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Skill Level Classification in Basketball Free-Throws Using a Single Inertial Sensor

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Abstract: Wearable sensors are an emerging technology, with growing evidence supporting their application in sport performance enhancement. This study utilized data collected from a tri-axial inertial sensor on the wrist of ten recreational and eight professional basketball players while they performed free-throws, to classify their skill levels. We employed a fully connected convolutional neural network (CNN) for the classification task, using 64% of the data for training, 16% for validation, and the remaining 20% for testing the model's performance. In the case of considering a single parameter from the inertial sensor, the most accurate individual components were upward acceleration (A_X), with an accuracy of 82% (sensitivity = 0.79; specificity = 0.84), forward acceleration (A_Z), with an accuracy of 80% (sensitivity = 0.78; specificity = 0.83), and wrist angular velocity in the sagittal plane (G_Y), with an accuracy of 77% (sensitivity = 0.73; specificity = 0.79). The highest accuracy of the classification was achieved when these CNN inputs utilized a stack-up matrix of these three axes, resulting in an accuracy of 88% (sensitivity = 0.87, specificity = 0.90). Applying the CNN to data from a single wearable sensor successfully classified basketball players as recreational or professional with an accuracy of up to 88%. This study represents a step towards the development of a biofeedback device to improve free-throw shooting technique.

Keywords: convolutional neural network; machine learning; IMU; accelerometer; gyroscope

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1. Introduction

Basketball is one of the most popular sports played around the globe. More than 450 million people worldwide play basketball [1]. According to the Australian Sport and Physical Activity Participation Survey published in 2021 [2], Australia has more than one million participants in basketball, with increasing trends in participation amongst children. Statistics show that around 20% of the total points scored in a basketball game are attributed to free-throws (FT), accounting for 48% of the points scored in the final 5 min [3]. Accurate FT shooting is an important contributing factor to team success, as it has been displayed that the team with a higher FT percentage will win 80% of games [3]. Although FT shots are the most standardized shot in the game and should be the easiest scoring opportunity within the game, FT accuracy is variable. In the 2020–2021 NBA season, the top 100 FT shooters ranged in success from 72.9% to 92.2%, with an average of 77.8%, whilst overall team averages ranged from 72.5% to 83.9% [4]. Despite the increased prevalence and importance of FTs towards the end of games, a correlation with decreasing accuracy has been shown [5]. Thus, there is a clear opportunity to further study FT shooting to better understand how it can be improved.

A few past studies have examined the parameters associated with successful FT shots. For example, a previous biomechanical analysis [6] reported a better success rate when the ball was launched at a 52-degree angle from horizontal, directed straight behind the center of the rim, and with approximately 3-Hz of back-spin. In terms of FT movement, higher skilled players exhibited a smaller center of gravity excursion and different joint kinematics at the wrist joint, when compared to those of lower skill [7–9]. Specifically, well-trained basketball players demonstrated a greater degree of wrist motion ($173 \pm 5.1°$) when compared to less skilled players ($156 \pm 10.2°$). Additionally, it has been noted that a correlation exists between shot success and joint coupling relationships between the knee, shoulder, elbow, and wrist [10,11]. In particular, these joint coupling relationships are the most vital with regard to wrist sagittal plane motion for the production of ball back-spin [7,11]. Hence, the tracking of wrist kinematics during FT shots should be focused on in order to understand differences between skill levels.

Conventionally, biomechanical analyses require sophisticated equipment, such as high-speed motion capturing cameras and force plates, and this approach is often confined to a laboratory environment. In recent years, there has been significant progress in the development of wearable electronics [12] and self-powered devices [13], including innovations in energy harvesting [14]. Until more recently, advances in wearable sensing technology have provided a lower cost solution for more realistic movement evaluation in sports [15]. For instance, inertial sensors have been used to accurately detect specific movements in Australian football, baseball, rugby, golf, swimming, cross country skiing, racket sports and more [15]. These wearable sensors are also a viable tool for ascertaining netball shooting kinematics, and do not affect the shooting technique [16]. It has been found that the combination of accelerometer and gyroscope inputs with machine learning algorithms can accurately classify sport movements [17–20], form the basis of training systems [21], and classify skill level in running and volleyball [19,22]. When compared to utilizing multiple wearable sensors, which likely jeopardizes user friendliness, application of a single sensor model improves user compliance [23]. Past wearable sensor studies in the field of basketball have mainly focused on ball handling, maneuver tracking and action recognition [24–26]. To the best of our knowledge, there is not yet a classifier to differentiate basketball players at different skill levels, which may be impactful for performance enhancement, coaching and talent identification.

