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CNN 및 센서 데이터 기반 농구 적중 예측 시스템의 설계 및 최적화

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Design and Optimization of Basketball Hit Prediction Model Based on Convolutional Neural Network and Sensor Data

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[요 약]

농구 슛 성공률은 선수의 기술 수준을 측정하는 중요한 지표 중에 하나이다. 기존의 슛팅 훈련 방식은 주로 코치의 경험과 선수의 개인 연습에 의존하기 때문에 객관성과 과학성이 부족하다. 본 논문의 목적은 합성곱 신경망과 센서 데이터를 기반으로 한 농구 슛 예측 모델을 제안하여 농구 슛 훈련의 효율성과 정확도를 향상시키는 것이다. 본 연구에서는 세 가지 센서를 사용하여 슛 과정에서 선수의 동작 데이터를 수집하고, 이러한 데이터를 분석 및 학습하기 위해 컨볼루션 신경망을 사용하는 농구 슛 예측 모델을 제안한다. 제안한 모델은 최대 98.5%의 슛 예측 정확도를 달성을 하였고, 기존 모델 보다 13.5% 높다. 최근 인공지능과 센서 기술의 급속한 발전으로 딥러닝을 기반으로 한 슛팅 적중 예측 모델이 점차 등장하고 있으며, 이는 농구 훈련에 새로운 과학적 수단을 제공할 것으로 기대된다.

[Abstract]

Basketball shooting percentage is an important index used to measure a player's technical skill. This paper presents a basketball shot prediction model based on a convolutional neural network (CNN) and sensor data, to improve the efficiency and accuracy of basketball shot training. First, three sensors were used to collect player motion data during the shooting process, and the CNN was used to analyze and learn these data. The proposed model achieved 98.5% shooting prediction accuracy, which is higher 13.5% than the existing paper method. Recently, the rapid development of artificial intelligence and sensor technology has led to the emergence of deep learning-based shooting hit prediction models, providing new scientific tools for basketball training.

색인어 : 컨볼루션 신경망, 각도 센서, 자기 센서, 자이로스코프, 물체 예측
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Ⅰ. Introduction

Achieving professional-level basketball training has been a challenge in many countries. Studies have shown that healthy adults can only maintain high concentration for only about 10~15 minutes, and that one-on-one personalized basketball training requires a lot of time and money[1],[2].

Recent research has shown that in the field of sports training, the use of advanced technological tools to improve the performance of athletes has become a hot topic of research. In the field of basketball, improving the shooting percentage is crucial for the team to win or lose. Some recent related papers include "Deep Learning-Based Basketball Player Positioning Recognition System Design" and "Motion Sensor-Based Basketball Motion Recognition Technology Research", which provide useful references for the application of technology and performance optimization in basketball training.

We proposes a basketball shot prediction model by using sensor and convolutional neural network technology. First, we use the angle sensor, magnetic sensor, gyroscope, then use convolutional neural networks to train models to predict whether a basketball is hit or miss. The method can adjust the shooting action according to the predicted result, then improve the basketball's hit percentage. This method can provide basketball players with more effective training guidance, help them better get the shooting skills and improve the percentage.

What we would like to do is as follows Based on the analysis of the latest papers, we plan to design a basketball hit prediction system based on CNN and sensors to improve the efficiency and effectiveness of basketball training. By collecting sports data and combining it with deep learning models for training, our goal is to propose a basketball hit prediction scheme with higher accuracy and more practicality to provide athletes with more accurate training guidance.

We will collect and analyze large amounts of basketball movement and performance data for personalized guidance and model training. We will also explore the application of sensor technology to monitor and capture dynamic data of players[3],[4].

The work presents innovative methods to enhance basketball particularly for individuals who are new to shooting skills, especially for individuals new to the sport. By combining convolutional neural networks and sensor technology, these approaches can also be applied to other sports, such as soccer or other sports.

Ⅱ. Related Works

2-1 Basketball Hit Prediction

Basketball hit prediction refers to the use of machine learning or deep learning techniques to predict the outcome of a basketball player's shooting maneuver, such as predicting whether the ball will go in or whether the shot will be successful[5]-[7].

