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Development and Application of a Body Joint Angle Detection System for Free-Throw Shooting Prediction and Posture Correction

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Abstract

The success rate of free-throw shooting is often a critical factor in determining game outcomes. This study employs machine learning to develop a low-cost, hardware-free joint angle measurement system for free-throw shooting and applies it to the scientific training of free-throw shooting skills. With the system, the joint angle curves of players can be measured without the need for reflective markers, thereby reducing setup costs and facilitating the integration of scientific training. This study presents several innovative features. The experimental results indicate that the amount of training data required for modeling is 50% of that required by the J48 decision tree classifier, with an accuracy 1.2 times higher. Additionally, when a shot is missed, the system compares the disparity in joint angles and provides feedback for posture correction, allowing players to target specific problem areas for training, improve free-throw performance, and assist the team in winning games.

Keywords: machine learning, joint angle, free throw, shooting prediction, posture correction

1. Introduction

Chatbots have become popular in recent years across a number of fields. According to Insider Intelligence, 40% of all basketball shots are either set shots, jump shots, or layups. Set shots mostly occur during free throws or when the offensive team immediately shoots after grabbing an offensive rebound [1]. The success rate of free-throw shooting is often a critical factor in determining the outcome of a game [2-5]. Teams with higher free-throw shooting percentages during games win up to 80% of the time [6]. Approximately 20% to 25% of points come from successful free-throw attempts [7-8]. Additionally, up to 35% of points in the last 5 minutes of a game are from free throws [9].

According to data from different basketball leagues, during the 2022-2023 season, the overall free-throw shooting percentage in the P. LEAGUE+, a Taiwanese men's professional basketball league, was 59.66% [10], whereas that in the National Basketball Association of the United States was 78.2% [11], showing a difference of nearly 19%. Studies have indicated that novice basketball players who receive movement coaching significantly outperform their counterparts in their free-throw technique and performance [12]. According to Liang [13], free-throw shooting skill is affected by the amount of practice and skill level. Thus, free-throw shooting performance is related to shooting posture, practice quantity, and skill level.

Scientific training has transformed traditional methods [14]. In terms of posture correction, the most common methods involve refining cycling and running postures [15-18]. These methods require costly equipment and reflective markers, which are attached to the athletes under training. Cameras are then used to capture the light reflected by the markers. Body curves formed by the light are then analyzed using software. Lee [19] examined the correlation between lower limb joint angles and shooting accuracy in basketball relocation jump shots. Participants were attached with joint location markers. High-speed cameras were then used to capture shooting motions. Subsequently, Kwon 3D motion analysis software is used for data

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acquisition and analysis. High equipment cost is the main barrier to implementing scientific training. The reflective markers attached to the body also limit the detection angles of the camera equipment.

Machine learning and deep learning are widely applied in practical applications [20-21]. MediaPipe is a multimedia machine learning model framework developed by Google Research. MediaPipe facilitates the development of applications with multiple modes (such as video, audio, or any time series data) and across various systems (such as PC, Android, or iOS). MediaPipe enables the construction of perceptual pipelines as modular component graphs, including model inference, media processing algorithms, and data transformations. Moreover, it serves as a tool for machine learning professionals, offering solutions such as full-body detection, hand tracking, face tracking, pose detection, face mesh, and object detection [22]. MediaPipe is currently in widespread use [23-26].

The present study develops a low-cost, machine-learning-based joint angle measurement system that does not require r eflective markers. This system is easy to use and can be employed for the scientific training of free-throw skills.

2. Literature Review

The following literature review focuses on the literature research related to shooting and joint angles.

Shung [27] employed a Biodex isokinetic dynamometer to conduct isokinetic peak torque tests in axial extension and flexion on knee, shoulder, and elbow joints at angular velocities of 60°/s, 180°/s, and 300°/s and on wrist joints at angular velocities of 60°/s, 180°/s, and 240°/s. The peak torque of wrist joint flexion at the angular velocity of 60°/s was significantly correlated with the shooting accuracy of close-range jump shots from 3.225 m. Additionally, the peak torque of elbow joint extension at the angular velocities of 180°/s and 300°/s was significantly correlated with the shooting accuracy of jump shots from 6.75 m.

Hamilton and Reinschmidt [28] investigated different release angles, speeds, and spin at release during free-throw shooting and categorized the ball trajectory into four scenarios: entry without touching the rim of the basket, rim contact, backboard contact, and trajectory too short to touch the rim. Their results showed that for a free-throw line situated less than 1 meter below the rim in parallel height, the optimal trajectory was predicted to require an initial angle of 60° and a speed of 7.3 m/s. The trajectory is related to both the anthropometric characteristics and accuracy of the shooter.

Lee [19] explored the relationship between lower limb joint angles and shooting accuracy during basketball relocation jump shots and observed that the angle of the left knee joint on the non-shooting hand side during the aiming-to-jumping phase was significantly and inversely correlated with shooting accuracy.

The key elements of the three aforementioned studies are described as follows:

(1) Research Objectives

All three studies focused on factors related to basketball shooting, primarily investigating the effects of multiple joint angles and speeds on shooting accuracy.

(2) Joint Angles and Speeds

Shung investigated the relationship between the isokinetic peak torque of multiple joints (wrist, elbow, and knee) and shooting accuracy and examined the effects of various angular velocities on these joints. Hamilton and Reinschmidt evaluated the effects of free-throw release angle, speed, and ball rotation on the trajectory and accuracy of shots. Lee explored the relationship between lower limb joint angles (especially the knee joint) and shooting accuracy during jump shots.

(3) Experimental Setup

Shung used an isokinetic dynamometer to test muscle strength at multiple angular velocities across multiple joints.

Hamilton and Reinschmidt analyzed free-throw trajectories to determine optimal release angles and speeds. Lee observed lower limb joint angles during relocation jump shots.