Hence, it is imperative moving forward that we utilize both inertial sensor and machine learning algorithms in the skill analysis of basketball players. In this study, we sought to classify the skill levels of basketball players using data collated via a single inertial sensor on the wrist during FT.

2. Materials and Methods

2.1. Participants

This study involved a total of 18 participants, including 10 recreational basketball players and 8 professional basketball players (Table 1). Recreational players were defined by having no participation in any formal competitions, with more than 1 year of basketball experience. Professional players were defined as a current player from an elite basketball club in top-level league games. In this study, the professional participants were team members from Sydney Kings in the Australian National Basketball League (NBL). To be included in the study, participants had to be aged between 18–45 years, right hand dominant and male. Female participants were excluded due to gender-related kinematic differences during shooting maneuvers [27] and differences in standardized ball size [28]. Left hand-dominant participants were excluded to ensure consistency between the data extracted and applicability to the majority of participants. Additionally, any subject who had sustained any injury in the three months prior to the experiment was excluded due to the risk of collating data consisting of abnormal or slightly compensated kinematics.

Table 1. Participants' demographics.

	Recreational (n = 10)	Professional (n = 8)
Age (years)	26.1 ± 1.7	24.3 ± 3.8
Body height (m)	1.70 ± 0.04	1.90 ± 0.10
Body weight (kg)	71.9 ± 10.5	94.5 ± 8.9

2.2. Experimental Procedures

The experimental procedures were reviewed and approved by the Human Research Ethics Committee of Western Sydney University (Reference number: H14515), and written consent was obtained from each participant prior to testing. A single tri-axial inertial sensor (see sensor specification in the Supplementary Materials) sampling at 50 Hz was securely affixed onto the midpoint of right third metacarpal bone with latex-free sports taping (Figure 1). Data were logged in the sensor's memory for further processing. After standard calibration, each participant was asked to perform 30 FT attempts on a standard basketball court. Specifically, the participants stood behind the FT line inside the FT semi-circle on a standard basketball court, as per the rules and regulations set by the International Basketball Federation. They were asked to make each attempt within 10 s, shooting 30 consecutive shots in a row, aiming to make as many successful shots as possible. Otherwise, no instructions were given. A synchronized side view video was recorded to identify events related to the FT attempts, e.g., commencement of the shot, time of ball release, and shot success (in/miss).

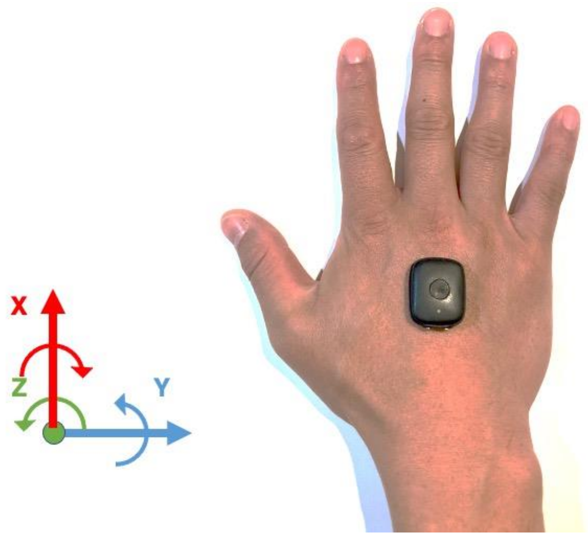

Figure 1. Wearable sensor positioned on the midpoint of right third metacarpal bone, containing a tri-axial accelerometer and gyroscope.

2.3. Data Processing and Model Development

Firstly, we calibrated the acceleration data in each direction by multiplying the sensitivity plus the mean, which is calculated from the static acceleration [29]. Then, we multiplied the acceleration data with the magnitude of local gravity where we conducted the experiment. Secondly, the acceleration and gyroscope data went through a moving average filter to remove high-frequency noise. Thirdly, the acceleration and gyroscope data were segmented into 6.4 s (320 points), which estimates a shooting time using a sliding window (3.2 s, 160 points). Because each shooting time of every athlete differs, a sliding window could maximize the shooting information. Finally, a short-time Fourier transform (STFT) was applied to the segmented time signal to transform it into the frequency domain after normalization. In STFT, we employed the Hanning window and set the window length to 40 data points, which gave good frequency resolution. The overlap length was set to 30 data points to increase the time resolution. Then, the generated value matrices (size: $30 \times 40 \times 3$) were inputted into our convolutional neural network (CNN). CNNs have become the go-to method for various image-centric tasks, including image classification, object detection, and semantic segmentation, owing to their inherent properties. A key feature of CNNs is their ability to utilize multiple layers of convolution and pooling operations to capture a hierarchical structure of features. In our study, we transformed input signals from the time domain into spectrograms that encompass both frequency and time information. As spectrograms can be regarded as a form of images, employing a CNN model is a well-suited approach for predicting basketball player performance levels based on these representations.

