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Research Article

An Improved Neural Network Model for Early Detection of Joint Injuries in Tai Chi Sports

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Medical experts and academics are progressively becoming aware of knee injuries faced by tai chi practitioners in China. This occurs when the knee is bent with weight on the foot turned during Tai Chi. We propose an enhanced convolutional neural network (CNN) technique for early warning of joint injury risk during Tai Chi exercise in this research. This improved neural network approach can detect the risk of knee joint injury in practitioners early on to aid in early precaution and treatment. A multiscale feature extraction module is developed by performing several scales of convolutional layer extraction on the input data features and then combining the results to maximize the amount of feature information included in the extracted joint data. The results revealed that in experiments on a Taiwanese Tai Chi community dataset, the proposed method had an average diagnostic accuracy greater than 90 percent, significantly higher than the average diagnostic accuracy of the comparison methods on the dataset.

1. Introduction

Human longevity serves as an eternal source of inspiration for anyone who wants to learn more about the mysteries of life. The term "unity of body and spirit" alludes to the need for the body and the spirit to work together to achieve health and long-term longevity. Form and spirit were defined in the medical classic "Huangdi Neijing," which stated that "the form and the spirit are joined, and they shall terminate their years." "Shape" refers to the physical human body that can be seen and felt in reality, and "God" alludes to the spiritual consciousness that is unseen to the naked eye [1–3]. Human life is defined as the union of the human spirit and the human body. The soul and the body are in sync with one another, which helps to improve the body and the mind, while also sustaining health and healing ailments, and improving the overall quality of human existence. These represent the most important aspects of health [4–8]. Physical health has long had importance in the West, but in recent years, people's health has begun to receive more attention in the East [9–12]. The "Emotion and Health Guide," which has received high praise from the American Medical Association Psychological Association, holds that a person's strong personality is more important than a person's strong body when it comes to health, and recommends that people maintain a positive attitude and harmonious interpersonal relationships. This substance is beneficial to the proper development of both the body and the spirit. Taijiquan and Health Qigong, which are considered intangible cultural heritage of the Chinese country, are slow-moving exercises that nourish the mind and quiet the qi and harmonise the body, breathing, and thinking. As a result, the practitioner will be able to achieve their goal of strengthening and developing the body while also healing ailments. A great deal of information is available regarding the health and fitness benefits of Taijiquan and Health Qigong and their promotion. Still, there is little information available about the physical state of the practitioners. The challenge in promoting Taijiquan and Health Qigong is not the unacceptability of certain age groups but rather the question of whether or not there will be "side effects" after practicing [13–15].

The growth of Taijiquan has progressed to the point that it has been approved as a mandatory course in martial arts by major institutions [16–19]. According to research and surveys, the total number of fitness qigong stations in the nation reached 27,838, as by the end of 2015, with more than 1.2 million individuals visiting the stations and more than 3.52 million practitioners. When looking at Taijiquan and Fitness Qigong in their present forms, they meet the needs of people all over the globe, and they may be able to meet the health needs of people all over the world, as well as the requirements of the Chinese cultural inheritance if they are practiced properly [20, 21]. The twenty-first century is characterized by the ageing of human society, which specialists refer to as "the silver wave." The population of China is gradually growing older, and the round and slow movements of Taijiquan and fitness qigong and the peaceful and soothing music are particularly well suited for middle-aged and senior people to learn and practice them. It appears that they are not only appropriate for middle-aged and old persons but also for contemporary young people, based on the available data. Young people are increasingly under pressure in today's fast-paced and highly industrialized environment, and some are even suffering from mental problems as a result. Exercises such as taijiquan and fitness qigong can help strengthen the body, but they can also help relieve stress, which is beneficial for the development of psychological health in today's young people. The evolution of taijiquan and fitness qigong has, as a result, been adapted to the advancement of modern society [22, 23].

However, numerous specialists and researchers have lately discovered that the practice of Taijiquan can cause varying degrees of harm to the knee joint, depending on the individual. Because most of those who practice fitness qigong are also Taijiquan practitioners, we would expect the practice of fitness qigong to impact those who practice it negatively. However, this has not been proven. There are no mutually exclusive things, and the inverse is true. Early discovery of its negative circumstances, mastery of its laws, and steering its development in a positive direction are all important [24–26]. After engaging in martial arts routines, injuries to the hip, knee, and ankle joints are common. Injuries to the neck and shoulder joints are common after engaging in combat sports, and injuries to the knee joints are common after engaging in Taijiquan sports. Taijiquan sports are primarily responsible for knee joint injuries.

