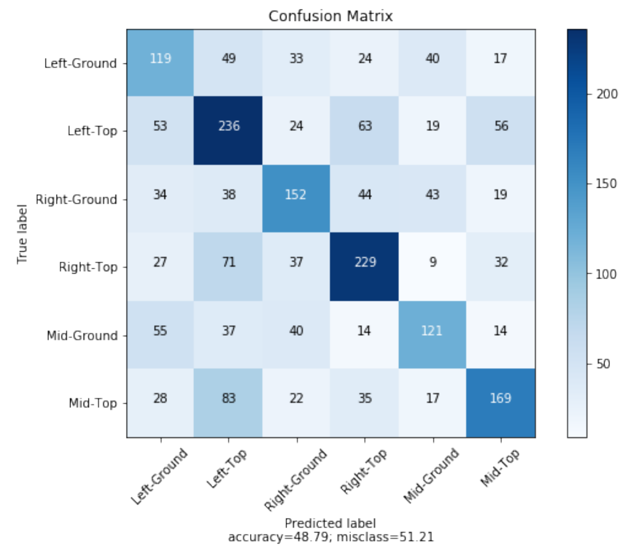

Fig. 5. Confusion matrix(SVM)

differentiating between the top and ground shots. Across different shots, the algorithm gets confused in differentiating. That encouraged us visually checking the six different types of shots.

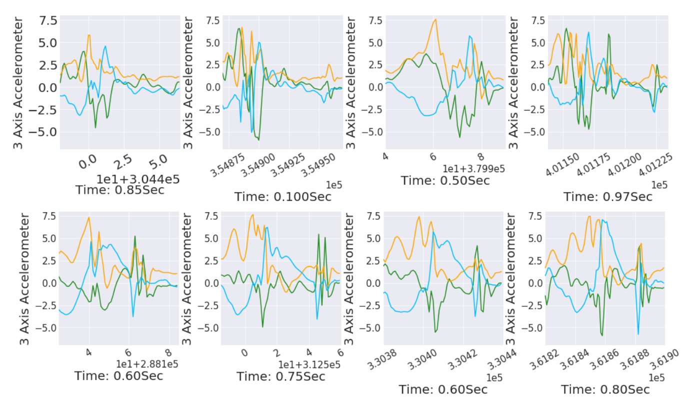

Fig. 6. Instances of four far most corner shots(Right-Ground, Right-Top, Left-Ground, Left-Top) from two participants(top: participant-1; bottom: participant-2

2) Shot Preparation Time Comparison: Among the four different segments of each shot, we analyze the "preparation" segment from the intended and scored shots. This segment indicates the time between run-up end and before the actual kick of the ball(kick foot back and front swing). We refer the time spent on this segment as preparation time, and this time provides the goalkeeper last opportunity to catch hints(non-dominant foot face direction, body posture) and guess the probable shot direction. In an ideal case for all different shots, a player should maintain a minimal consistent time such that the goalkeeper can not read the direction. Fig 7 plots the average preparation time of four participants for six different shots. Participant-1 consistently takes minimal time(except for mid-top shot) among all the participants. Whereas a close observation reveals that participant-3 also maintains a consistent time in placing the shots in three regions - left, right, and mid sections of the goalpost but in case of the left-region shots, the player takes a longer time than other four shots. Participant-4 has comparatively higher preparation time and inconsistent among all the shots. Along with the shot detection, algorithmic preparation segment detection could be valuable feedback to the penalty shooter.

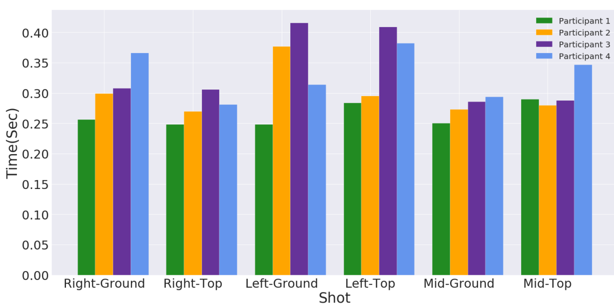

Fig. 7. Shot preparation time comparison among four participants for six different shots

3) Convolutional Neural Network Performance: In addition to the traditional machine learning algorithms, we also experimented with a simple deep learning architecture for the classification task and have seen substantial increase of 23% in classification accuracy. The increase of accuracy is realizable as the convolutional neural network(CNN) provides the advantage of feature engineering instead of using manual hand-crafted features. We obtain the proposed deep architecture through several grid search among various hyper-parameters. Table III summarizes the architecture details of the architecture. We use a server equipped with an NVIDIA GeForce GTX 1060 Ti GPU and 8 GB memory with an Intel Core i7-8700 (3.20GHz) processor for the experiments.

