Swish or Miss
CS 6762 Final Project

1st Utkarsh Chirimar, 2nd John Chrosniak, 3rd Emory Ducote
University of Virginia, Charlottesville, VA
{uc6gq, jlc9wr, etd4sv}@virginia.edu

***Abstract*—Sports analytics have become increasingly important in today's digital era. Professional and college sports teams heavily rely on wearable devices to track athletes' health metrics. This can span from tracking their heart rate during a workout to acceleration during a game to quality of sleep at night. While many of these metrics can be useful to determine the overall health of an athlete, it remains difficult to digitally analyze form for very technical movements, such as shooting a basketball. We propose a wearable device that uses machine learning to provide athletes with real-time feedback on their form when shooting a basketball. This feedback can help improve an athlete's shooting form and alert coaches if fatigue is impacting their player's form, which could help prevent injuries from overuse.**

I. Introduction

Smart watch gesture recognition can be used for a variety of applications. From tracking sleep to walking cadence, there are infinite gestures that can be recognized. One particularly interesting use case for this gesture recognition is that in sports analytics. Many sports are composed of repeatable gestures, and the quality of those gestures can indiciate if the player is good or bad. Throwing a pitch in baseball, arm movement in sprinting, running a route in football–all of these actions can be recorded with gesture recognition and analyzed.

One of the most common motions in basketball is the shooting motion. The player first does a sort of windup, moving their hands from chest height to at or above head height. Following this motion, the player flicks their wrist forward on the ball, pushing it into the air. This combination of actions is quite recognizable, and an algorithm should be able to notice this motion using a smartwatch for example. What is interesting is not the motion recognition itself, but the small discrepancies between a good shot and a bad shot. While these motions may appear identical to the naked eye, by analyzing accelerometer data there can be more information drawn from shot to shot.

In the NBA the league average of free throw percentage usually hovers around 80% [1]. While this average is decent, there are plenty of players that do not shoot free throws well. As the free throw is located at the same particular location on the court for every shot, it can be reasoned that the motion of shooting should be the exact same every time for the optimal shot. Thus, we will analyze whether it is possible to distinguish good and bad form for a free throw shot for a particular player. We will accomplish this using the accelerometer data from the Asus ZenWatch 2 and multiple strategies for analysis.

II. Prior Work

There exist many different areas of prior work regarding sports analytics tracking using wearables and sensor devices. There have been studies done with large sensor setups that require complex environments for recording and improving form. One such study was done by Rahma et al. [6], in which they analyzed free throws via kinetic analysis. They accomplished this using a camera setup that required a complex image pipeline for analysis of the shooting motion. While this may provide accurate results, this analysis setup is not nearly as lightweight at solely using a smartwatch–and thus is cumbersome.

Another analysis was done by researchers at CMU [5], using a camera setup to predict whether a shot would score, depending on camera analysis of the balls trajectory. While this work is novel and useful, it relies heavily on the trajectory of the ball, not the shooting motion, for analysis. This method is not as helpful for the player, as even bad form can produce positive results when analyzing in this manner.

III. Methods

We hypothesize that a machine learning model can be used to predict whether or not a free throw shot was made or missed based on accelerometer readings collected from a smartwatch worn on the shooting wrist. The Asus ZenWatch 2 and the WaDa application [4] were used to collect data from fifty free-throw attempts.

A. Data Collection

To limit the potential for variability in shooting form having an impact on results, data was only recorded for free throw shots by John. The first twenty-five attempts were recorded as a make or miss depending on the result of the shot, with every attempt at least hitting the rim of the basket. The later twenty-five were intentional airballs. Two separate datasets were then constructed: *make-or-miss* uses only the first twenty-five free throws with shot results as labels and *airball-or-not* uses all free throws shot, with the first twenty-five labeled as not airballs and the later twenty-five labeled as airballs. The intention behind the two datasets is to measure how well the machine learning model can distinguish slight differences in form and substantial differences that could signal an athlete is at-risk of an injury.