As depicted in Figure 2, the net contains five layers with weight; the first four are convolutional, and the remaining one is fully connected. The output from the fully connected layer is fed to a sigmoid function, producing a distribution over two class labels. The kernels of the second layer are connected to all kernel maps in the first layer. The neurons in the fully connected layer are connected to all neurons in the previous layer. There is also max-pooling layer following the second and fourth convolutional layer, respectively. The pooling layer operates independently on the feature map extracted through the convolution layer. To reduce overfitting and the number of extracted features, it decreases the spatial size of the feature map and returns the essential features. In this study, the rectified linear unit (Relu) function is selected as the activation function of the convolutional layer. An early stopping rule is also applied to avoid the overfitting problem.

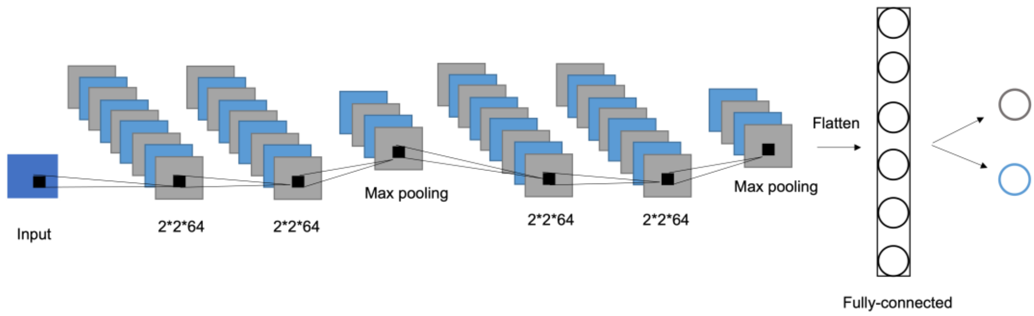

Figure 2. Structure of the convolutional neural network.

The first convolutional layer filters the $30 \times 40 \times 3$ input image with 64 kernels of size 2×2. The output of the first convolutional layer is fed into the second convolutional layer to be filtered with 64 kernels of size 2×2. Then, a max-pooling layer is set, followed by the third and fourth convolutional layers, both with 64 kernels of size 2×2. Finally, a max-pooling layer is connected to the fourth convolutional layer, after which the fully connected layer with 64 neurons is added.

2.4. Statistics

We compared the raw 3-dimensional IMU data between the two groups using statistical parametric mapping. We used the remaining 20% of the data to evaluate the performance of the CNN model by assessing the classification accuracy (i.e., (true positive + true negative)/(true positive + true negative + false positive + false negative)), sensitivity (i.e., true positive/(true positive + false negative)) and specificity (i.e., true negative/(true negative + false positive)). In addition, we extracted the features that were associated with prediction accuracy, sensitivity, and specificity.

3. Results

Initially, the accelerometer and gyroscope data collected from the IMU were segmented for each shooting attempt. Figure 3 displays the segmented accelerometer and gyroscope data in the time domain for participants from the two groups, with the solid line representing the mean and the shadow indicating the standard deviation across athletes in each group. We investigated whether any differences between the two skill levels could be detected utilizing traditional statistical methods. Statistical parametric mapping indicated no significant differences in the acceleration and gyroscope data between the groups in the time domain ($p > 0.05$). Based on these findings, we explored the use of frequency domain information from the IMU data to predict basketball player performance levels. Then, the spectrograms of each player's shooting attempts from both the professional and recreational groups were calculated using FFT. Considering that the spectrograms are two-dimensional variables and could be regarded as an image, a CNN model was utilized to predict the basketball players' levels. Ultimately, we discovered that the CNN could predict the two types of players depending on the direction and type of kinematic datasets. A summary of the classification model's results can be found in Table 2.