Harmonet et al.[8] use a convolutional neural network combined with a feed forward network on basketball shot prediction. Wright et al.[9] used a factorization machine model to make shot predictions based on 2015~2016 National Basketball Association data. Oughali et al.[10] proposes a comparative study using machine learning algorithms to predict the shooting success by basketball players in the NBA (national basketball association).

2-2 Convolutinonal Neural Network

Convolutional Neural Networks[11] is a class of feedforward neural networks with convolutional computation and deep structure and is a representative algorithm of deep learning. The convolutional neural network structure includes input layer, convolutional layer, pooling layer and fully connected layer. Among them, the convolutional layer is the core part of the convolutional neural network, and features are extracted from the input data by convolutional operation. The pooling layer is used to reduce the dimensionality of the data, reducing computation and overfitting problems. The fully connected layer is used to combine the features of the previous layers to output the final classification or regression result.

2-3 Sensor

1) Angle Sensor

Angle sensor[12]-[14] is a sensor that measure the angle of rotation or orientation of an object. They are used to detect changes in the angle of an object relative to a reference point, axis or plane and convert these changes into a corresponding electrical or digital signal. Angle sensor consist of sensing element, measurement circuit, intelligence component and interface component. The sensing element is the core component of the angle sensor and is used to sense and convert the angular movement of an object into an electrical signal. The measurement circuit is the circuit responsible for processing and converting the signals generated by the sensitive element. It is capable of amplifying, filtering, digitizing, or analog converting the signals received from the sensitive element to accurately measure and calculate the angle. Intelligence component is usually built-in processors or chips that are used to analyze, process, or store sensor data. These elements are capable of processing and interpreting the data collected by the sensor to provide more advanced functions such as calibration, alignment, or data decoding. Interface component is used to communicate with other devices or systems. The integration of these components enables angle sensor to measure the angular motion of an object and convert this information into corresponding electrical or digital signals to meet the needs of different fields and applications accurately and reliably.

2) Magnetic Sensor

Magnetic sensor[15]-[17] is a device used to measure the strength and direction of the surrounding magnetic field, it converts magnetic field signals into electrical signals with a high degree of accuracy and precision. It measures magnetic field direction, strength and changes.

3) Gyroscope

Gyroscope[18]-[21] is a device based on the conservation of angular momentum that is used to sense and maintain direction. A gyroscope consists primarily of a rotor that is centered on its axis and can be rotated. Due to the angular momentum of the rotor, gyroscope tends to resist a change in direction once they begin to rotate.

The primary use of gyroscopes is in the inertial navigation system, where they play a crucial role in determining the attitude and position of carriers, including airplanes, ships, missiles, and more. Gyroscopes are also critical in attitude control systems, enabling the measurement and regulation of carrier orientation to maintain stability. Moreover, they are crucial components in a variety of toys, such as gyros and gyro dashboards.

2-4 Kalman Filter

The Kalman filter[22] is a set of mathematical equations that provides an efficient computational (recursive) solution of the least-squares method. The filter is very powerful in several aspects: it supports estimations of past, present, and even future states, and it can do so even when the precise nature of the modeled system is unknown.

The Kalman filter formula is as follows:

$$x_k = A \times x_{k-1} + B \times u_k \tag{1}$$
$$P_k = A \times P_{k-1} \times A^T + Q \tag{2}$$
$$z_k = C \times x_k + v_k \tag{3}$$

Where, k is the end time, $k-1$ is the start time, x_k is the state estimation of the end time, P_k is the state covariance matrix of the end time, z_k is the observed value of the end time, A is the system matrix, B is the control matrix, C is the observation matrix, Q is the system matrix. v_k is the observation noise.

2-5 Human Activity Recognition (HAR)

Motion recognition technology, on the other hand, refers to the identification of specific sports movements by analyzing the trajectory or posture of the athlete. This technology also plays an important role in sports training and can be used to assess the accuracy of athletes' movements and monitor training effects. It has been shown that movement recognition technology can help coaches and athletes better master the technical elements of sports and improve the relevance and effectiveness of training.