Although Tai Chi is a leisurely form of movement, poor practice can result in harm. It is very easy for Taijiquan exercise to cause knee joint damage, especially when done incorrectly by the elderly. When the elderly practice Taijiquan body undulation incorrectly, it increases the friction between the patella and femur joint surfaces, which causes osteoarthritis symptoms when they are unable to adapt. Boxing postures that are too low can increase the load on the knees, resulting in increased knee wear; excessive movement, increasing flexion and extension strength, twisting strength, and causing muscle and tendon strains, which can cause damage to the knee joint tissues; loose movement rhythm confusion, insufficient weight transfer, loss of natural support, which can result in sprains and strains; excessive movement, fatigue caused by knee joint injury Taijiquan practitioners may also suffer from a range of knee problems, including chondromalacia of the patella, meniscal damage, fat pad injury, and other conditions. The most common reasons for these accidents include uneven technical movements, poor lower limb strength, a low centre of gravity, and extreme exhaustion throughout the activity. Many injuries can be avoided during practice as long as instructors and students take them seriously. Preventing injuries is more important and effective than treating them after they occur.

There are many causes of taijiquan practitioners that lead to knee injuries. The most common causes of knee pain include poor posture, excessive physical activity, and unsuitable exercise selection. The knee joint is always in a semisquatting position of static support when practicing taijiquan, and when the action posture is incorrect, it can result in knee injury; when the exercise prior to the preparation activities is not sufficient or after the exercise is not properly organized and relaxed, the fatigue generated by the practice of the accumulation of injury; from the perspective of biomechanical analysis, due to the knee joint femur condyles inside and outside, it can result in knee injury, when the exercise before the preparation femur. The medial femoral muscle is weak or will become atrophied, which increases the rotational instability of the knee and has the potential to cause chondromalacia of the knee (bone spur formation). As a result, the medial femoral muscle strength is insufficient to maintain the stability of the knee joint, which is another essential factor in the development of knee injury. It is very easy to sustain a specific or several joint injuries of varying degrees during an exercise session of Taijiquan due to inappropriate movement or accidents, for example. Depending on the degree of exertion, the characteristics of knee joint injuries in Taijiquan practitioners can differ. With the increase in knee joint injuries due to Taijiquan, there is a need for a proper mechanism in order to realize the classification of Taiji sports joint injury data, which is then used to realize the classification of Taiji sports joint injury data.

This paper outlines the deep learning approaches which have been carried out in the detection of joint injuries and joint damage diagnosis in the literature view. Then, the solution to the research problem is explained in detail along with experimental test analysis and results of the research. In the end, the conclusion of the research work is presented with the future scope and limitations of the study.

2. Literature Review

On the basis of the obtained data, traditional joint injury diagnostic technology depends on experts and technicians to execute multi-step arduous human feature extraction on the data. Manual feature extraction, which does not match the needs of the big data age, is not an option. Researchers have used SVM, BP NN, and KNN methods [1–8] in machine learning for rolling bearing fault diagnosis; although these methods have a certain nonlinear fitting ability and have achieved a certain effect in the field of joint damage diagnosis, but the shallow network structure makes it difficult to extract deep feature information and reduce the joint damage diagnosis accuracy. The accuracy of joint damage diagnosis, on the other hand, is diminished because deep feature information is difficult to extract from a shallow network structure [8–14].

As a result of its powerful automatic feature extraction capabilities, deep learning has emerged as a new research hotspot in the development of machine learning in recent years. Hinton first proposed deep learning in 2006, and it has been applied to the field of joint injury diagnosis because of its powerful automatic feature extraction capabilities [15]. CNN in deep learning is a supervised deep learning technique that can accomplish end-to-end joint injury detection without preprocessing the original obtained fault data [16–21]. It is one of several deep learning algorithms that may be used to diagnose joint injuries. A defect detection approach based on an LSTM paired with CNN has been suggested by Zhou et al. [22]. However, even though the methods described above achieved good fault classification results in their respective damage diagnostic tasks and high accuracy of damage detection when compared with traditional diagnosis methods and machine learning methods, they suffer from issues such as complex network structure and the failure to use optimized network structure, which can easily cause the network to be difficult to train or even degrade.