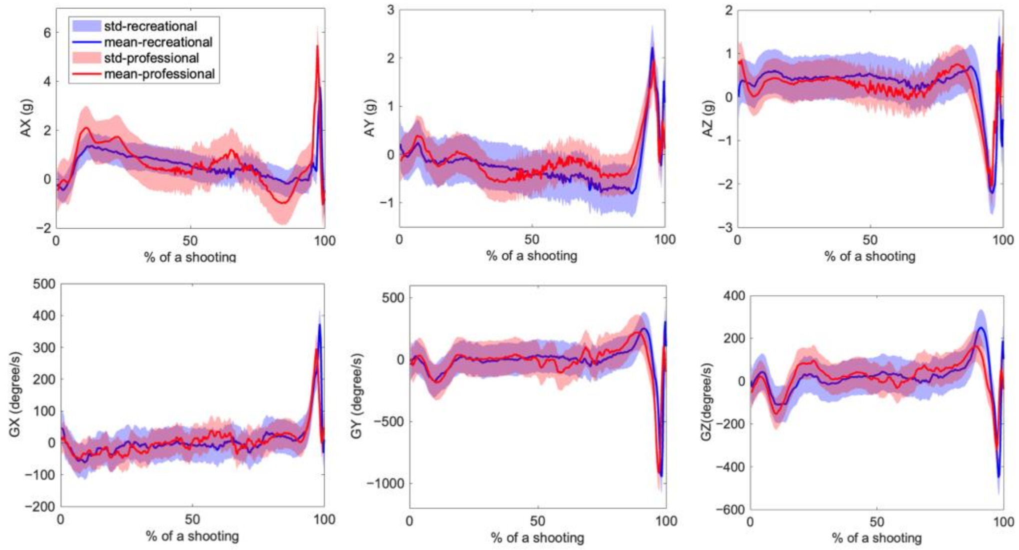

Figure 3. Mean (bold line) and standard deviation (shaded) of raw accelerometer and gyroscope data between recreational (blue) and professional basketball players (red).

Table 2. Results of the classification model.

Input Feature	Accuracy	Sensitivity	Specificity
A_X	**0.82**	0.79	0.84
A_Y	0.71	0.68	0.74
A_Z	0.80	0.78	0.83
G_X	0.73	0.69	0.75
G_Y	0.77	0.73	0.79
G_Z	0.74	0.72	0.76
A_XA_Y	**0.85**	0.84	0.87
A_XA_Z	**0.87**	0.86	0.87
A_YA_Z	0.82	0.81	0.83
G_XG_Y	0.82	0.81	0.83
G_XG_Z	0.80	0.77	0.82
G_YG_Z	0.81	0.78	0.83
A_XG_X	**0.85**	0.83	0.87
A_YG_Y	0.84	0.82	0.85
A_ZG_Z	0.83	0.82	0.85
$A_XA_YA_Z$	0.87	0.86	0.88
$G_XG_YG_Z$	0.86	0.84	0.88
$A_XA_ZG_Y$	**0.88**	0.87	0.90

From the result in Table 2, we found that the most accurate individual component was upward acceleration, i.e., A_X (accuracy = 82%; sensitivity = 0.79; specificity = 0.84). The second component with the highest accuracy was forward acceleration, i.e., A_Z (accuracy = 80%; sensitivity = 0.78; specificity = 0.83), and the third was the wrist angular velocity on the sagittal plane, i.e., G_Y (accuracy = 77%; sensitivity = 0.73; specificity = 0.79). Other individual inputs presented lower accuracies, including A_Y (71%), G_X (73%), and G_Z (74%). When two components combined as the input of the CNN model, the best classification accuracy was 0.87 (0.86 sensitivity and 0.87 specificity) for A_X and A_Z, higher than the other combinations. When the A_X was with A_y or G_x, the accuracies were both 85%. The accuracy remained similar when all three acceleration axes were conjoined (A_X, A_Y, A_Z); however, the specificity slightly improved. The highest accuracy, sensitivity, and the specificity of the classification were achieved when the three most accurate individual inputs were employed in a CNN stack-up matrix, producing an accuracy of 88% (sensitivity = 0.87, specificity = 0.90). From the above results, we observed that A_X was a consistently key input to achieve accurate classification. The entropy loss in the training and testing of the model is illustrated in Figure 4. There was no overfitting or underfitting in our experiment.

