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All-in-Net: Scorekeeping in Basketball Training using a Mobile Phone Camera and Image

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Abstract

As basketball is one of the crowd's favorite invasion games, methods are being developed to enhance players' performance as technology improves. Recording large parts of training significantly reduces subjective training assessment compared to objective aspects. In this paper, basketball players and coaches use a mobile application based on image processing for achievements, measuring shooting the basket from different positions on the court and displaying feedback. The shooting technique and the percentage of success are measured using an algorithm that identifies the angle of the shot to the basket. The system monitors players' knowledge of results during training using one mobile phone camera. The paper describes the architecture and design of the mobile computing and application: Pre-training (define goals based on past performance and level of training difficulty), during training (data collection and compatible camera), and post-training (analysis and visualization of results). Finally, the paper discusses validation and implications.

Keywords: Mobile Computing Systems and Applications, Smart training systems, Image recognition

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1. Introduction

Basketball is one of the most popular invasion games, with a history of about 130 years and an estimated 450 million spectators [1]. The revenue of the National Basketball Association (NBA) for 2021-2022 is projected to be 10 billion US$ [2], and the revenue of the European counterpart, the EuroLeague, for 2025/25 is projected to be over a billion US$ [3]. From a coach's and player's oriented perspective, a three stages model has been described for the development of a motor skill such as throwing to the basket [4], suggesting (a) the cognitive stage, where processes need to be mediated through a coach, using verbal explanation, describing and physical prompts, (b) the associative stage, where the learner is using knowledge of results (KR) for improving performance, as well as knowledge of performance (KP) that is understanding kinetic and kinematic choices to determine the conditions supporting or hindering performance [5]. This can be facilitated by the coach, using various augmented feedback modalities, such as those using performance analysis software, (c) the autonomous stage, where the learner is more or less independent in decision-making and can adapt the movement pattern and integrate it into a movement sequence (e.g., dribbling and shooting a basket within the lay-up pattern), and cope with unexpected perturbations. Supporting the coach and player with KR on basketball scoring from different positions provides essential cues for skill mastering progression across all learning stages. In addition, visual feedback improves the efficiency of the training [6]. Therefore, it is imperative to monitor skill performance during games for the benefit of spectators and during training sessions to improve performance.

Given the athletic and commercial interest associated with basketball, external, objective players' performance analysis systems have been implemented for designing training content and talent identification in basketball and monitored mainly during games [7]. Specifically, free throws, 2- and 3-point throws, as well as passes, turnovers, and defensive and offensive rebounds, have been highlighted as valuable criteria for evaluating players' performance [8]. Currently, expensive compositions of inertial monitoring units (IMU) and video capturing systems are utilized [9]. Tracking players or balls and providing performance analysis regarding actions such as throwing and kicking enables the visualization of technical and tactical moves in ball games to benefit players, coaches, and fans [10]. Therefore, the development of computer vision systems has attracted enormous interest among computer scientists [11].

In the current paper, we describe a mobile computing system for monitoring players' KR during training, whereby an inexpensive smart video capturing and recording mobile application is demonstrated to track and monitor the players' shooting performance during training conditions. The current paper aims to present a single-camera mobile computing system with ball recognition and detection capabilities, as well as ball position recognition and validation. All features are encapsulated in a comprehensive mobile application, accessible for coaches and trainers. We focus on describing the functional specifications, system architecture, and validation.

2. Related Work

Recent research has focused on developing mobile applications to enhance basketball training. These apps utilize smartphone sensors and machine learning algorithms to assist players in improving their skills. One study developed an Android-based app called "My Basketball Coach" to help users practice independently, receiving positive feedback from users [12]. Another app was created to aid players in perfecting their free throw technique using gyroscope and accelerometer sensors [13]. Researchers have also explored the use of wearable devices and Support Vector Machine algorithms to automatically recognize different basketball training types with high accuracy [14]. Additionally, an Android-based learning media application was developed for basketball education, containing tutorials on basic techniques and referee regulations, which showed promising results in improving students' skills and comprehension [15].

