Predicting Free Throw Success and Identifying Bad Form: Analyzing Temporal and Biomechanical Patterns

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Abstract

Purpose - This study leverages artificial intelligence to analyze the biomechanical and temporal factors influencing free throw success in basketball, providing practical insights for athletes and coaches to optimize shooting form.

Design/Methodology/Approach - A recurrent neural network (RNN) was trained on markerless motion capture data from a professional athlete's free throw attempts. By tracking joint angles, limb extensions, and body alignment across 125 frames per shot, the model identifies movement patterns linked to shot outcomes. Key metrics such as precision, recall, and F1 score evaluate the model's effectiveness.

Findings - Results show that the model accurately identifies biomechanical patterns associated with successful free throws and detects instances of poor form that still lead to a made shot. This AI-driven tool provides athletes and coaches with detailed, data-backed feedback on specific form elements, supporting targeted improvements to achieve more consistent shooting performance.

Originality/Value - This AI-driven approach provides a new tool for sports performance analysis, enabling data-driven feedback that can enhance training programs with individualized, actionable insights. The study underscores AI's role in advancing personalized coaching and real-time skill development.

1 Introduction

This project aims to develop a predictive model for free throw success using biomechanics data collected by Maple Leafs Sports & Entertainment's (MLSE) Sport Performance Lab (SPL). The dataset comprises raw, markerless motion capture data from 125 free throw attempts by a professional basketball player, providing a unique opportunity to analyze the biomechanical and temporal factors that contribute to successful shots. By identifying these patterns, this project seeks to offer actionable insights for players and coaches, potentially aiding in the refinement of shooting techniques and training programs. Biomechanical factors such as joint angles, body alignment, and coordinated movement patterns are known to be critical for free throw success, yet they are often studied in isolation. This analysis combines multiple biomechanical variables into a cohesive model, revealing how complex, whole-body movement patterns influence shot success. To achieve this, a recurrent neural network (RNN) is incorporated to capture temporal dependencies across sequences of movement. This approach leverages the high-quality temporal data provided by MLSE, addressing a gap in current research by applying advanced modeling techniques for improved predictive accuracy. Ultimately, this analysis aims to advance understanding of the biomechanics behind successful free throws and enhance data-driven decision-making in sports.

2 Method

2.1 Data Collection

The data for this study was provided by Maple Leafs Sports & Entertainment's (MLSE) Sport Performance Lab (SPL). The dataset includes raw, markerless motion capture data of 125 free throw attempts by a professional basketball player. This data captures three-dimensional joint positions and body part movements over a large (variable) number of frames for each free throw attempt, allowing for detailed temporal and biomechanical analysis. The data also includes the outcome of each free throw attempt, as well as the three dimensional positional data of the basketball (which was not used for this project as it is not relevant to the biomechanics of the free throw).

2.2 Data Preprocessing

Prior to model development, several preprocessing steps were applied to ensure data quality and consistency:

- **Frame Handling**: A function `is_valid_frame()` was defined to identify frames with missing values (NaNs) in either the player or ball data, and these frames were excluded from analysis to avoid introducing biases, and to isolate the shooting movement itself.
- **Feature Engineering**: The model utilizes biomechanical features manually derived from key body parts in each frame, focusing on distances, angles, and symmetry measurements that capture the player's form and movement patterns during the free throw sequence (see Figure 1). This results in a temporal dataset that captures both static and dynamic biomechanical characteristics of the free throw attempt. By combining these biomechanical measurements, the model gains a comprehensive representation of the player's form and movement patterns, enabling the analysis of key factors that contribute to successful free throw shots. These features are extracted using the following methods:
  - **Distance Calculations**: Distances between specific body joints are calculated to represent limb extensions and body postures. For instance:
    - *Right Arm Extension*: Distance between the right shoulder and right wrist.
    - *Left Arm Extension*: Distance between the left shoulder and left wrist.
    - *Right Knee Bend*: Distance between the right hip and right ankle.
    - *Left Knee Bend*: Distance between the left hip and left ankle.
  - **Angle Calculations**: Joint angles are computed to capture limb flexion and alignment. Using three key points per angle, the following joint angles are calculated:
    - *Right Elbow Angle*: Angle between the right shoulder, right elbow, and right wrist.
    - *Left Elbow Angle*: Angle between the left shoulder, left elbow, and left wrist.
    - *Right Knee Angle*: Angle between the right hip, right knee, and right ankle.
    - *Left Knee Angle*: Angle between the left hip, left knee, and left ankle.
  - **Symmetry Measurement**: Body symmetry is evaluated by calculating the height difference between the shoulders, based on the y-coordinates of the left and right shoulders. This feature provides insight into posture and balance during the free throw.
- **Sequence Padding**: To ensure uniform sequence lengths, all free throw attempts were padded to the same number of frames, with zero padding applied where necessary. This allowed for consistent input dimensions across all attempts, enabling efficient batch processing.