(4) Main Findings

Shung observed a significant correlation between joint muscle strength at specific angular velocities and jump shot accuracy. Hamilton and Reinschmidt identified the ideal release angle and speed for free throws as well as their relationship to shot trajectory. Lee discovered that the lower limb joint angle significantly affected shooting accuracy during jump shots.

These three studies all primarily focused on the effects of joint angles and speeds on shooting accuracy in basketball. More specifically, all three examined the effects of knee, shoulder, and elbow joint angles. Finally, these studies investigated the relationship between biomechanics and shooting techniques by performing experimental analyses.

3. System Design and Implementation

This section describes the proposed joint angle measurement system. The system design, posture angle detection, operating model, and implementation approach are presented. Additionally, challenges related to joint angle detection, and solutions for optimizing posture angle detection are also presented.

3.1. System design

The joint angle curve detection mainly focuses on free-throw shooting. Testing is conducted on a standard basketball court. A complete detection process begins with the preparatory posture and ends at ball release. Skills such as jump shots and moving shots are not within the scope of this study.

For the environmental setup, the hardware requirements only consisted of a computer with an Intel i5 processor and a 720p HD webcam (Fig. 1). Regarding software, the system employs Microsoft’s Visual Studio Code as the program editor, along with the Open-Source Computer Vision Library initiated and developed by Intel and the MediaPipe Pose detection landmark model in the MediaPipe multimedia machine learning model application framework. The software is developed using Python 3.9.1 managed by the Python Software Foundation (Fig. 2). Because reflective markers are not used and the software is open-source and free, setup is simple and cost-effective.

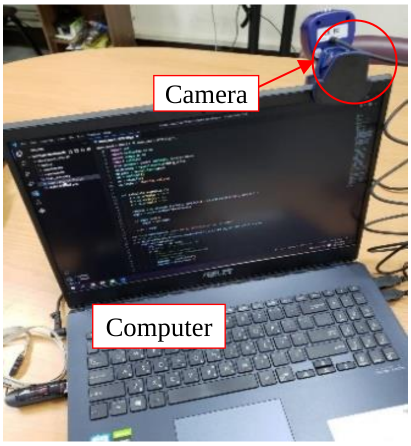


Fig. 1 Hardware used in the experiment

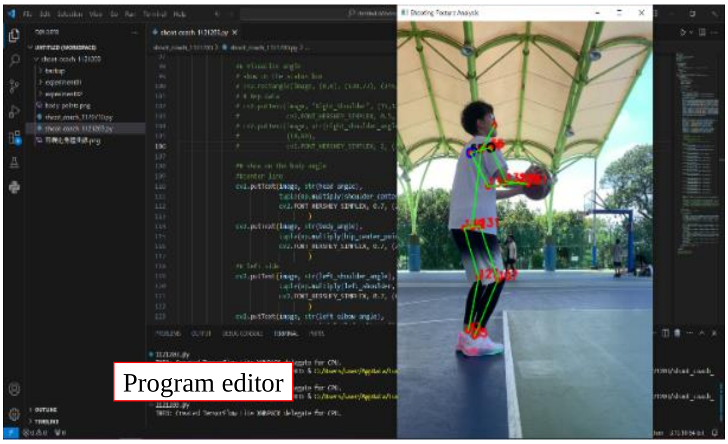


Fig. 2 Software used in the experiment

3.2. Posture angle detection

Through the MediaPipe Pose detection landmark model in the MediaPipe multimedia machine learning model application framework and the BlazePose model [29], the midpoint of a person’s hips, the radius of the circle enclosing the entire person, and the inclination angle of the line connecting the midpoint of the shoulders to the midpoint of the hips are predicted to detect the positions of 33 body pose landmarks (Fig. 3).

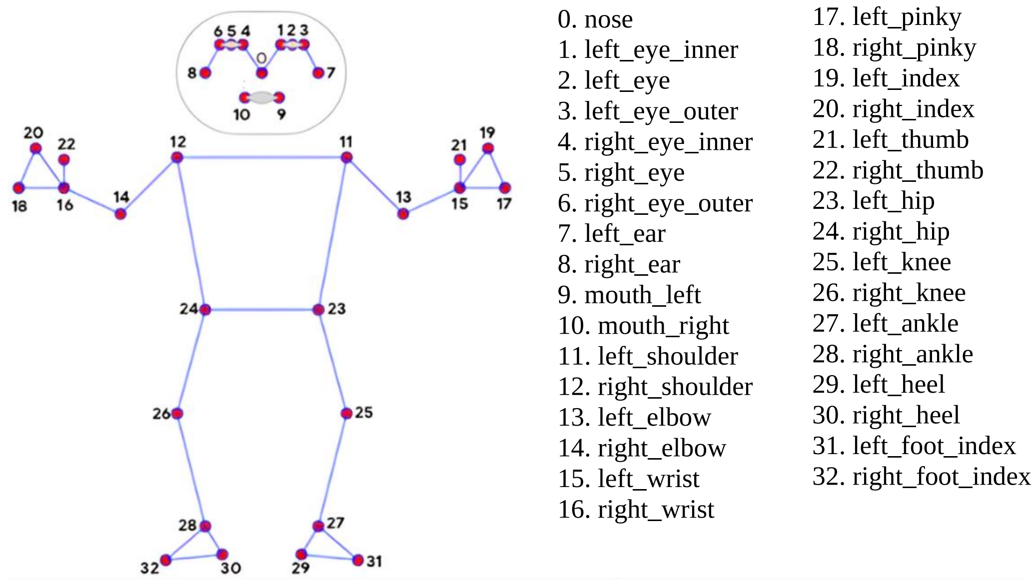


Fig. 3 MediaPipe Pose landmark model [30]

After the landmarks are detected, the angles of each joint point are calculated. From every three landmarks, a joint angle can be calculated. The method of angle calculation is explained as follows. Points a(x,y), b(x,y), and c(x,y) are sequentially marked on the coordinate graph (Fig. 4). First, Eq. (1) is used to calculate the angle θ' between line ab and the x-axis. Then, Eq. (2) is employed to calculate the angle θ'' between line cb and the x-axis. Finally, by subtracting θ'' from θ', Eq. (3) is applied to determine the angle between these three points. Thus, the angle formed between the line segments connecting the middle point b(x,y) to the other two points is calculated using Eq. (4).