Some studies have focused explicitly on ball shooting performance, describing technologies to measure and improve basketball shooting. Wearable IoT devices have been designed to monitor and analyze shooting forms in real time, offering a more efficient alternative to conventional methods [16]. Classification and Regression Trees (CART) have been employed to estimate scoring probabilities under various game pressures, leading to the development of player-specific shooting performance indices [17]. These approaches allow comparing factors affecting shooting performance across different leagues and evaluating individual players. Additionally, mobile applications have been developed to assist players in independent training. These technological advancements offer promising tools for enhancing performance measurement and training of basketball shooting.

Using a mobile phone camera for basketball training and analysis is gaining attention in recent studies. A compatible camera is essential for ball and player tracking [18]. Cricri et al. [19] developed algorithms for detecting salient events in basketball videos using smartphone cameras and magnetometer data. Bertasius et al. [20] proposed a method to assess player performance from first-person videos using convolutional LSTM networks and Gaussian mixtures. Liu et al. [21] introduced BetterSight, an immersive vision training system that combines virtual reality with real-world ball handling to improve players' visual skills and decision-making. Wen et al. [22] presented a technique for camera calibration in broadcast basketball videos, enabling accurate player tracking and tactical analysis. These studies demonstrate the potential of mobile technology and computer vision in enhancing basketball training, performance assessment, and video analysis, offering new tools for players, coaches, and analysts to improve various aspects of the game.

The use of image-based technological means to improve performance in sports exists in various sports fields. Examples include using a mirror as a screen showing the poses a dancer is required to perform while dancing [23], displaying visual cues on training instructional videos [24], or using an augmented reality system for home training that presents training video guides [25]. To objectively assess the players' performance, advanced recording and image processing technology is becoming accepted in other sports. For example, in tennis, all the movements of the tennis players on both sides are recorded, including technical aspects, efficiency factors, and physical analysis to improve their technique [26]. Regarding accessibility in sports, DanceVibe is a wearable device that translates the beats of the music into vibrations for the benefit of hearing-impaired dancers [27]. Dantu and Jonnada [28] refer to healthcare, capturing the heart rate using a mobile phone's camera and extracting a breathing pattern from the heartbeat during workouts. Rusho et al. present a wearable device connected to a mobile computing application for safe navigation for kick scooters [29].

Although various uses are made by mobile phones in the fields of sports, with or without complementary components, as a wearable device, a camera, or algorithms of artificial intelligence, image processing, and computer vision, there is still a lack of a system that combines (1) an automatic method, which uses image processing and computer vision, for scorekeeping in basketball aiming to measure performance (2) an interface- for the trainees to see their performance and for the coaches to define training programs and see their players' improvement trends.

This document presents All-in-Net, a mobile computing system that applies these two primary goals. The following sections elaborate on the proposed solution, starting with use case scenarios to understand the application. The paper continues with explanations regarding functional requirements and system architecture

3. All-in-Net Mobile Application Use Cases

The following use cases demonstrate how the mobile computing system is utilized for various learning and improvement purposes. From a coach's perspective, the system allows them to define a training program based on past performance, as seen in Figure 1.

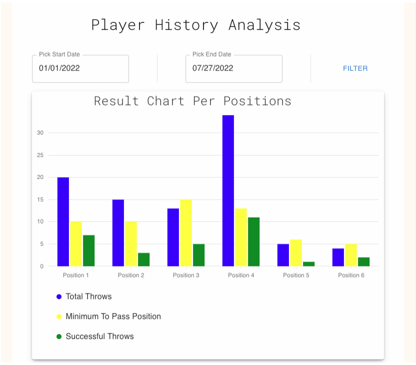

Fig. 1. Player history analysis

As shown in Figure 2, each training program can contain shots from six different positions, five from outside the three-line arc and the sixth from the free-throw line.