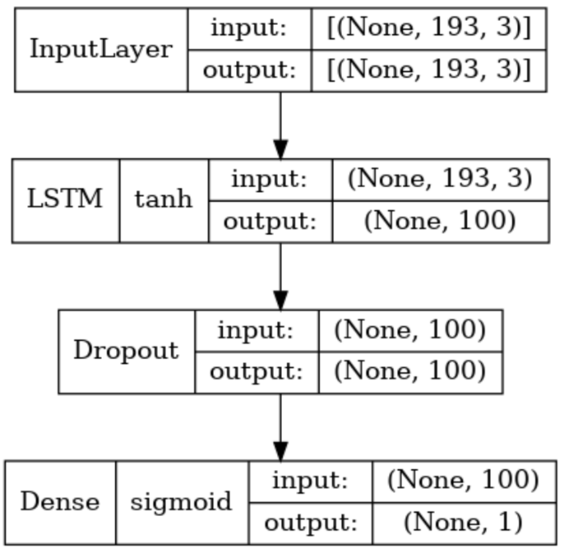

Fig. 1: The model consists of an LSTM layer with 100 recurrent units, a dropout layer to help prevent overfitting, and an output dense layer with a sigmoid activation function for binary classification.

B. Machine Learning Techniques

Random forest and LSTM classifiers were trained on data from both datasets, with a portion of data from each saved for evaluation. The raw accelerometer data was used when making predictions through the random forest classifier. More specifically, we used the *accel_x*, *accel_y*, *accel_z* from the watch's IMU to make real-time predictions on whether the motion is in a basketball motion or not.

The LSTM models were developed using TensorFlow and trained using the raw accelerometer data. To keep the length of each input sequence constant, the length of the longest sequence in each dataset was used as the input shape to the model. Shorter sequences were padded to match the length of this sequence. The architecture of the model is shown in Figure 1.

Given that the model must run in real-time on a small embedded device, we limited the model size to under 200 KB so that most microprocessors could accommodate the model. The average inference time of the model was also recorded when run on the CPU of a laptop, coming out to approximately 0.18 seconds. This time will likely increase with a less capable processor but the fast performance without the need for a GPU shows promising potential.

IV. Results

A. Random Forest Classifier

The first classifier experimented with is the random forest classifier from WEKA [2]. A random forest classifier is a machine learning algorithm that uses a collection of decision trees to make inferences. We chose to use a random forest classifier because it tends be more resistant to overfitting, compared to decision trees especially.

The accuracy of the random forest classifier on both datasets can be found in Table I.

Dataset	**Test Accuracy (%)**
Make or Miss	62.06
Airball or Not Airball	71.12

TABLE I: Random forest classifier test accuracy for the Make or Miss and Airball or Not Airball datasets

B. LSTM Classifier

The test set accuracies of the LSTM classifier can be seen in Table II.

Dataset	**Test Accuracy (%)**
Make or Miss	81.82
Airball or Not Airball	94.44

TABLE II: LSTM classifier test accuracy for the Make or Miss and Airball or Not Airball datasets

The LSTM classifier [3] performed better than the Random Forest Classifier on both datasets due to its increased capability of modeling sequence data. The LSTM was likely able to indirectly measure how much total force was required to get the ball within the basket, as well as what angles the wrist must move to push the ball towards the center of the hoop.

V. Conclusion

In all, the results proved that it is definitely possible to differentiate whether a basketball shot will be made, missed, or airballed. Two prediction methods were used: random forest classifier and LSTM. The LSTM outperformed the random forest classifier because it is more robust, especially when it comes to time-series data. Indeed, machine learning can be used to analyze and improve basketball players' shooting forms. Many professional players in the NBA are shooting below 50% from the free throw line, and these models can help improve their form and shot accuracy.

Next steps for the project are to perform shot analysis in different areas of the basketball court to see if machine learning can still predict shot outcomes. Also, since only John was shooting the balls, we would like to learn if the model is over-fitting to his shooting motion or if it can be as accurate with someone else's motion as with John's. Lastly, we would also like take this a further step and integrate a system with localization, so given the location of the shot, the model can predict if the shot will go in or not based on the force and form of the shooter.

This research for this extends much past basketball. Now that we know we can classify shooting motions, we can use similar sensors on other parts of the body to help other athletes improve their form. We can place the watch around a swimmers' ankles and notify them if their kicks are powerful and controlled or around a baseball pitchers' wrist to evaluate if their pitching form is not injury-prone.

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