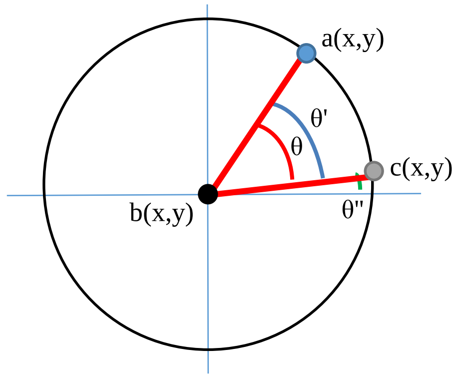


Fig. 4 Coordinate graph of three points

$$\theta' = \text{arctan2}\left(\frac{a_{(y)} - b_{(y)}}{a_{(x)} - b_{(x)}}\right) = \text{atan2}\left(a_{(y)} - b_{(y)}, a_{(x)} - b_{(x)}\right) \tag{1}$$

$$\theta'' = \text{arctan2}\left(\frac{c_{(y)} - b_{(y)}}{c_{(x)} - b_{(x)}}\right) = \text{atan2}\left(c_{(y)} - b_{(y)}, c_{(x)} - b_{(x)}\right) \tag{2}$$

$$\theta = \left|(\theta' - \theta'') \times \frac{180}{\pi}\right| \tag{3}$$

$$\theta = \left|\left(\text{atan2}\left(a_{(y)} - b_{(y)}, a_{(x)} - b_{(x)}\right) - \text{atan2}\left(c_{(y)} - b_{(y)}, c_{(x)} - b_{(x)}\right)\right) \times \frac{180}{\pi}\right| \tag{4}$$

The default body lines between all landmarks of the MediaPipe Pose landmark model are relatively complex. For the detection of free-throw shooting movements, not all joints and lines need to be included. Therefore, the body lines are simplified in accordance with the joint angles required for free-throw shooting analysis (Fig. 5).

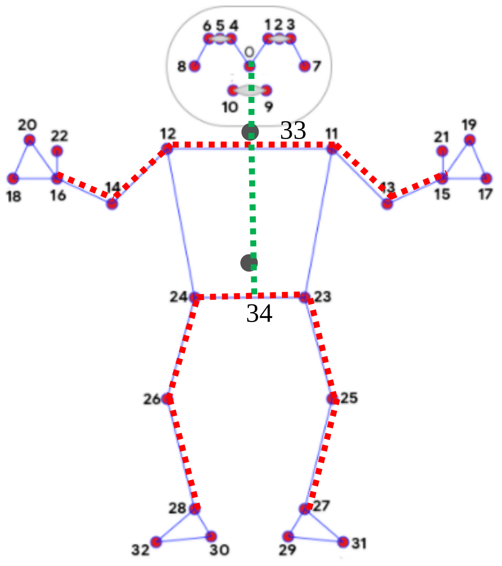


Fig. 5 Customized body line design diagram

The red dashed lines in the figure represent the existing lines in the original model, and the green dashed lines represent the segments that need to be redrawn. The remaining lines are segments that can be excluded. To form new lines, points 33 and 34 are added. The coordinates of point 33 are the midpoint between points 11 and 12, and the coordinates of point 34 are the midpoint between points 23 and 24. After calculating the coordinates of points 33 and 34, the first new line is formed by connecting point 0 to point 33, and the second new line is formed by connecting point 33 to point 34.

3.3. System operating model

During system operation, the main tasks are establishing prediction models for the shooter, predicting the shooting results, and providing posture correction feedback.

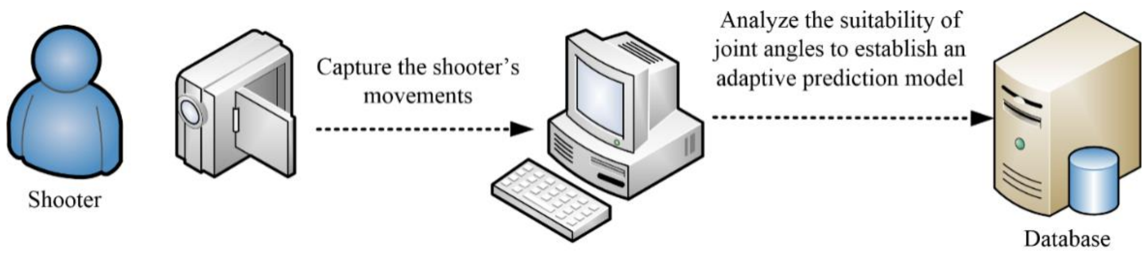


Fig. 6 Establishment of prediction model

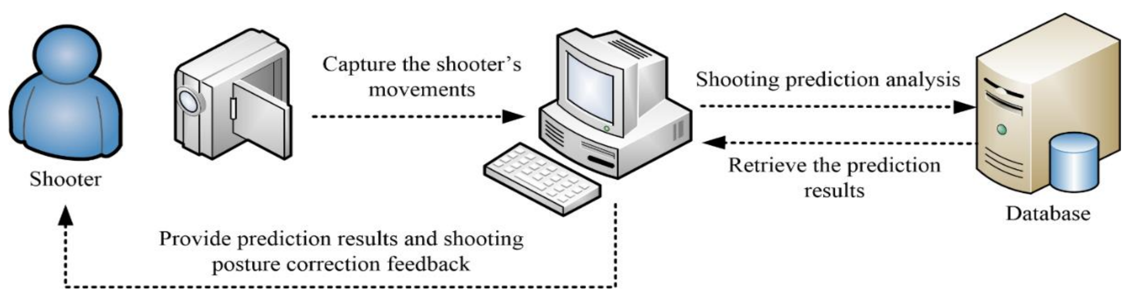


Fig. 7 Shooting result prediction and posture correction feedback

The process of establishing the prediction model is demonstrated in Fig. 6. Initially, the system captures the movements of the shooter through the camera and then uses machine learning techniques to draw joint angle curves. Subsequently, the system analyzes the suitability of various joint angles to establish an adaptive prediction model for the shooter. Finally, all analysis results and prediction models are stored in the database for subsequent shooting result prediction and posture correction.