We use Python and PyTorch [21] framework for the dataset preprocessing and the overall architecture implementation. We split each class data from each participant into 60-20-20% to form train, validation and test sets. Combining the individual sets we obtain the final train, validation and test dataset dataset.

TABLE III
HYPER-PARAMETERS OF CNN MODEL

Hyper-parameters	Values
No. of conv. layers	2
No. of filters in conv. layers	64, 64
Conv. filter dimension	1x9, 1x7
No. of fully connected layers	2
No. of units in fully connected layers	32, 6
Batch size	16
Dropout	0.9
Epochs	500
Learning rate	0.0005

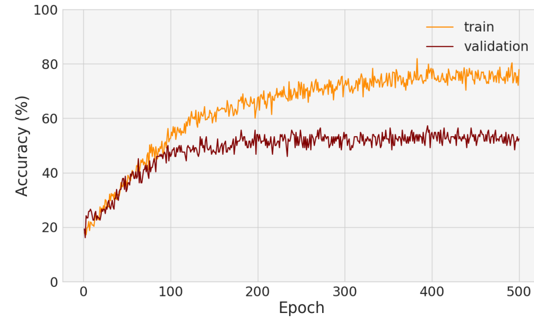

Fig. 8. CNN Accuracy

V. Discussion and Future Work

In this section, we discuss a few issues and factors that could impact the classification performance. Usage of multiple body positional data could increase the overall classification performance. Different ball flight directions demand unique dominant foot trajectories and posture. Subsequently, for a successful kick, the player requires to maintain a balanced body posture by manipulating hands and upper body so that the postural change becomes less evident to the goalkeeper. We assume that augmenting data from multiple body positions would result in increased performance. Similar but in a different domain(dance rather than soccer), Faridee et al. [22] found a significant improvement in the overall accuracy after accumulating data from different body positions. We plan to explore collecting multiple body positions data from participants in the future.

Participants overall kicking style is another issue that we face during the data collection. For example- one player tends to lean more backward than other players, and subsequently, the ball travels mostly in the air even when the player is attempting the ground shots. Considering the “follow through”, one participant does not perform follow-through just after kicking the ground shots-dominant foot stops right after kicking the ball. Some participants tend to make a forward jump as the kick preparation, whereas some tend to take long follow through - these are some additional observations. Other than our observations, in literature, [23] also mentions the influence of body parts while kicking a ball. Incorporating these factors into the modeling might improve performance. In the future, we aim to explore the effect of individual segments of a kick over the performance.

In addition to the sensor placement and kick style, the duration of the kick shot is also another challenge. Among multiple segments of a shot, we consider the final three segments for labeling a shot contributing 60-100 accelerometer entries from a single kick- refer to fig 4. Classifying six different shots within this shorter activity time makes the problem a challenging one. Subsequently, although we collect more than five hours of data, the resulting instance number is still considerably low. On top of that, six different goal shots possess a subtle signal signature difference among themselves.

Resolving the issues mentioned above make the scope of such a micro activity classification task enormous. A similar classification approach will not only applicable in profiling soccer penalty kick but also in other sports domains where the action time is short. It is promising that leveraging only a single body position data, deep learning-based approach achieves a classification accuracy of approximately 60%. In future we plan to collect a dataset using multiple sensors placed at different body positions to resolve the above issues. Besides, we also aim to explore and experiment with different network architectures to find out any potential advantages that could be achieved in the arena of sports analytic.

VI. Conclusion

In this work, we develop a process for penalty shoot detection and evaluate that approach with various machine learning methods. We collect a real-life penalty kick dataset from the four participants in a realistic scenario. The proposed deep learning framework outperforms the rest machine learning algorithms by a significant margin for this challenging classification task- given the induced heterogeneity in users' body posture, movement preferences, and the signature proximity among the considered shots. The goal of this work is not yet to replace a person-centric progress tracking approach but to evaluate the feasibility of a sensor-based approach. In the future, we plan to address the issues and incorporate the factors discussed in the discussion section to develop an automated penalty shoot-out profiling system.