2.3 Data Splitting

To address the imbalance between successful (88 makes) and unsuccessful (37 misses) free throws, a balanced subset was created:

- **Training Data**: A balanced subset of 60 attempts (30 makes and 30 misses) was used for training.
- **Validation Data**: The remaining free throws, comprising 7 makes and 7 misses, were initially reserved for validation. However, this setup was later adjusted to use the entire remaining dataset for validation, ensuring a more comprehensive evaluation.
- **Data Loaders**: PyTorch `DataLoader` objects were created for both the training and validation datasets, enabling batch processing with a batch size of 16.

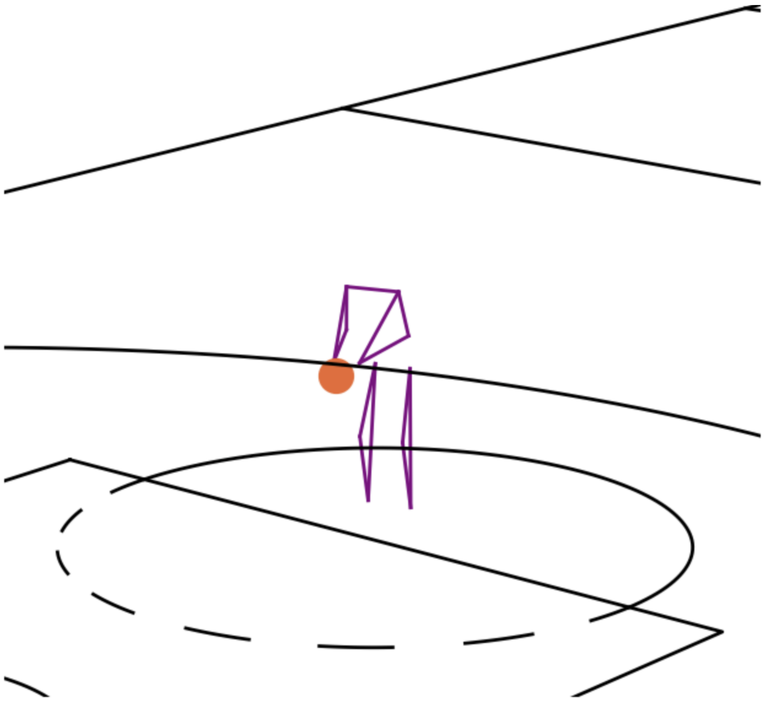

Figure 1: Engineered Features of Free Throw Biomechanics

2.4 Model Selection and Architecture

A recurrent neural network (RNN) model was implemented using **Long Short-Term Memory (LSTM)** units to capture temporal dependencies in biomechanical data sequences. Each sequence consists of frame-by-frame measurements of biomechanical features, including joint angles and distances, over the course of a free throw. The model is designed to process these temporal patterns and predict the likelihood of a successful free throw based on sequential dependencies within the data.

- **Model Architecture**: The model architecture is a bidirectional Long Short-Term Memory (LSTM) network designed to capture sequential dependencies in biomechanical free throw data. It features two LSTM layers with a hidden dimension of 128 and dropout of 0.3 for regularization. The bidirectional configuration enables the model to process each sequence in both forward and backward directions, capturing temporal context from the entire motion. Final hidden states from both directions are concatenated and passed through two fully connected layers, with ReLU activation applied to introduce non-linearity. The output layer provides a single probability value, indicating the likelihood of a successful free throw based on the sequential biomechanical patterns of each attempt.