After the prediction model is established, the shooter's free-throw prediction results are obtained, and feedback for posture correction can be provided. The operational process is illustrated in Fig. 7. During free-throw shooting practice, the system captures the shooter's movements with the camera and then compares the captured data of various joints with the prediction model stored in the database for shooting prediction analysis. Finally, the system provides the predicted shooting results and feedback for shooting posture correction to the shooter for reference. The shooter can continue their shooting practice with the provided correction feedback. The system continuously provides prediction results and correction feedback to facilitate ongoing improvement in shooting skills.

3.4. System implementation

The system interface is shown in Fig. 8. After capturing the movements of the shooter through the camera, the system immediately draws the joint angle curves and displays the angles of each joint. The analysis results are then stored in the database for subsequent prediction model establishment.

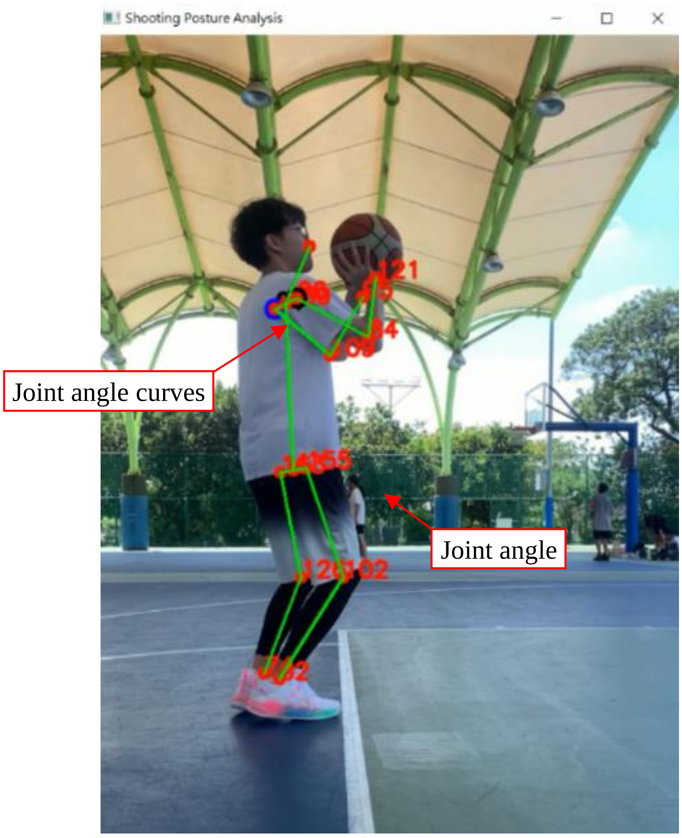


Fig. 8 Detection of body joint angles during shooting

3.5. Joint angle detection problems and solutions

Before starting experimentation with the system in the study, it was discovered that camera placement affects the accuracy of the MediaPipe Pose detection model in detecting the curve of joint angles on the shooting hand side.

Another participant is selected as a test subject from the samples. This participant is also right-handed. The system is tested on them to detect the release movements of the shooting hand. When the camera is placed on the left side, the joint angle curves on the shooting hand side shows unstable jitter (Fig. 9). However, when the camera is placed on the right side, the detected joint angle curves on the shooting hand side are more stable (Fig. 10).

The distortion in the detection on the left side is due to the obstruction of the body during the detection process, affecting the detection angle of the right shooting hand. To improve accuracy, the study adopts the right-side detection method for subsequent experimentation.