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References

[1] D. Johnson, "Training sensors for soccer (aka football) players." https://gadgetsandwearables.com/2019/02/19/soccer-training-sensor/, visited 2019-11-20.
[2] C. Fernandez and H. Pettit, "The secret to winning a world cup penalty shootout: Going first gives you a 20% greater chance of victory because shooting second puts players under more pressure." https://www.dailymail.co.uk/sciencetech/article-5909537/Secret-winning-World-Cup-penalty-shootout-Going-gives-20-greater-chance-victory.html, visited 2019-11-20.
[3] "Fifa approved gps tracker." https://statsports.com/apex-athlete-series/, visited 2019-11-21.
[4] "Training smart ball." https://www.adidas.com/us/smart-ball/G83963.html, visited 2019-11-21.
[5] "Smart fitness gifts for your entire fam." https://dribbleup.com/, visited 2019-11-21.
[6] T. McGarry and I. M. Franks, "On winning the penalty shoot-out in soccer," *Journal of Sports Sciences*, vol. 18, no. 6, pp. 401–409, 2000.
[7] M. Bar-Eli and O. H. Azar, "Penalty kicks in soccer: an empirical analysis of shooting strategies and goalkeepers' preferences," *Soccer & Society*, vol. 10, no. 2, pp. 183–191, 2009.
[8] M. Hughes and J. Wells, "Analysis of penalties taken in shoot-outs," *International Journal of Performance Analysis in Sport*, vol. 2, no. 1, pp. 55–72, 2002.
[9] E. Misirlisoy and P. Haggard, "Asymmetric predictability and cognitive competition in football penalty shootouts," *Current Biology*, vol. 24, no. 16, pp. 1918–1922, 2014.
[10] R. P. Institute, "Left or right? early clues to soccer penalty kicks revealed." https://www.sciencedaily.com/releases/2010/06/100624112310.htm, visited 2019-11-20.
[11] B. Zhou, H. Koerger, M. Wirth, C. Zwick, C. Martindale, H. Cruz, B. Eskofier, and P. Lukowicz, "Smart soccer shoe: monitoring football interaction with shoe integrated textile pressure sensor matrix," in *Proceedings of the 2016 ACM International Symposium on Wearable Computers*, pp. 64–71, ACM, 2016.
[12] H. S. Hossain, M. A. A. H. Khan, and N. Roy, "Soccermate: A personal soccer attribute profiler using wearables," in *2017 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)*, pp. 164–169, IEEE, 2017.
[13] R. Li and B. Bhanu, "Fine-grained visual dribbling style analysis for soccer videos with augmented dribble energy image," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, pp. 0–0, 2019.
[14] S. Sarkar, A. Chakrabarti, and D. Prasad Mukherjee, "Generation of ball possession statistics in soccer using minimum-cost flow network," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, pp. 0–0, 2019.
[15] R. Theagarajan, F. Pala, X. Zhang, and B. Bhanu, "Soccer: Who has the ball? generating visual analytics and player statistics," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, pp. 1749–1757, 2018.
[16] P. Power, H. Ruiz, X. Wei, and P. Lucey, "Not all passes are created equal: Objectively measuring the risk and reward of passes in soccer from tracking data," in *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 1605–1613, ACM, 2017.
[17] P. Lucey, A. Bialkowski, M. Monfort, P. Carr, and I. Matthews, "quality vs quantity: Improved shot prediction in soccer using strategic features from spatiotemporal data," in *Proc. 8th annual mit sloan sports analytics conference*, pp. 1–9, 2014.
[18] "Actigraph." https://www.actigraphcorp.com/, visited 2019-11-20.
[19] H. Sloetjes and P. Wittenburg, "Annotation by category-elan and iso dcr," in *6th international Conference on Language Resources and Evaluation (LREC 2008)*, 2008.
[20] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.
[21] A. Paszke, S. Gross, S. Chintala, G. Chanan, E. Yang, Z. DeVito, Z. Lin, A. Desmaison, L. Antiga, and A. Lerer, "Automatic differentiation in PyTorch," in *NIPS Autodiff Workshop*, 2017.
[22] 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*, pp. 49–54, ACM, 2018.
[23] A. Lees, T. Asai, T. B. Andersen, H. Nunome, and T. Sterzing, "The biomechanics of kicking in soccer: A review," *Journal of sports sciences*, vol. 28, no. 8, pp. 805–817, 2010.