Another study presents a method using convolutional neural networks for rheumatoid arthritis using two-dimensional images [23]. A study was done on the detection of weakened joints using one-dimensional convolutional neural network-based damage detection for finding damage in members [27]. Advanced machine learning methods using deep neural networks were used in a study to distinguish between knees with pain and without pain to be used in the detection of knee-related injuries [28]. A dense neural network approach which uses multiple layers for feature extraction was used for the diagnosis problem of knee osteoarthritis classification in elderly people [29]. Another research on convolutional neural networks for the task of initial knee MRI diagnosis was able to locate tears in knees without localization information [30]. Another method for detecting knee joints and quantifying knee osteoarthritis severity was carried out using convolutional neural networks. The process was based on localizing and quantifying the knee joints using a fully convolutional neural network [31].

However, despite the fact that the methods described above achieved good fault classification results in their respective damage diagnostic tasks and high accuracy of damage detection when compared with traditional diagnosis methods and machine learning methods, they suffer from issues such as complex network structure and the failure to use optimized network structure, which can easily cause the network to be difficult to train or even degrade. A multiscale feature extraction module for knee joint injuries due to Tai Chi sport is designed to extract feature information from fault data effectively; a channel attention mechanism is introduced to assist the network in obtaining more important feature information, and a convolutional module with jump connection line is designed in order to obtain more feature information of the front layer network, all of which are designed in order to address the above-mentioned shortcomings [32, 33].

3. Methodology

In this paper, a multiscale feature extraction module is developed by performing several scales of convolutional layer extraction on the input data features and then combining the results to maximize the amount of feature information included in the extracted joint data. The deep learning approach was used for feature extraction to develop an early warning model for joint injuries in Tai Chi sports due to convolutional neural networks' powerful feature extraction capabilities as demonstrated by past work on joint damage diagnosis.

3.1. Convolutional Neural Network Model.

During deep learning, a CNN is a feed-forward neural network with powerful feature automatic extraction capability. It extracts deep features from an input data set at each level, layer by layer, by constructing multiple convolutional kernels and performing space up and down sampling, with the goal of reducing the input data's dimensionality. On the left is an example of a typical CNN structure diagram. The neural network is made up primarily of three layers: the convolutional layer, the pooling layer (down sampling), and the loss function Softmax or SVM classifier.

Figure 1 depicts a convolution procedure in which a convolutional kernel is convolved with the preceding layer of the feature map, and the excitation function is non-linear. It is the convolutional layer that is responsible for the majority of the feature extraction from the input data. There are a number of convolution kernels, and each element of the convolution kernel includes a different type of information. Each member of the convolution kernel is comprised of a weight factor and a bias factor, respectively. As previously stated, the output feature map is created by performing a nonlinear transformation on the excitation function, which is derived as follows:

$$X_{i,j}^{l+1} = f\sum_{j=1}^{L}\sum_{i=1}^{m}\left(X_{i,j}^{l}, \varpi_{i,j}^{l}\right) + bj, \tag{1}$$

where the input data $X_{i,j}^{l}$ signifies the j^{th} eigenvalue of the i^{th} eigenvalue map in the l^{th} layer of the network; L denotes the convolution kernel size; $\varpi_{i,j}^{l}$ denotes the weight coefficients; b denotes the deviation value; and f (-) denotes the activation function.

The Softmax function is an extension of the Logistic classifier, which is represented by the following expression:

$$P\left(y_i = c_k \mid x_i\right) = e^{x_i^T c_k}\frac{1}{\sum_{k=1}^{K} e^{x_k^T c_k}}, \tag{2}$$

where $e^{x_i^T c_k}$ represents the correlation between category c_k and the whole x_i classification category, and $1/\sum_{k=1}^{K} e^{x_k^T c_k}$ represents the normalizing function.

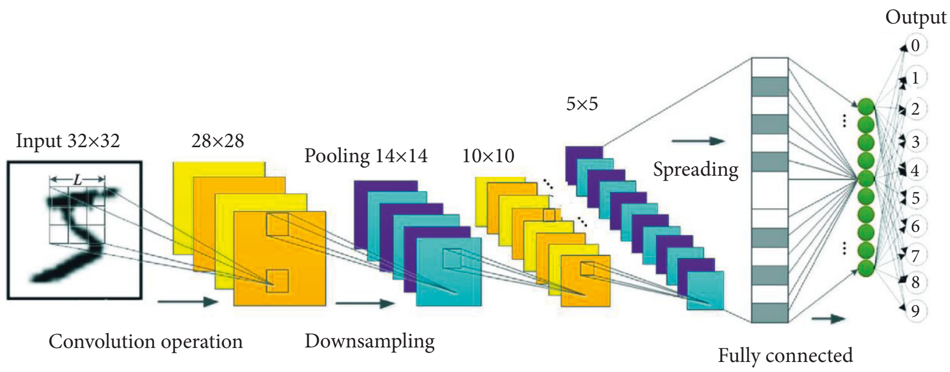

Figure 1: Structure of CNN.