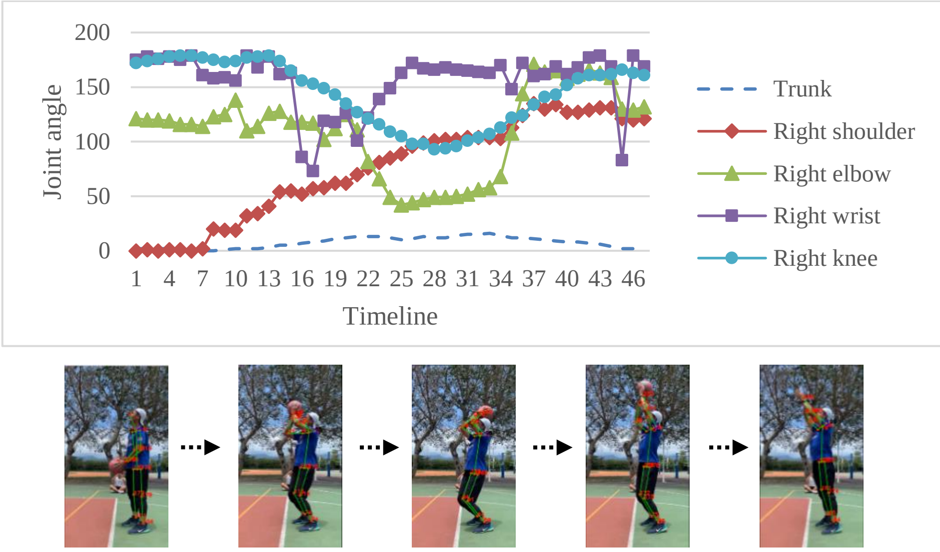


Fig. 9 Joint angle curves detected from the left side

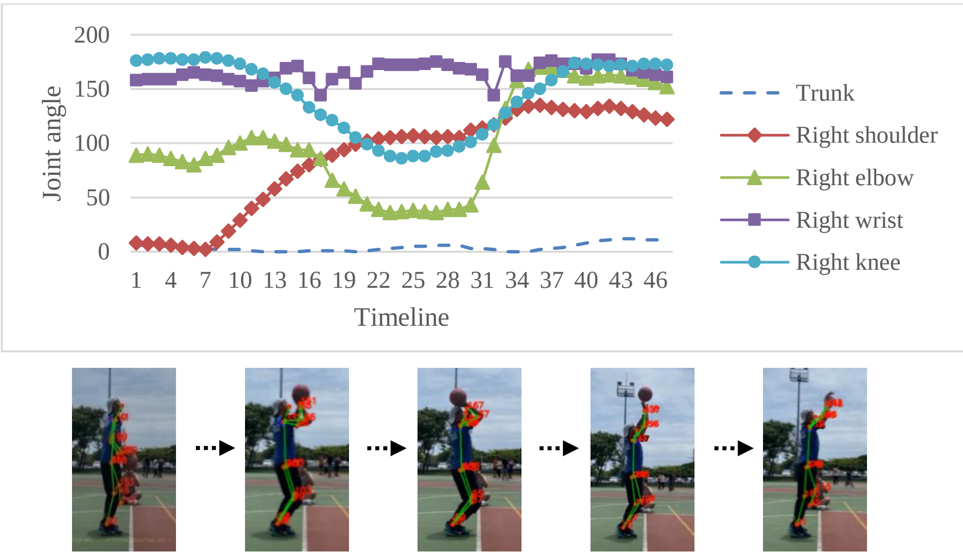


Fig. 10 Joint angle curves detected from the right side

4. Experimental Design and Analysis

After the proposed system is fully developed, system experiments are subsequently conducted. This section introduces the present experimental design and experimental analysis. In the experimental analysis, this study analyzes and compares the prediction results between the proposed prediction model and the J48 decision tree classifier.

4.1. Experimental design

This study recruits 24 freshman students who are enrolled in an elective basketball physical education class at a vocational school in Taitung, Taiwan, during the 2023–2024 academic year. One student is then randomly selected to participate in the study. The participant is right-handed. The participant provides informed consent and completes a demographic information survey before undergoing free-throw shooting experiments.

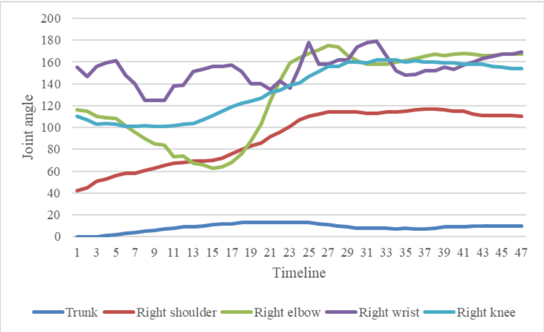
Fig. 11 Experimental design

The experimental design is illustrated in Fig. 11. First, a literature review is conducted, and a joint angle measurement system is developed. The system is tested. The participant performs free-throw shooting. Cameras are positioned on both the left and right sides of the participant to capture the movement of the participant's shooting hand. The system measures the participant's joint angles during shooting, collects relevant joint angle data for adaptive prediction model training, and then employs the prediction model to forecast the free-throw shooting results. Finally, the accuracy of the model is compared with that of the prediction model established by the J48 decision tree classifier to validate the performance of the model developed in this study, and the research findings are presented.

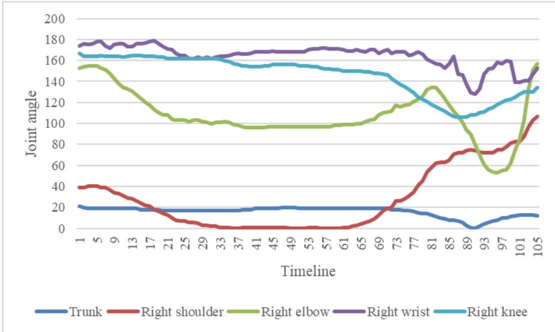
4.2. Experimental analysis

(1) Analysis of the proposed prediction model

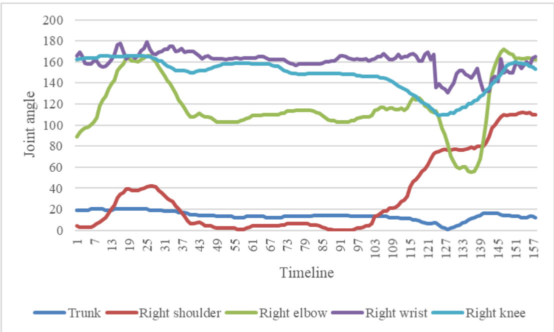
In the system experiment, one student is randomly selected as the participant. The participant shoots with his right hand, and a total of 50 free throws are attempted from the free-throw line. After each shot, the system generates a joint angle curve chart depicting the entire shooting process, from the preparatory posture to ball release. According to the results of the literature review, the study focuses on analyzing the instantaneous joint angle curves of the trunk, right shoulder, right elbow, right wrist, and right knee. The joint angle curve charts generated for the first 10 shots are presented in Fig. 12.