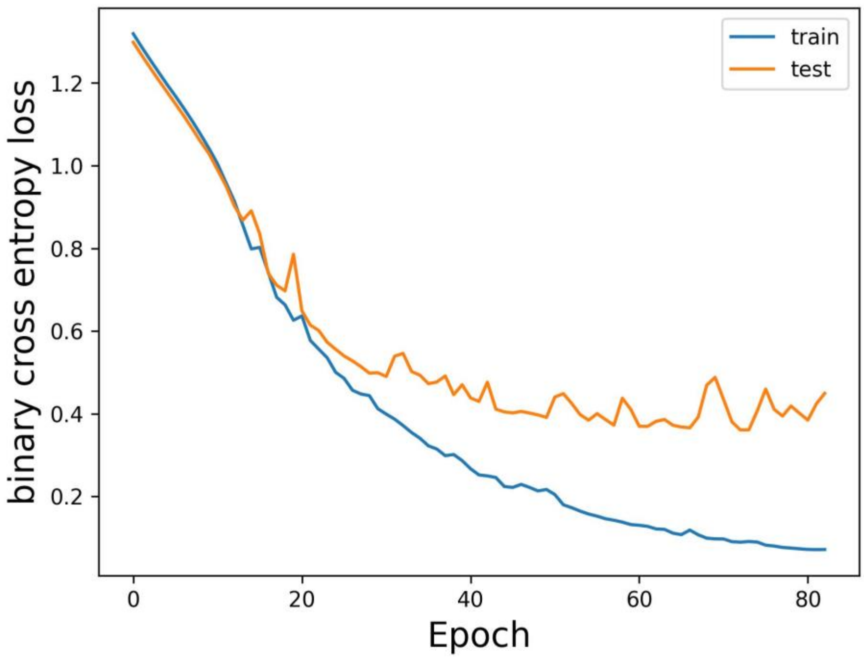

Figure 4. Training result of the model.

4. Discussion

The overall objective of the current study was to develop an advanced computational model to classify the skill level of basketball players during FT shots using data from a single inertial sensor. We obtained a satisfactory result, with classification accuracy, sensitivity, and specificity greater than 85%.

Emerging evidence has shown that machine learning algorithms based on data from wearable sensors can be applied in sports movements classification [17–20], which may form the basis of biofeedback systems for sports performance enhancement [30]. We utilized a CNN, which has been found to be more effective than other approaches, such as random forest and support vector machines, in accurately classifying sports movements using data from a single inertial sensor [20].

While conventional statistical approaches are unable to classify two groups through sliding window data, the CNN demonstrates satisfactory classification accuracy in analyzing the spectrograms of the IMU data. When the IMU data are segmented and aligned manually with video data, we could observe the preparatory rhythmic lower limb actions of the professional players to establish a comfortable stance or reinforce a rhythm before the shot, while the lower limbs of recreational players remained relatively static. Additional low frequency rippling components of A_X, and A_Z are observable in professional players, yet were statistically insignificant for classification for two groups in the temporal domain. Such rhythmic extension of lower limbs was also shown to be important to score a shot [31]. These rhythmic lower limb movements are expected to generate energy to increase ball's speed while shooting, as well as facilitate energy transfer from the lower body through the trunk to the upper limb [32].

Our results showed that the classification performance is optimized by considering inputs from A_X, A_Z and G_Y. Similarly to previous similar studies (e.g., Bulling et al. [17]), combining both accelerometer and gyroscope can increase the classification rate of data. A_X and A_Z refer to acceleration in upward direction (elevation) and forward translation, respectively. Collectively, these two motions manifest in the trajectory of the ball to formulate the primary ball movement. The results of this study indicate that the speed and concise linear nature with which professional athletes shoot an FT can be distinguish them from recreational players. This is consistent with a previous study [33] which found that highly trained players shoot FTs faster than novice shooters (0.39 ± 0.09 s vs. 0.60 ± 0.14 s). The study also demonstrated that professional athletes show fewer lateral deviations at the wrist (holding the ball) throughout the entirety of the shot. It can be argued that professional athletes exhibit smoother and more controlled wrist motion during an FT shot. It has been well established that highly skilled athletes show differing kinematics to those of a lower skill, and this study expands upon these differing kinematics [7–9]. Whilst the inclusivity of G_Y only increases the accuracy by 1% (88%) (compared to 87% if only consider A_Z and A_X), it increases the sensitivity by 1% and specificity by 3%. When adding G_Y into account, we take into consideration the angular velocity occurring at the wrist joint. This is related to wrist flexion at the end of the shot, known to be prominent in highly skilled athletes as a compensatory technique to maintain shot consistency [34]. This increase in specificity and sensitivity is anticipated to be due to the high importance of the wrist joint in the shot technique of elite shooters [7].