The Inception module is the initial optimization module in the GoogletNet neural framework, and it is used to optimize the performance of the neural framework. This paper's main idea is to use convolutional kernels of different sizes to increase the network width by stacking, allowing it to extract rich feature information while simultaneously using 11 scale convolutional kernels to downscale the input feature map and reduce the parameter computation, allowing the network to be trained faster. The Inception module has been upgraded to include the Inception-v4 and Inception-ResNet modules, which have been developed through a number of cycles. The Inception-ResNet module makes the network layers deeper by adding the concept of residuals into the ResNet network.

4. Proposed Model

4.1. Tai Chi Joint Injury Risk Warning Method. This paper proposes an improved CNN method for Taiji sports joint injury diagnosis to be used in order to fully exploit the feature extraction capability of CNN networks and avoid the gradient disappearance and degradation problems. It also designs a multiscale feature extraction module and a jump-connected convolution module and introduces a channel attention mechanism in order to realize the classification of Taiji sports joint injury data. This approach can be used to realize the classification of Taiji sports joint injury data.

This approach presents the design of a multilayer multi-channel multiscale feature extraction module that is intended to optimize the amount of feature information recovered from the input data. Inception module was used to create this module because it has a greater feature extraction capacity when compared to the typical CNN network input data pooling layer. Its construction is depicted in Figure 2: (1) in layer 1, 1 1, 3 3, and 5 5 parallel convolutional layers are used to extract features at different scales from the input fault data, and the number of channels is set to 16, 8, and 8, respectively; (2) in layer 2, 5 5 and 3 3 convolutional layers are concatenated behind the 3 3 and 5 5 convolutional layers, both with a channel count of 16; (3) in layer 3, two 1 1 convolutional layers with channel counts of to optimize the fault data and improve network diagnosis, batch normalization and activation functions that are used behind each convolutional layer. Then, the Concat layer stacks the feature dimensions of different branches together and uses the channel attention mechanism to obtain the importance of different feature information, and enhances the useful features.

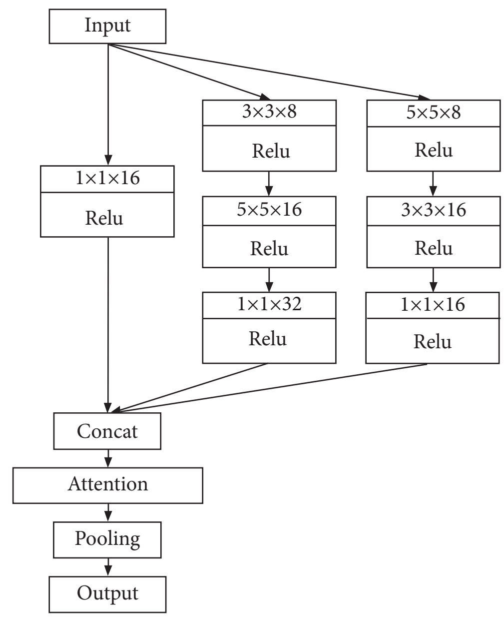

Figure 2: Structural design of a multiscale module for feature extraction.

Traditional convolutional neural networks have the convolutional layer module of the previous layer connected end-to-end with the convolutional layer module of the next layer, which means that the convolutional layer module of the previous layer cannot effectively utilize the correlation between the input vector of the layer and the next layer, thereby limiting the learning efficiency of the convolutional network for feature information. As a result, the convolutional module with a jump connection line proposed in this study has the structure seen in Figure 3. A d-fold line is inserted between the input vector of the first convolutional layer and the output vector of the second convolutional layer in Figure 3. The second convolutional layer learns not only the features following the first convolution operation but also learns the information from the previous input layer, as shown in Figure 3. It learns the transfer information of the input vector of the preceding layer, resulting in greater learning efficiency.