For the advantages and disadvantages of the prediction model, we will describe its accuracy, real-time and scalability in detail. Accuracy is one of the most important indicators of the performance of a prediction model. A good prediction model should have high accuracy and be able to accurately predict basketball hits. However, some traditional prediction models may suffer from insufficient accuracy, limited by factors such as feature representation capability or model complexity[24].

Ⅲ. Basketball Hit Prediction Model

3-1 Design Philosophies

The basic design ideas of this model mainly include three parts, as shown in Fig. 1. It includes data collection, sensor's data calculation and training CNN model.

The system uses three sensors to collect motion data during the player's shooting:

- Angle sensor: used to measure the angle of the player's shooting shot.
- Magnetic Sensor: Used to measure the force of the player's shot.
- Gyroscope: Measures the rotation of the player's shot. Sensor data is collected at a rate of 100 times per second and stored in a local database.

1) Data Processing

The collected raw data needs to be pre-processed, including:

- Data cleaning: removing noise and anomalous data.
- Data normalization: mapping the data to a uniform scale.
- Feature extraction: extract features related to shooting hits.

2) Model Training

The basketball shot prediction model is trained using a Convolutional Neural Network, a machine learning model that specializes in image and time series data.

The model training process is as follows:

- Divide the preprocessed data into a training set and a test set.
- Use the training set to train the CNN model.
- Evaluate the model performance using the test set.

3) Model Prediction

The trained model can be used to predict whether the new shot data will hit or not. The prediction process is as follows:

- Input the new shot data into the model.
- The model outputs the prediction, i.e., the probability of the shot hitting.

4) Apply to Training

The prediction results can be applied to the basketball training process, for example:

- Real-time feedback: Provide players with real-time feedback on shot prediction to help them adjust their shooting posture and movement.
- Training plan development: Based on the player's shooting prediction results, personalized training plans are developed to improve training efficiency.

5) System Advantage

- Objectivity: The system analyzes data to make predictions without being influenced by subjective factors.
- Scientific: The system utilizes CNN and other machine learning technologies to learn the key factors of shooting from data.
- Efficiency: The system can automatically analyze data and provide real-time feedback to help players quickly improve their shooting percentage.

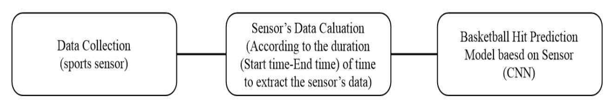

Fig. 1. Overview of the proposed model

3-2 Function Description

Using the sports sensor to collect the data during the basketball training. It includes the three sports data, angle sensor, magnetic sensor and gyroscope. The basketball shot time as start time, the basketball hit time as end time. Then based on the start time and the end time. The sensor data from the start time to the end time is collected as a data in the model training. Wherein, the data includes angle sensor data, magnetic sensor data, and gyroscope data.

The angle vector, angular velocity vector, control input matrix, state transition matrix, measure matrix of start time, measure matrix of end time, initial state vector, initial covariance matrix and covariance matrix at each timestamp (from start time to end time) are computed using the proposed Kalman filter based method. The results of the nine matrices over each timestamp were then using CNN to train basketball hit prediction based on sensor model.

3-3 System Design

1) Sensor Data Collection

The sensors were calibrated, so the raw data output from the basketball player's hand-worn sensors was used directly in the collection section. In the following we will proceed to the detailed.

- Angle Sensor

Angle sensor is typically used to measure the angle of rotation of an object relative to some coordinate system. Its output is also provided in the form of three axes(x, y and z), representing the angle of rotation of the object around each of the three axes of the coordinate system.

x-axis usually represents the angle of rotation around the sensor's x-axis. This axis is usually aligned with the long axis of the object(e.g., the front-to-back orientation of a vehicle).

y-axis represents the angle of rotation around the y-axis of the sensor. This axis is usually aligned with the horizontal axis of an object(e.g., the left/right direction of a vehicle).

z-axis represents the angle of rotation around the sensor's z-axis. This axis is usually aligned with the vertical axis of an object(e.g., the up and down directions of a vehicle).