- **Training and Optimization:** The model was trained using binary cross-entropy with logits loss (`BCEWithLogitsLoss`), which is suitable for binary classification and integrates a sigmoid activation layer for stable output probabilities. The Adam optimizer, with a learning rate of 0.0001, was employed to balance learning speed and stability. The model was trained for 200 epochs, with metrics such as accuracy, precision, recall, and F1 score recorded at each epoch to monitor model performance and convergence. True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN) were tracked for the validation data, where True or False indicates whether the model's prediction was correct, and Positive or Negative indicates the predicted class.

$$\text{Precision} = \frac{TP}{TP + FP} \quad \text{Recall} = \frac{TP}{TP + FN} \quad \text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

3 Results

The results of this study reveal insights into both the predictive performance of the model and the biomechanical patterns associated with free throw success and failure. Evaluation metrics, including accuracy, precision, recall, and F1 score, provide a quantitative measure of the model's ability to classify free throws correctly. Importantly, the interpretation of the confusion matrix offers further insight into player form and outcome consistency. True positives represent instances where good form led to a successful free throw, reinforcing the model's ability to identify effective mechanics. False negatives, on the other hand, represent cases where poor form still resulted in a successful shot, indicating possible compensatory mechanisms or luck in these attempts. True negatives confirm the link between poor form and missed free throws, while false positives, had they occurred, would capture cases where good form did not result in success, suggesting that even well-executed mechanics may not always guarantee a positive outcome. These distinctions provide a nuanced understanding of the relationship between form and result, highlighting key areas for potential improvement in training and technique.

3.1 Overview of Model Performance

The model's performance (see Figure 2) over 200 epochs is visualized in terms of accuracy, precision, recall, F1 score, and loss for both the training and validation sets. Training accuracy steadily improves, reaching around 95% by the final epochs, while validation accuracy fluctuates, generally stabilizing around 65–80%. Validation metrics like precision, recall, and F1 score show variability throughout training, suggesting the model captures certain patterns in the data effectively but might struggle with specific edge cases.

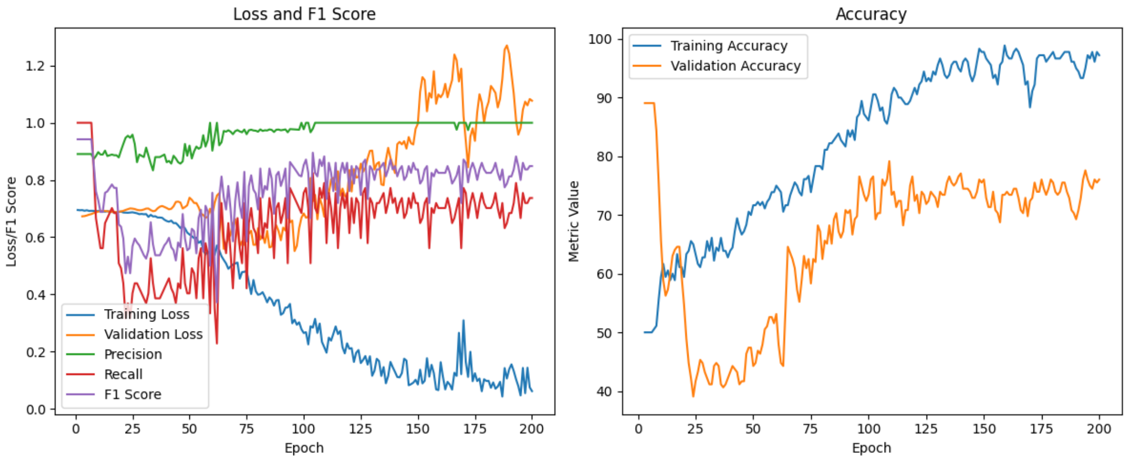

Figure 2: Model Performance

3.2 Learning Curves

The **Training Loss** curve (blue line) decreases consistently over the 200 epochs, indicating that the model learns to minimize errors on the training data and successfully adapts to the dataset's patterns. The **Validation Loss** (green line), however, remains relatively stable after an initial drop, suggesting that the model's learning on training data does not fully generalize to the validation set. This pattern is often interpreted as overfitting, as the model fits well to the training data while achieving more limited performance on validation data. In this particular context, though, overfitting may not be as problematic. Since the model is applied to a specific set of controlled conditions (consistent biomechanics data from a professional player), high training performance indicates that the model effectively captures these unique patterns. While the validation set shows fluctuations in metrics like precision, recall, and F1 score, this might reflect the controlled nature of the dataset rather than a true deficiency in model performance.

3.3 Generalization Ability

The **Accuracy** plot (right side) reveals that while **Training Accuracy** continues to increase, **Validation Accuracy** remains lower and less stable. However, given the controlled dataset and the goal of maximizing prediction accuracy within a specific context, perfect generalization may not be necessary. Instead, the high training accuracy suggests that the model effectively captures relevant biomechanical patterns. The model's ability to "overfit" to these patterns can actually be beneficial for extracting actionable insights specific to the conditions under which the data was collected. **Precision, Recall, and F1 Score** fluctuations further indicate the inherent variability in validation cases, which may be due to subtle biomechanical differences rather than a true deficiency in model robustness. This may suggest that some validation shots differ from the training shots in ways that are less critical for the overall problem objective—identifying key patterns in player form and technique under controlled conditions.