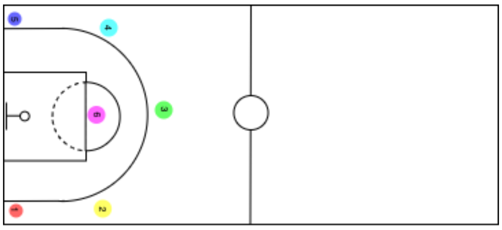

Fig. 2. Shot positions

The trainer can define new training programs for their players by choosing court positions in the application. Figure 3 displays how trainers define new training programs for their players.

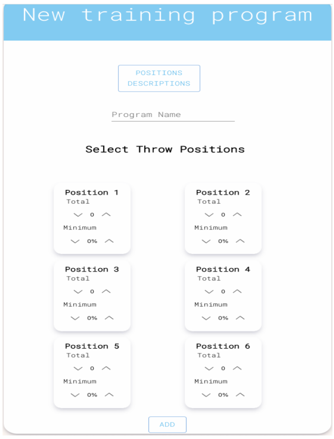

Fig. 3. Defining a new training by positions

From the players' perspective, they see the pre-defined training (Figure 4). Each training details the required throws from each position and the number of shots the player is requested to hit to complete it successfully.

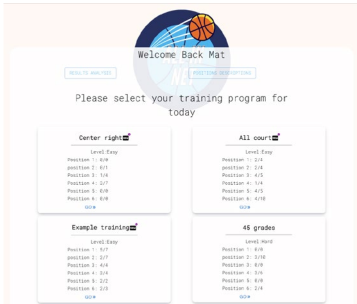

Fig. 4. Available training and success requirements

At the end of the training, the player and the coach can view the training statistics and visualization regarding the training, such as shots per position (Figure 1 above) and the conversion rate per position (Figure 5 below) in the mobile application interface.

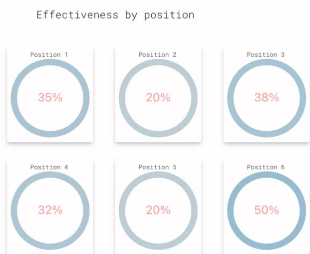

Fig. 5. Conversion rate per position

In addition, the mobile computing system displays specific information and instructions regarding each shot. This information includes the position on the court from where the shot was thrown, pictures, and the shot's path toward the basket (Figure 6). Multiple images are saved for each throw. The ball path is marked in green for a successful throw and red for a miss.

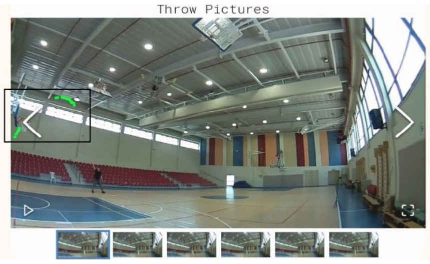

Fig. 6. Shot ball path

Figure 7 displays the training history, enabling progress detection over time. The coach can define a training sequence in a training program to improve the shooting technique into the basket from a specific position. By examining the improvement of the achievements between training sessions in the sequence determined by the coach, the player can decide whether to improve the shot from the same position or move to improve the technique in another position.

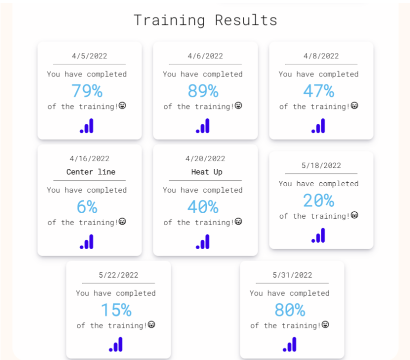

Fig. 7. Historical training results displayed in the GUI

The functional options described above are expected to strengthen the players' associative stage, where one can use KR to improve performance.
The following section details the general architecture, data acquisition, and analysis of the mobile computing system from an engineering perspective.