- Gyroscope

Gyroscope is typically used to measure the rotational velocity of an object, and their output is also provided in the form of three axes(x, y, and z) that represent the rotational velocity of the object around each of the three coordinate axes.

x-axis represents the angular velocity of an object rotating around the sensor's x-axis. Positive values indicate clockwise rotation and negative values indicate counterclockwise rotation.

y-axis represents the angular velocity of an object rotating around the y-axis of the sensor. Positive values indicate clockwise rotation, negative values indicate counterclockwise rotation.

z-axis represents the angular velocity of an object rotating around the z-axis of the sensor. Positive values indicate clockwise rotation, negative values indicate counterclockwise rotation.

- Magnetic Sensor

Magnetic sensor is typically used to detect the strength and direction of the surrounding magnetic field. Their output typically consists of magnetic field strength values in three axes(x, y and z), representing the component of the magnetic field strength in each axis at the location of the object.

x-axis represents the strength of the magnetic field in the x-axis direction of the magnetic sensor. Positive values indicate that the magnetic field is oriented in the positive x-axis direction, while negative values indicate that the magnetic field is oriented in the negative x-axis direction.

y-axis represents the magnetic field strength in the y-axis direction of the magnetic sensor.

Positive values indicate that the magnetic field is oriented in the positive direction of the y-axis, while negative values indicate that the magnetic field is oriented in the negative direction of the y-axis.

z-axis represents the magnetic strength in the z-axis direction of the magnetic sensor. Positive values indicate that the magnetic field is oriented in the positive direction of the z-axis, while negative values indicate that the magnetic field is oriented in the negative direction of the z-axis.

2) Sensor Data Calculation

This is because our data timestamps are highly aligned with the visually labeled portion of the data at the time of data collection, and because the sensor manufacturer has built-in denoising algorithms so that the output is very smooth data that can be used directly.

We propose to use a Karman filter-based method to calculate the angle vector, angular velocity vector, control input matrix, state transition matrix, measure matrix of start time, measure matrix of end time, initial state vector, initial covariance matrix and covariance matrix.

- Angle Vector

Angle vector is output value of the angle sensor. Angle vector is used to describe the rotational state of an object relative to some reference coordinate system. Typically, the angle of rotation around three axes (Yaw, Pitch, Roll) can be chosen to represent the angle.

The angular vector θ is represented as follows :

$$\theta = \begin{bmatrix} \theta_{Yaw} \\ \theta_{Pitch} \\ \theta_{Roll} \end{bmatrix} \tag{4}$$

Where, θ_{Yaw} denotes the angle of rotation around the z-axis, θ_{Pitch} denotes the angle of rotation around the y-axis, θ_{Roll} denotes the angle of rotation around the x-axis.

- Angular Velocity

Angular velocity vector is output value of the gyroscope. Angular velocity vector is used to describe the speed of rotation of an object around three axes. In our system, it comes directly from the output of the gyroscope. The angular velocity vector is expressed as follows :

$$\omega = \begin{bmatrix} \omega_{Yaw} \\ \omega_{Pitch} \\ \omega_{Roll} \end{bmatrix} \tag{5}$$

Where, ω_{Yaw} denotes the rotation speed around the z-axis, ω_{Pitch} denotes the rotation speed around the y-axis, ω_{Roll} denotes the rotation speed around x-axis.