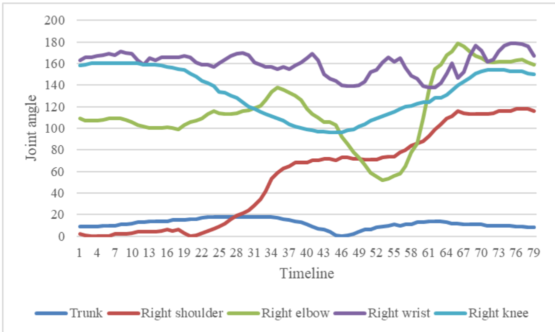
(a) First shot



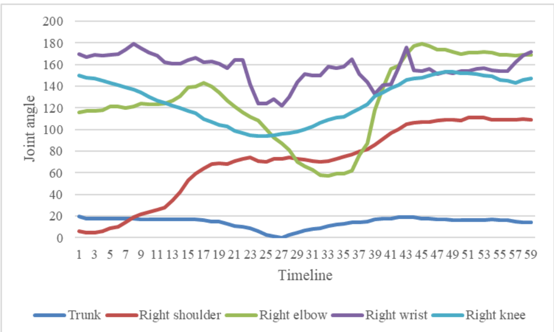
(b) Second shot



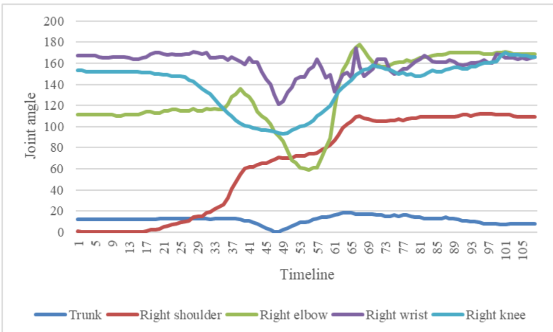
(c) Third shot



(d) Fourth shot

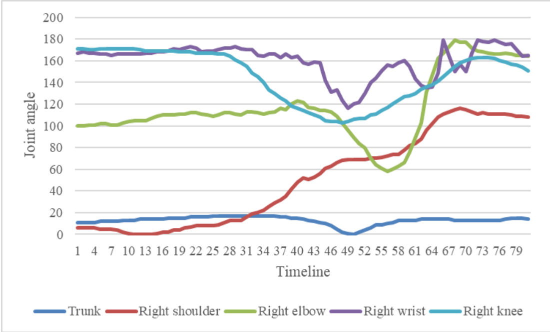


(e) Fifth shot

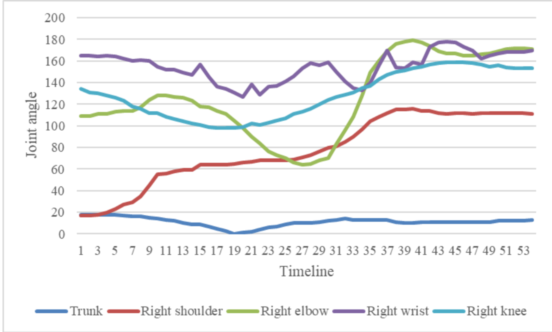


(f) Sixth shot

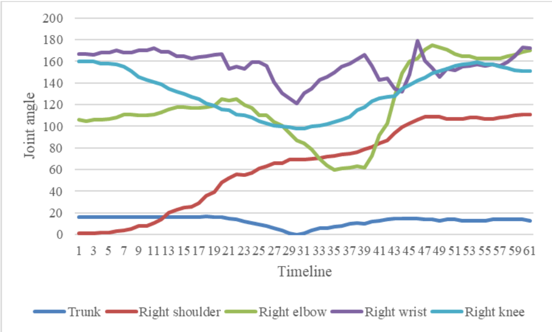
Fig. 12 Joint angle curve charts generated for first 10 shots



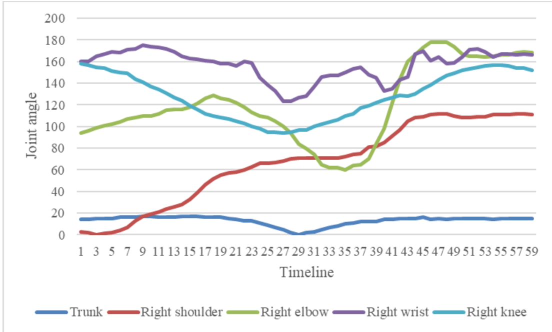
(g) Seventh shot



(h) Eighth shot



(i) Ninth shot



(j) Tenth shot

Fig. 12 Joint angle curve charts generated for first 10 shots (continued)

From the shooting experiment results, 20 sets of joint angle curve charts for successful shots and 20 sets for missed shots are selected to form the dataset for training the prediction model. Because the prediction model needs to undergo processes such as model training and model validation, the dataset is divided into training and testing datasets. In total, 16 sets of successful shots and 16 sets of missed shots are used as the training dataset, and 4 sets of successful shots and 4 sets of missed shots are used as the testing dataset.

The joint angle curves of five key joints (the trunk, right shoulder, right elbow, right wrist, and right knee) for each shooting attempt are analyzed, as shown in Fig. 12. Even though the shooting process involves continuous movement, during each shooting attempt, the study observes two static intersection points in the joint angle curves of the shoulder and elbow during each shooting attempt, as shown in the joint angle curve charts (Fig. 13) obtained from the experiment. After simplification, the joint angle curves of the right shoulder and right elbow are extracted (Fig. 13). The two static instantaneous joint angles, where the shoulder and elbow joint angle curves intersect in every shooting curve chart, are treated as eigenvalues for training the prediction model. Although pre-trained models for continuous movement can be used for free-throw shooting training, dynamic classification requires more powerful hardware and longer training durations compared with static classification. This study opts to train the model using the two static instantaneous joint angles observed during each shooting attempt, which offers the advantage of lower hardware requirements and shorter training durations.