4. All-in-Net Specification and Architecture

In this section, we describe the mobile computing application that we developed. The application automatically counts the number of shots taken and the number of scores performed from each throwing position, using image processing to enable basket shooting performance analysis during training and facilitate ongoing performance assessment. The application facilitates training management by showing players' statistics and progress based on the shooting percentages from different positions on the court.

The system's specifications are divided into three phases: Pre-training, During-training, and Post-training.
In the *pre*-training phase, the coach and the player can define training based on past performance and level of training difficulty. Two parameters determine the level of training difficulty. The first is the type of the throw, which may be a "Free" throw from the foul line or a "Three-point" throw from five positions on the three-point line. The second parameter is the count of throws for each position. This data is the input for the analysis process in the post-training phase.
The *during*-training phase is activated once the pre-training phase is completed and the player starts the training. Data is collected through a Raspberry Pi unit, using a built-in camera, until training is done. The collected data is transmitted to the mobile computing system during this phase.
The *post*-training phase is responsible for analyzing and processing the collected data. Moreover, this phase detects the player's weak and strong points and visualizes detailed reports for the player and coach. The coach can suggest a new training program by comparing the player's session result to the predefined desired outcome. The player can then accept the suggestion or build a new training program.
Two subsystems—the training management subsystem and the analytical engine—handle the three phases. The training management subsystem stores and displays the collected data as valuable information. Hence, it enables coaches and players to define training and view statistics from previous training sessions. The above is implemented by a client application connected to a web server and database.
The second subsystem is the analytical engine. It is responsible for collecting, analyzing, and transmitting the collected data to a web server. This engine is implemented by Raspberry Pi and a compatible camera, computer vision, and image processing library. It records each shot and detects whether it is successful or a miss. Figure 8 displays the system architecture, divided into pre-, during, and post-phases.

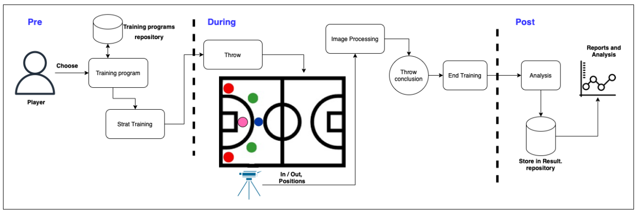

Fig. 8. System architecture

4.1. Data Collection

The current paper describes a single inexpensive camera for data collection and analysis. The process of gathering data for improved performance in basket shooting includes automatic recording of a video from the moment the training starts. The data is transmitted to Amazon Web Server (AWS) in the cloud, where it is saved and analyzed in the database. We use docker containers to manage the system infrastructure. The dockers manage the production step (uploading to the cloud) and the internal network. The UI is written in React. The system has a proxy that routes the UI to the server. Figure 9 details the data collection process. The Raspberry Pi, a Linux operating system that runs packages of Python, sends commands to turn on the camera when the training starts. All recorded frames are extracted and analyzed, as described in the next two sub-sections.

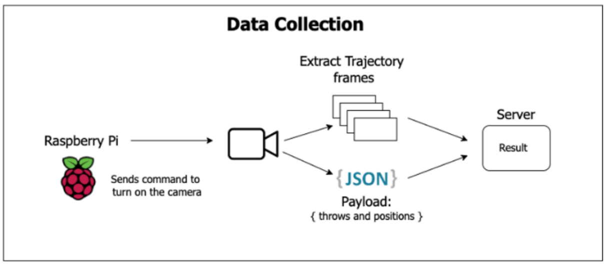

Fig. 9. Process and components of the system

* JSON (JavaScript Object Notation) is a lightweight format for data interchange

Any smartphone camera can be used for this operation. The camera should be placed on the left side of the court and connected to a power supply and Wi-Fi.

4.2. Basketball Detection

Court, ball, and basket detections present problems and challenges, such as vision occlusion, false detection, changes in light and colors, and different quality of videos with varying frame rates [11]. In our mobile app, basket detection is one of the two main recognition algorithms that have been implemented. This algorithm includes five steps:

(1) Frame readjustment—From the basketball court's full frame, the system crops a rectangle that includes the basket and its surroundings to avoid background noise behind the hoop and to focus on the ball (Figures 10 and 11).