- Control Input Matrix

The control input matrix B_k is typically used to incorporate external control inputs(e.g., gyroscope measurements) into the calculation. In this system, we assume that the gyroscope output is used directly to update the angular velocity.

$$B_k = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \tag{6}$$

- State Transition Matrix

In the prediction step of the Kalman filter, we use the state transfer matrix F_k and the control input matrix B_k to update this state vector, the formular is as follow:

$$x_k = F_k x_{k-1} + B_k U_k + \omega_k \tag{7}$$

Where, k is the end time, $k-1$ is the start time, x_k is the state vector at end time k, including Yaw, Pitch and Roll and their angular velocities. x_{k-1} is the state vector at start time $k-1$, including Yaw, Pitch and Roll and their angular velocities. F_k is the state transfer matrix that describes how the state vector evolves from start time $k-1$ to end time k. U_k is the control input vector, which can include external control inputs, such as measurements from gyroscope. ω_k is the process noise, which represents the unmodeled uncertainty or random perturbations in the system model.

The state vector is a combination of the angle vector and the angular velocity vector. Therefore, the whole state vector x is expressed as:

$$x = \begin{bmatrix} \theta_{Yaw} \\ \theta_{Pitch} \\ \theta_{Roll} \\ \omega_{Yaw} \\ \omega_{Pitch} \\ \omega_{Roll} \end{bmatrix} \tag{8}$$

Where, θ_{Yaw} denotes the angle of rotation around the z-axis, θ_{Pitch} denotes the angle of rotation around the y-axis, θ_{Roll} denotes the angle of rotation around the x-axis, ω_{Yaw} denotes the rotation speed around the z-axis, ω_{Pitch} denotes the rotation speed around the y-axis, ω_{Roll} denotes the rotation speed around x-axis.

According to the data we obtained from the angle sensor and gyroscope, each segment of data includes a state vector for the start time $k-1$, the formula is as follow:

$$x_{k-1} = \begin{bmatrix} \theta_{Yaw_{k-1}} \\ \theta_{Pitch_{k-1}} \\ \theta_{Roll_{k-1}} \\ \omega_{Yaw_{k-1}} \\ \omega_{Pitch_{k-1}} \\ \omega_{Roll_{k-1}} \end{bmatrix} \tag{9}$$

Where, $\theta_{Yaw_{k-1}}$ denotes the angle of rotation around the z-axis at the start time $k-1$, $\theta_{Pitch_{k-1}}$ denotes the angle of rotation around the y-axis at the start time $k-1$, $\theta_{Roll_{k-1}}$ denotes the angle of rotation around the x

-axis at the start time $k-1$, $\omega_{Yaw_{k-1}}$ denotes the rotation speed around the z-axis at the start time $k-1$, $\omega_{Pitch_{k-1}}$ denotes the rotation speed around the y-axis at the start time $k-1$, $\omega_{Roll_{k-1}}$ denotes the rotation speed around the x-axis at the start time $k-1$.

State vector for the end time k, the formular is as follow formular:

$$x_k = \begin{bmatrix} \theta_{Yaw_k} \\ \theta_{Pitch_k} \\ \theta_{Roll_k} \\ \omega_{Yaw_k} \\ \omega_{Pitch_k} \\ \omega_{Roll_k} \end{bmatrix} \tag{10}$$

Where, θ_{Yaw_k} denotes the angle of rotation around the z-axis at the start time k, θ_{Pitch_k} denotes the angle of rotation around the y-axis at the start time k, θ_{Roll_k} denotes the angle of rotation around the x-axis at the start time k, ω_{Yaw_k} denotes the rotation speed around the z-axis at the start time k, ω_{Pitch_k} denotes the rotation speed around the y-axis at the start time k, ω_{Roll_k} denotes the rotation speed around the x-axis at the start time k.

The magnetic orientation vector is obtained from the magnetic sensor data and is represented as follows:

$$B = \begin{bmatrix} B_x \\ B_y \\ B_z \end{bmatrix} \tag{11}$$

Where, B_x represents the magnetic field strength on the x-axis measured by the magnetic sensor, B_y represents the magnetic field strength on the y-axis measured by the magnetic sensor, B_z represents the magnetic field strength on the z-axis measured by the magnetic sensor.

The state transition matrix F_k is calculated according to the following formular:

$$F_k = \frac{x_k - B_k U_k - \omega_k}{x_{k-1}} \tag{12}$$

- Measurement Matrix of Start Time

Measurement vector computation is another key step in Kalman filtering that describes how state vector is mapped to measurement space. Measurement vectors typically involve mapping angles in the state vector to actual measurements, such as those of a magnetic sensor.