In prior basketball research, the focus has predominantly been on predicting postures or actions using deep learning algorithms rather than classifying players into skill groups, which limits the potential for providing feedback to improve basketball skills. For example, one study utilized a deep learning model to recognize basketball shooting maneuvers and achieved an average precision rate of 98.8% [25]. Another study employed a CNN-based algorithm to identify common basketball actions in video streams, attaining an accuracy rate of up to 95.6% [26]. In a third study [24], the authors recognized jump shots in a series of arbitrary basketball motion sequences using a CNN model applied to IMU signals in the time domain, obtaining recall and precision values over 0.97. Although these studies demonstrate high accuracy in posture or shot recognition, they do not offer additional bio-feedback information about the differences between varying levels of basketball performance. In contrast, our research aims to identify the key factors that contribute to different levels of basketball play, rather than focusing solely on individual shooting actions.

Our primary recommendation for future research is the development of a biofeedback device that track the identified features of wrist joint movements related to FT shooting success. In doing so, it will allow real-time, externally focused feedback which has been shown to be optimal for motor learning in sports [35]. Wulf et al. (1998) have developed growing evidence to support the use of externally focused feedback, that is, feedback that focuses on the effect of the movement relative to the goal, manipulated through the apparatus. In the context of this topic, external feedback involves features such as wrist motion speed or acceleration, for example, that contribute to the outcome of an FT shot (in/miss). Wulf et al. [35] confirmed that externally focused feedback provided immediate after or during a trial is more effective for motor learning compared to delayed feedback. This parallels the findings of Shea and Wulf [36], who additionally found that external feedback prompted smoother movement, lower errors, and skill improvements that were retained after the concurrent feedback was removed. Thus, there is a need to develop a biofeedback device for training FTs through utilizing machine learning, as this is a solution allowing instant motion analysis and feature extraction to provide real-time, external feedback. Shankar et al. set the foundation for this in their study, finding that data-analyzed feedback from a single wrist-worn inertial sensor could refine shooting kinematics and consistency, leading to improved accuracy in one semi-professional athlete shooting FTs [37].

A strength of this study was the inclusion of the professional athletes, who then proceeded to win the NBL championships in the same year and following year. Recruiting these participants highlights exemplary FT shooting and contributes to the strength of the classifier (88% accuracy). There are, however, limitations to this study. First, only two skill levels were included in the current classification, which does not accurately represent the spectrum of players, e.g., novice and semi-professional players. The classifier accuracy may be compromised when applied to a broader scope of athletes who may lie between recreational and professional levels. Additionally, this study had a relatively small sample size (n = 18). Ideally, we would expand the sample size; however, difficulties arose when recruiting participants due to the international prevalence of COVID-19. We could expect that an increase in participant numbers may further increase the robustness of the model. However, despite the small sample size, the algorithm has displayed success in skill level classification. Furthermore, due to the methodology of our study, we have only focused on one aspect of basketball shooting, that of FT shots. This does not directly impact our results, as the purpose of the study was in fact to differentiate skill levels during FT shooting. However, this concept can be applied to other basketball maneuvers, including jump shots, 3-point shots, lay-ups, etc. In doing so, it will allow for skill classification based on a plethora of shooting maneuvers, broadening the applicability of the framework to the entire shooting game.

5. Conclusions

Our established machine learning algorithm on data from a single wearable sensor can successfully classify basketball players between novice and professional with up to 88% accuracy. This study is a step towards creating a biofeedback device to improve FT shooting technique. By utilizing reverse engineering, the sensor and machine learning algorithm can provide real-time feedback to improve FT shooting technique and train novice athletes to develop the skill set of a professional.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/app13095401/s1, Sensor specification.

Author Contributions: Conceptualization, R.T.H.C. and R.H.M.C.; methodology, R.T.H.C., R.H.M.C., X.G. and P.P.K.C.; data collection, R.T.H.C., E.B. and P.P.K.C.; formal analysis, X.G. and R.H.M.C.; writing—original draft preparation, E.B.; writing—review and editing, X.G., P.P.K.C., R.H.M.C. and R.T.H.C.; supervision, R.T.H.C.; project administration, R.T.H.C. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and approved by the Human Research Ethics Committee of Western Sydney University (Reference number: H14515).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The dataset and the CNN presented in this study can be found at https://github.com/cityuCompuNeuroLab/Basketball-skill-prediction (accessed on 26 March 2023).

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Conflicts of Interest: The authors declare no conflict of interest.

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