(2)

Fig. 10. Entire court frame recorded with the camera

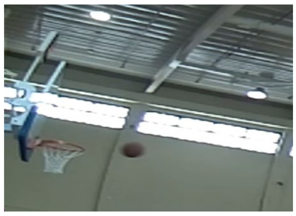

Fig. 11. Frame view after the system crops the original frame

(3) Configure HSV values—Using OpenCV's ColorFinder library, the system defines the frame's background in black and white tones to identify and isolate the ball from the background.

(4) Find contours—Apply the color value to Mask the frame and ball contour detection (Figure 12). When the system finds the ball within a predefined minimum area, it adds contours (Figure 13).

Fig. 12. Mask of the frame and detection of the ball contours

Fig. 13. Ball contours detection

(5) Detect throw results—The system defines two additional rectangles in the hoop area to identify whether the shot was successful. The algorithm searches for three dots of ball trajectory inside the upper boundary box and immediately after that for three points inside the lower boundary. Figure 14 displays the two additional rectangles.

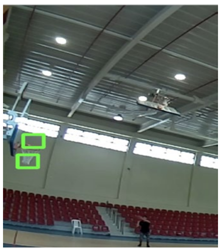

Fig. 14. Boundary boxes around the hoop to detect successful shots

Next, speed is detected near the additional rectangles to detect false positive cases. For each throw, the shot trajectory is initially marked using red dots (Figure 15). If the ball passes through both rectangles without a significant change in speed, the dots' color changes to green, meaning a successful throw (Figure 16).

Fig. 15. Not a successful shot

Fig. 16. A successful shot

Figure 17 describes the comprehensive detection algorithm. The algorithm process includes the five steps described and details how the system works to detect and save the results of each shot.

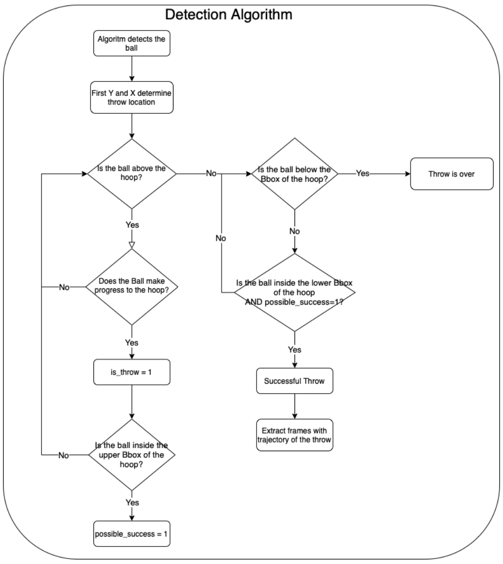

Fig. 17. Shot detection algorithm process

4.3. Position Detection

To automatically recognize the position from which the player throws the ball, the basketball court has been divided into six central positions (seen in Figure 2 above), where the behavior and trajectory of the ball from each position are different. Following, a graph of the throws is plotted (Figure 18). According to the point where the ball enters the frame and the trajectory curve, the mobile computing system determines the position from which the player throws the ball.

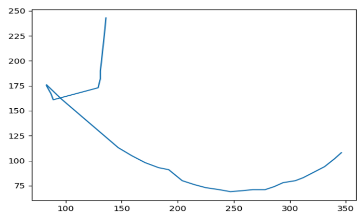

Fig. 18. Graph showing a shot path from position #3

5. Methods and Application Validation

Validation of the mobile computing system reported in this paper refers to basketball identification under different conditions.

5.1. Basketball Identification

Basketball identification was validated in open and closed courts. Validations results are displayed in Table 1.