The formula for the measurement vector of end time k is as follows:

$$z_{k-1} = H_{k-1} x_{k-1} + v_{k-1} \tag{13}$$

Where, z_{k-1} is the measurement vector for end time $k-1$, including the measurements from the magnetic sensor. H_{k-1} is the measurement matrix of end time $k-1$, which describes how the state vector is mapped to the measurement space. v_{k-1} is the measurement noise, representing the uncertainty or random error in the measurement.

The measurement matrix of start time $k-1(H_{k-1})$ is calculated according to the following formula:

$$H_{k-1} = \frac{z_{k-1} - v_{k-1}}{x_{k-1}} \tag{14}$$

- Measurement Matrix of End Time

The formula for the measurement vector of end time k is as follows:

$$z_k = H_k x_k + v_k \tag{15}$$

Where, z_k is the measurement vector for end time k, including the measurements from the magnetic sensor. H_k is the measurement matrix of end time, which describes how the state vector is mapped to the measurement space. v_k is the measurement noise, representing the uncertainty or random error in the measurement.

The measurement matrix of end time $k(H_k)$ is calculated according to the following formula:

$$H_k = \frac{z_k - v_k}{x_k} \tag{16}$$

- Initial State Vector

The initial state usually consists of the initial angle and angular velocity, it means the state at the start time $k-1$, and the initial state vector x_0 formula is as follows:

$$x_0 = x_{k-1} = \begin{bmatrix} \theta_{Yaw_{k-1}} \\ \theta_{Pitch_{k-1}} \\ \theta_{Roll_{k-1}} \\ \omega_{Yaw_{k-1}} \\ \omega_{Pitch_{k-1}} \\ \omega_{Roll_{k-1}} \end{bmatrix} \tag{17}$$

Where, $\theta_{Yaw_{k-1}}$ denotes the angle of rotation around the z-axis at the start time $k-1$, $\theta_{Pitch_{k-1}}$ denotes the angle of rotation around the y-axis at the start time $k-1$, $\theta_{Roll_{k-1}}$ denotes the angle of rotation around the x-axis at the start time $k-1$, $\omega_{Yaw_{k-1}}$ denotes the rotation speed around the z-axis at the start time $k-1$, $\omega_{Pitch_{k-1}}$ denotes the rotation speed around the y-axis at the start time $k-1$, $\omega_{Roll_{k-1}}$ denotes the rotation speed around the x-axis at the start time $k-1$.

- Initial Covariance Matrix

The initial covariance matrix describes the uncertainty of the initial state (start time $k-1$). Elements on the diagonal represent the variance of the corresponding state variable, and elements on the off-diagonal represent the covariance between the two state variables. The covariance matrix is usually initialized to a larger value to indicate higher uncertainty in the initial estimate.

The formula of the initial covariance matrix P_0 is as follow:

$$P_0 = P_{k-1} = \begin{bmatrix} \sigma^2\theta_{Yaw} & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma^2\theta_{Pitch} & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma^2\theta_{Roll} & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma^2\omega_{Yaw} & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma^2\omega_{Pitch} & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma^2\omega_{Roll} \end{bmatrix} \tag{18}$$

- Covariance Matrix

The ending time k covariance formula P_k is as follows:

$$P_k = F_k P_0 F_k^T + Q_k \tag{19}$$

Where, P_k is the covariance matrix of end time k, F_k is the state transition matrix representing the dynamics of the system from start time $k-1$ to end time k, P_0 is the initial covariance matrix, Q_k is the process noise covariance matrix, representing the uncertainty or variance in the system's dynamics.

3) Basketball Hit Prediction based on Sensor Model

The process of the basketball hit prediction based on sensor model as follow.

- Data Preparation

Organize the angle vector, angular velocity vector, control input matrix, state transition matrix, measure matrix of start time, measure matrix of end time, the initial state vector, initial covariance matrix and covariance matrix into tensor form and make sure that they have the same size or shape.