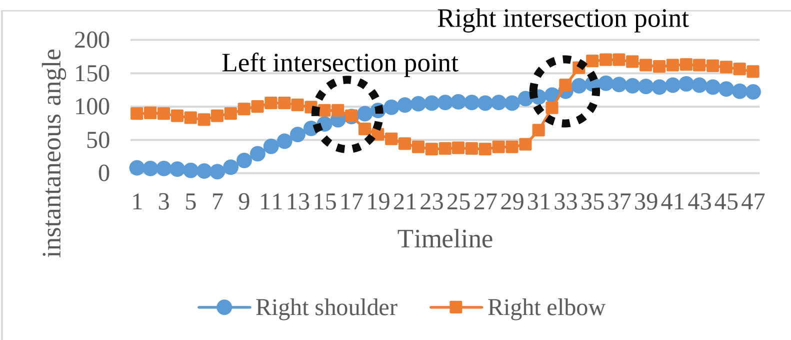


Fig. 13 Joint angle curves of right shoulder and right elbow

When constructing the prediction model, the study focuses on predicting shooting accuracy. Hence, only 16 successful shooting data points are used for training. The remaining eight data points, consisting of four successful and four missed shots, are used for testing. The datasets are listed in Table 1.

Table 1 Datasets used for constructing the prediction model

Dataset Name	Successful Shots	Missed Shots	Successful Shots Used	Missed Shots Used	Total Used
Training dataset	16	16	16	0	16
Testing dataset	4	4	4	4	8
Total	20	20	20	4	24

The distribution of the training dataset obtained in the experiment is displayed in Fig. 14. The figure clearly illustrates the influence of the joint angles at the intersection points on shooting accuracy during each free-throw attempt. The proposed algorithm, which is illustrated in Fig. 15, can summarize the dataset to determine the maximum and minimum ranges of the left and right intersected points when a basket is scored. This serves as a basis for building the subsequent prediction model.

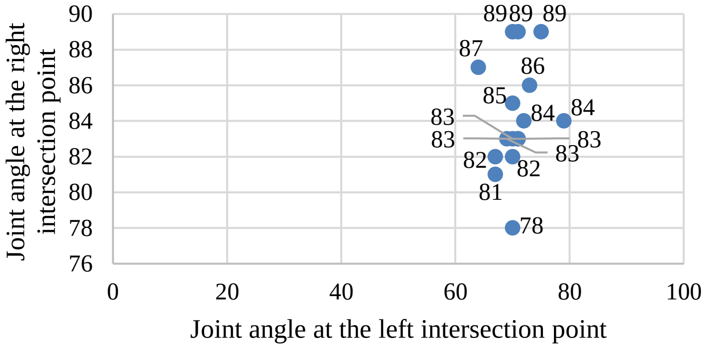


Fig. 14 Distribution of the training dataset

A decision tree model is employed to establish the prediction model. According to the distribution results of the training dataset (Fig. 14), when a shot is successful, the joint angle at the right intersection point falls between 78° and 89°, whereas the left intersection point falls between 64° and 79°. The established shooting prediction model is depicted in Fig. 16. During the prediction of shooting outcomes, the eigenvalues of the left and right intersection points in the shooting process are compared. If they both fall within the shooting joint angle range, the attempt is determined as a successful shot; otherwise, it is deemed a missed shot. In the case of a missed shot, the disparity in joint angles is assessed, and feedback for posture correction is provided to the shooter for reference.

Subsequently, the accuracy of the prediction is verified using the testing dataset, with the analysis results shown in Table 2. The testing dataset consists of eight entries, with six correct predictions-an accuracy of 75%.

Table 2 Accuracy verification of the proposed shooting prediction model

Dataset	Joint Angle at the Left Intersection (°)	Joint Angle at the Right Intersection (°)	Actual Result	Prediction Result	Accuracy
Entry 1	74	89	Successful Shot	Successful Shot	Correct
Entry 2	77	89	Successful Shot	Successful Shot	Correct
Entry 3	69	82	Successful Shot	Successful Shot	Correct
Entry 4	75	85	Successful Shot	Successful Shot	Correct
Entry 5	75	89	Missed Shot	Successful Shot	Incorrect
Entry 6	73	96	Missed Shot	Missed Shot	Correct
Entry 7	72	86	Missed Shot	Successful Shot	Incorrect
Entry 8	72	92	Missed Shot	Missed Shot	Correct

```
def record_shot_angles(shots):
    left_intersected_angles = []
    right_intersected_angles = []
    for angle, side, is_goal in shots:
        if is_goal:
            if side == 'left':
                left_intersected_angles.append(angle)
            elif side == 'right':
                right_intersected_angles.append(angle)
    results = {
        'left': {
            'min': min(left_intersected_angles) if left_intersected_angles else None,
            'max': max(left_intersected_angles) if left_intersected_angles else None
        },
        'right': {
            'min': min(right_intersected_angles) if right_intersected_angles else None,
            'max': max(right_intersected_angles) if right_intersected_angles else None
        }
    }
    return results
```