Table 1. Open vs Closed courts

Court type	Validation	Discovery	Improvements
Open Court	Identification of the basketball in open courts	An image of a basketball shot in an open court includes independent background noise, which cannot be observed and controlled. The angle of the sun and the amount of light at different hours affect quality of ball detection in the analyzed image.	A decision was made to analyze the shots only in a closed court.
Closed Court	The initialized process included configuring the court. The configuration process was tested in several different basketball courts.	In closed courts, orange objects such as fans' chairs and advertising signs prevent the orange ball from being identified in the image of the entire field.	Two frames analyzed: one above and one below the basket, not the entire court.

The second validation procedure includes detecting colors in the closed court to isolate the orange ball. Table 2 displays tests and discoveries.

Table 2. Color detection

Ball detection	Testing	Discovery
Detect colors	A series of tests was carried out during basketball players' shooting practice. We identified red, blue, green, and orange colors.	The algorithm improved between tests until the ball was fully identified within the photographed frame.

6. Discussion and Conclusion

Basketball performance analysis has attracted a variety of technological solutions. From one- to multiple video camera tracking and analysis solutions [30], equipped courts with technology such as Playsight with six or eight fixed cameras [31] to wearable sensors [32]. PlaySight camera system is built with advanced tennis analysis technology that requires permanent installations of six HD cameras on the court [33]. This technology analyzes professional tennis matches. In addition, RSPCT [34] uses an optical sensor placed on the backboard to track basketball shooting, focusing on the point of interaction between the ball and the basket. In contrast, the current paper offers an accessible and inexpensive mobile computing system for amateur basketball players, with the help of a single smartphone camera that captures the entire trajectory of the ball - from its separation from the player's hand through the arc in the air to the interaction with the basket.

We present an inexpensive analytical and engineering one—camera—based solution designed to provide basketball coaches and players with software tools to improve shooting performance. The paper describes an engineering perspective, including the architecture and design of a three-step model for developing a motor skill such as throwing into a basket.

A three-stage model has been developed to improve motor skills, such as throwing a ball to the basket [4]. The second stage in the model refers to the associative stage, in which the learner uses knowledge of results (KR) to improve performance and knowledge of the performance. Hence, in the current paper, we describe an automatic mobile application for monitoring the players' KR during training, according to which a low-cost intelligent video capture and recording system is demonstrated to monitor and track the players' shooting performance under training conditions. The system's analytical engine identifies the court, the position from which the ball is thrown, ball identification, and basket identification.

The system identifies six separate positions on the court and visualize the user statistics of throws, shots, goals achievements, displays instructions and suggestions, and allows to define personalized and dynamic training programs.

The mobile computing system is divided into pre-training, during-training, and post-training. Each part has a separate engine for identification, analysis, drawing conclusions and recommending actions. Detection operations include color detection, background noise removal, and shot angle detection.

The paper describes validations carried out technically both on the basket detection engine and on the detection of the shot positions on the court. The solution presented in this paper allows a combination of analytical and engineering tools to improve the achievements of amateur basketball players.

In terms of accessibility to technological solutions – this paper presented a ubiquitous and mobile computing system which uses accessible, cheap technologies- a phone

camera, Internet and an easy to use mobile application. Precisely as the technology becomes accessible and available, it is necessary to continue to develop quality solutions that can be available to everyone, especially for young players [35].
In terms of cost-competitiveness, national teams have professional and more expensive means, as we have detailed above. However, amateur players, or teams from the periphery, from developed countries, for teenagers who are in a non-competitive promotional framework, do not have the means to invest in expensive and massive developments, that require complex maintenance and support. For them, an inexpensive solution can improve both performance and confidence. In addition, the current solution.
In terms of using a dedicated mobile computing system for training and learning needs, the solution paves the way for engineering outdoor learning systems that are not based on displaying instructions on a computer screen. The ability to identify the style and quality of the shot to the basket ahead, suggest ways to improve, and change the training plan in collaboration with the opinion of the professional coach significantly enhances the user experience and its effectiveness.

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