For each of the 9 data (vectors and matrices) for each timestamp (start time to end time), add the corresponding label indicating whether the basketball shot was hit or not. In this paper, 0 means basketball hit miss, 1 means basketball hit make.

- Build CNN Model

CNN model includes convolutional layer, pooling layer, flatten layer and fully connected layer. Feature extraction is performed on 9 data (matrices and vectors) within a timestamp by means of a convolutional layer. From the convolutional layer can get the feature map. Maximum pooling operation using pooling layer reduces the size of the feature map and preserves important information.

The Flatten layer is used to flatten multidimensional data into one dimension for passing to the fully connected layer for classification or regression. A fully connected layer is added to the top of the CNN to map the extracted features to the label space. For classification problems, the last layer can be used with a softmax activation function to make probabilistic predictions for each class.

- Training Model

The prepared sensor data is divided into training set and testing set and the CNN model is trained using the training set by adjusting the model parameters to minimize the loss function.

- Basketball Hit Prediction

Use the trained model to make predictions that the basketball hit is make or miss.

IV. Evaluation and Result

4-1 Experiments

1) Dataset Collection

In this paper, for human skeleton detection model, we uses the dataset from website of the CMU (Carnegie Mellon University) Panoptic Dataset. For other models, we collected the dataset by using the camera and labeled by labelme tool.

The details of the dataset collection are as follows, for basketball shot prediction we have chosen 2000 training sets and 2000 test sets and all these 4000 data are labeled and from completely different people. Therefore, the robustness of the program is enhanced and the fitting rate is reduced.

2) Dataset Labeling

For training purposes, we again labeled the data twice, keeping only the core motion data as much as possible, which led to a significant reduction in arithmetic, in the program, where we labeled the key main clauses with hits as makes and misses as misses in order to minimize the effective sampling time.

Similarly, after labeling the visual aspects, we accurately intercepted the corresponding sensor changes per unit of time and labeled them in the same format.

3) Dataset Training

Due to the huge amount of data, we had to purchase expensive experimental equipment, even using up to two EPYC9004 processors and four NVIDIA A100 GPUs, as well as the fact that our experimental environment needed to be switched between different operating systems, since the sensors could only be driven in Windows, we started with a Windows server 2022 acquired the data and when labeling was done continued to Ubuntu for training, the whole process was done in such a huge experimental environment that because of this we were unable to use quantitative (dimensionless) reduction for data processing to reduce the data loss rate to an absolute low.

For our own model, we accurately intercepted the changes in the sensor per unit of visual time, so it greatly reduced the workload in cases where we had accurate data.

4-2 Performance Evaluation

We use the accuracy, confusion matrix, precision, recall, F1-Score, and support as the performance metrics for model. In this section, we describe the results for basketball hit prediction model.

The confusion matrix of basketball hit prediction model is shown in Fig. 2. The performance of accuracy, precision, recall, F1-Score, support is shown in Table 1 and the result image of basketball hit prediction model is shown in Fig. 3.

Our processing flow is such that when the camera captures the player hitting the basket, the motion data per unit of time of the sensor worn by the player is immediately saved, taking into account the delay of the camera, we also carry out a time correction process, so that the error is no more than ±100ms.

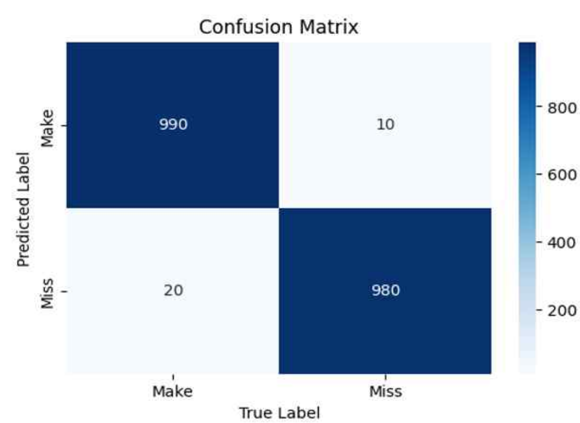

Fig. 2. Confusion matrix of basketball hit prediction model

Table 1. Performance of accuracy, precision, recall, F1-Score, support

Class	Accuracy	Precision	Recall	F1-Score	Support
0	0.98	0.99	0.98	0.98	1,000
1	0.98	0.98	0.99	0.99	1,000
Total	0.950	0.99	0.98	0.98	2,000