Fig. 15 Proposed algorithm

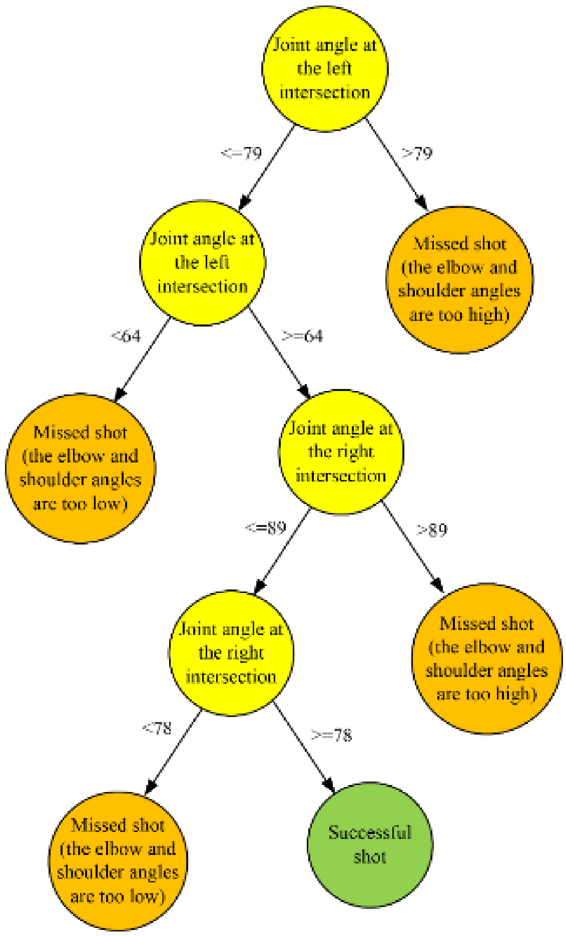


Fig. 16 Proposed prediction model

(2) Analysis of the prediction result using the J48 decision tree classifier

The J48 decision tree classifier is commonly used for making decision tree classification predictions. It uses the C4.5 algorithm for decision tree generation. To understand the validity of the prediction model proposed in this study, the prediction results of the proposed model are compared with those of the J48 decision tree classifier.

The same datasets are employed, with 40 entries in total. Because of the requirements of modeling with the J48 decision tree classifier, in addition to the 16 successful shot data points that are previously selected, another set of 16 missed shot data points is included. The testing dataset remains the same, consisting of eight entries. The datasets used for constructing the J48 decision tree classifier are listed in Table 3.

Table 3 Datasets used for constructing the J48 decision tree classifier prediction model

Dataset Name	Successful Shots	Missed Shots	Successful Shots Used	Missed Shots Used	Total Used
Training Dataset	16	16	16	16	32
Testing Dataset	4	4	4	4	8
Total	20	20	20	20	40

Next, the decision tree modeling is conducted using the J48 decision tree classifier in the Weka data mining software. The resulting prediction model is illustrated in Fig. 17. This prediction model has a maximum depth of 1 and consists of two leaf nodes. The joint angle at the left intersection point is used as the root node for classification. When the joint angle at the left intersection point is less than or equal to 71°, the model predicts a successful shot; otherwise, it predicts a missed shot.

The prediction accuracy is then verified using the testing dataset. The analysis results are presented in Table 4. The testing dataset comprises eight data points, of which five are predicted correctly-an accuracy of 62.5%.

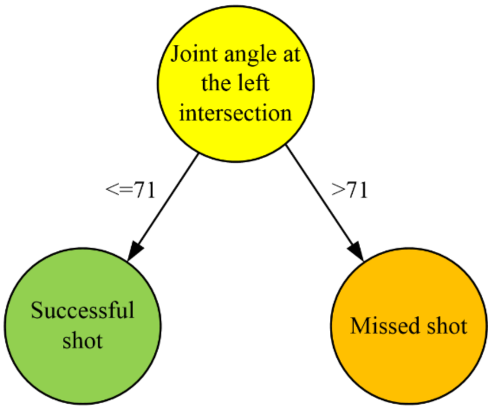


Fig. 17 J48 decision tree classifier prediction model

Table 4 Accuracy verification of the J48 decision tree classifier prediction model

Dataset	Joint Angle at the Left Intersection (°)	Joint Angle at the Right Intersection (°)	Actual Result	Prediction Result	Accuracy
Entry 1	74	89	Successful Shot	Missed Shot	Incorrect
Entry 2	77	89	Successful Shot	Missed Shot	Incorrect
Entry 3	69	82	Successful Shot	Successful Shot	Correct
Entry 4	75	85	Successful Shot	Missed Shot	Incorrect
Entry 5	75	89	Missed Shot	Missed Shot	Correct
Entry 6	73	96	Missed Shot	Missed Shot	Correct
Entry 7	72	86	Missed Shot	Missed Shot	Correct
Entry 8	72	92	Missed Shot	Missed Shot	Correct

4.3. Brief summary

The amount of training data used in establishing the prediction model proposed in this study is 50% of that used in establishing the J48 decision tree classifier prediction model. The prediction accuracy is 1.2 times that of the J48 decision tree classifier. In addition to providing predictions for successful free throws, the proposed model can also compare the disparity in joint angles when a free throw is missed, providing feedback and suggestions to the shooter for posture correction. This allows the shooter to focus on training for specific areas of weakness to enhance free-throw accuracy.

5. Conclusion

The success rate of free-throw shooting is often a critical factor in determining game outcomes. This study employed machine learning to develop a low-cost, hardware-free joint angle measurement system for free-throw shooting and applied it to the scientific training of free-throw shooting skills. With this system, the joint angles of players can be measured without the need for reflective markers, thereby reducing setup costs and facilitating scientific training. Through system testing, this study discovered that camera placement affects the accuracy of MediaPipe Pose in detecting the joint angles on the shooting hand side. Therefore, to improve experimental accuracy, the camera was positioned on the shooting hand side during the movement detection process, and joint angle data were collected for prediction model training. A prediction model was thus trained and subsequently used for free-throw shooting outcome prediction and posture correction. According to the literature, knee, shoulder, and elbow joint angles affect shooting accuracy.

(1) This study discovers that during the free-throw shooting process, from the preparatory posture to ball release, the two static instantaneous joint angles, namely those where the shoulder and elbow joint angles intersect, can be used to predict the shooting outcome.

(2) Through the proposed method, adaptive prediction models for successful shots can be constructed for individual shooters.

(3) The experimental results indicate that the amount of training data required for modeling is 50% of that required by the J48 decision tree classifier, with an accuracy 1.2 times higher.

This study presents innovative features and contributes to system development, technological innovation, experimental findings, data requirements, and system application. Furthermore, when a shooter misses a shot, the system compares the disparity in joint angles and provides feedback for posture correction as a reference. This enables shooters to improve on specific problem areas and enhance their free-throw performance, thereby helping teams win games.

Conflicts of Interest

The authors declare no conflicts of interest.

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