3.4 Confusion Matrix

The best-performing model iteration achieved a training accuracy of 100.0% with a training loss of 0.0610, and a validation accuracy of 78.12% with a validation loss of 0.8962. Additionally the model had a F1 score of 0.88, which is considered a near excellent score ($\tilde{0}$.9) for a machine learning model. The confusion matrix on the validation data (see Figure 3) reveals an intriguing outcome: the model achieved 100% accuracy in identifying missed free throws and 75.43% accuracy in identifying made free throws. This result highlights the model's capability to detect biomechanical patterns associated with poor form, even when a free throw is successful. False negatives, in this case, represent made free throws with biomechanical features commonly seen in missed attempts, suggesting potential areas for form improvement.

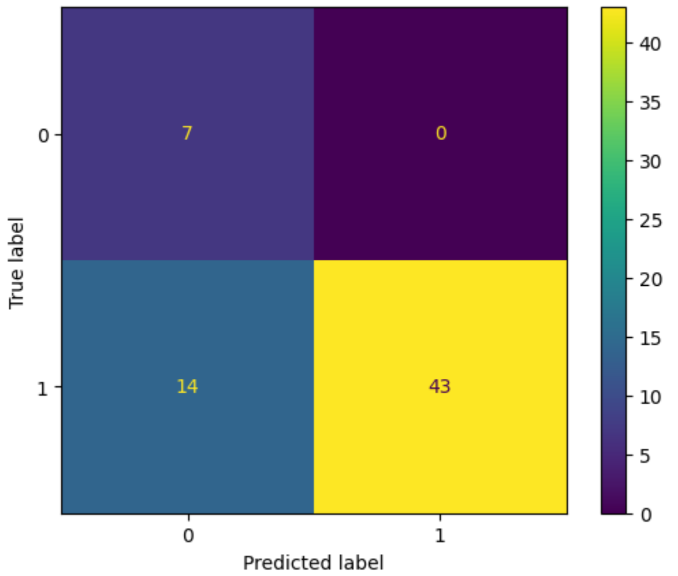

Figure 3: Confusion Matrix

4 Discussion

The model's results reveal significant potential for supporting athletes and coaches in refining free throw mechanics, particularly by identifying instances of poor form, even when a free throw attempt is successful. This capability is crucial, as it enables athletes to recognize and correct compensatory movements or suboptimal techniques that might still result in a made shot, ultimately fostering long-term consistency and performance improvement. The model's applicability is straightforward, requiring minimal adjustments to tailor it to individual athletes. The primary customization involves training the model on athlete-specific data, ensuring that its predictions align closely with the unique biomechanics and shooting styles of the player being analyzed. Increasing the dataset size with additional samples of the athlete's free throw attempts is expected to enhance model accuracy and reliability, allowing it to generalize more effectively to diverse movement patterns and subtle biomechanical variations. The model also offers flexibility in feature engineering, making it highly adaptable for coaches and trainers. Coaches can easily modify or add specific biomechanical features to the model, allowing it to focus on particular aspects of a player's form, such as shoulder alignment, elbow angles, or wrist positioning. This customization enables a targeted approach to identifying inconsistencies within individual components of the shooting motion, providing more granular feedback tailored to the athlete's unique needs. By adjusting features to analyze different elements of form, coaches can refine training programs to address specific biomechanical weaknesses, ultimately enhancing overall performance and consistency in free throw shooting. This adaptability underscores the model's practical value as a tool that evolves with the athlete's progress and specific coaching objectives.

5 Conclusion

This project demonstrates the potential of artificial intelligence to provide valuable, data-driven insights into the biomechanics of free throw shooting. By analyzing temporal and biomechanical patterns through a recurrent neural network (RNN) trained on markerless motion capture data, the model was able to identify factors associated with both successful and unsuccessful free throw attempts. Importantly, the model showed a strong capacity for recognizing instances of poor form, even when a shot was made, offering athletes and coaches a targeted tool for improving shooting consistency. The ability to detect subtle variations in form that contribute to missed or made shots suggests that this AI-driven approach could enhance training programs with individualized feedback. Future work could focus on refining the model with larger, more diverse datasets and exploring real-time feedback capabilities, further expanding its utility as a personalized coaching tool.