Fig. 3. Result image of basketball hit prediction model

4-3 Analysis of the Prosed Model

In Table 2, we compare the pure vision and the combination of motion sensors and vision, the modern research direction is mainly the non-invasive vision approach and the invasive wearable sensor approach, if the research direction is pure vision, such as e.g., refer to Liu et al.[23] and Redmon et al.[24] because the GPU needs to be handle both person identification and basketball trajectory and considering the environment, a lot of noise reduction algorithms are needed to make the source data accurate, then the complexity is too high in terms of computational power resulting in a slow program, and because of this the cost of real-time monitoring is too high, we can achieve this by annotating the changes of the sensors per unit of time and combining it with computer vision by setting up Bluetooth tags for the different players as well as transmitting the accurate data in real time back to the computer. in real times. This allows for faster processing and improved accuracy for the same amount of computing power.

In Table 3, we compare the efficiency of similar studies when the control data source is unchanged, such as CNN Multi-Position[25] which uses a multi-modal CNN, which makes the accuracy slightly inferior to ours because the other party does not have precise control of the timing; and Sensor-based human activity[26], which uses a temporal-based motion Sensor-based human activity[26], which uses a time -series based motion detection method.

If we use the time-series method, according to the articles we refer to in the past, time-series networks are generally used in weather prediction and other projects, which are not the same as our research method, so we will not list them here. In short, if the data set is bigger, the accuracy of his algorithm can be improved, so we are still beyond the other party here.

Table 2. Comparison of single vision and sensors

Model	Scheme	Method	Accuracy
Basketball Hit Prediction based on Sensor	Proposed Scheme	CNN + Sensor	98.5%
	Liu et al. Scheme[23]	SSD	85%
	Redmon et al. Scheme[24]	YOLO	90%

Table 3. Comparison of different algorithms for similar products

Model	Scheme	Method	Accuracy
Basketball Hit Prediction based on Sensor	Proposed Scheme	CNN + Sensor	98.5%
	CNN Multi-Position[25]	CNN	91.5%
	Sensor-based human activity[26]	LSTM	81.5%

V. Conclusion

Our research has made significant contributions to the field of basketball hit prediction through our research. Our study has demonstrated the effectiveness of using CNN and sensor data to predict the outcome of basketball shots. We have shown that our proposed system achieves notable accuracy in predicting whether a shot will hit the target, leveraging both spatial and temporal information extracted from sensor data.

Our comparative analysis of different models, including CNN[25], RNN, LSTM[26] and Transformer, has provided valuable insights into their respective strengths and weaknesses in the context of basketball hit prediction. This analysis can guide future research efforts in selecting the most suitable model architecture for similar tasks. There are several directions for future research in this area. One potential avenue is to explore the integration of additional sensor modalities or data sources to further enhance prediction accuracy and robustness.

Additionally, investigating real-time prediction capabilities and the deployment of the proposed system in practical basketball training scenarios could yield valuable insights and practical applications.

Moreover, addressing the challenges associated with data collection, annotation, and model training for large-scale datasets remains an important area for future investigation. By addressing these challenges, we can potentially improve the scalability and generalization capabilities of the proposed system.

Our research lays a solid foundation for advancing the field of basketball hit prediction, and we anticipate that future studies will build upon our findings to develop more sophisticated and effective predictive models for sports analysis and training applications.

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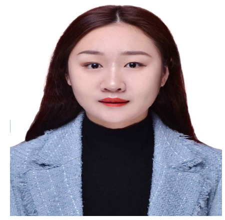

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