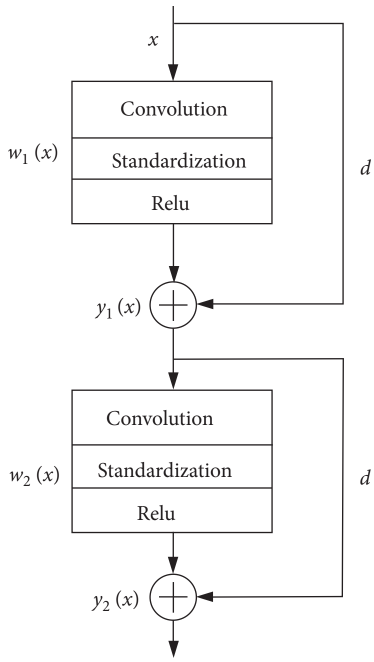

Figure 3: Structure of convolution module with skip operation.

It is assumed that the convolutional module with a jumper connection has the input value x. After the first convolutional layer, the output is $y_1(x)$, and after the second convolutional layer, the output is $y_2(x)$,

$$\begin{aligned} y_1(x) &= \varpi_1(x) + \mathrm{d}x, \\ y_2(x) &= \varpi_2(y_1) + \mathrm{d}x. \end{aligned} \tag{3}$$

From equation (3), we know that,

$$y_2(x) = \varpi_2(\varpi_1(x) + dx) + d\varpi_1(x) + d^2x. \tag{4}$$

Equation (3) contains the first convolutional module input x and $d\varpi_1(x)$, the next convolutional module receives more feature information, which is conducive to extracting tiny fault features from the data and improving the accuracy of fault diagnosis, the following convolutional module is called the second convolutional module. However, although the jump connection can allow each convolutional module to receive more feature information, this also results in the final output of the whole network model being quite big, as well as the computation of parameters being extremely time-consuming. In the case of rolling bearings, this is not favorable for rapid defect detection. As a result, following the Inception module, we just need to add two layers of convolutional modules with jump functions. To achieve the desired low weight of the network after the Inception module, we proposed adding two layers of convolutional modules with jump line connections after the Inception module.

The correction between the input layer and the implied layer is given by the following equation:

$$\begin{aligned} \Delta w_{ik} &= -\eta \frac{\partial E}{\partial \,\mathrm{net}\, 1_k} y_i, \\ w_{ik} &= w_{ik} + \Delta w_{ik}. \end{aligned} \tag{5}$$

As seen in Figure 4, the revised CNN model developed in this study has a more complex structure. When the reconstructed two-dimensional data are fed into the multiscale feature extraction module, it is transformed into an improved effective fault data information through the use of different scales of convolution kernels and channel attention mechanisms. The entire multiscale feature extraction module is equivalent to a convolution block. The Inception module constitutes the second convolutional block, and it is composed of convolutional layers of sizes 1, 3, and 5, as well as maximum pooling layers of size 3. The feature information in the joint damage data is further retrieved by stitching together these convolutional layers and maximum pooling layers. Lastly, a convolutional module with a jump connection line is introduced, which is primarily intended to expand the number of network channels and learn more feature information. Once this is accomplished through the fully connected layer, the one-dimensional data obtained from the first three convolutional blocks are turned into two-dimensional data, and the fault diagnostic findings are calculated by the cross-entropy loss function.

5. Experiments and Results

Tai Chi association members participated in the experiment which was designed to evaluate the effectiveness and accuracy of an improved CNN model proposed in this paper for joint injury diagnosis. The experiment collected image datasets related to joint injuries from members of the association, which were then analyzed.

The initial step in this study was to rebuild the input data format. Specifically, this research reconstructs the image data into a two-dimensional input feature map of the kind described in [30], which can then be used to adapt the enhanced CNN network model input data format for effective convolution and downsampling operations.

In addition, the input data are normalized in preparation for the procedure. To improve the speed of network model training, to make the data easier to compute, and to produce more generic findings, the input data are normalized and the mathematical expression is transformed into a symbolic representation.

$$X = \frac{X - X_{\min}}{X_{\max} - X_{\min}}. \tag{6}$$

The test samples under different data sets were selected as variable noise test samples, and Gaussian white noise (SNR) with varied signal-to-noise ratios was added to the test samples to create variable noise test samples, which were then used to perform variable noise studies. When evaluating the normalized prediction results and the associated sample labels, cross-validation of the normalized prediction results and the accompanying sample labels is done. In this case, the cross-entropy loss function is used to compute the MSE loss function, and the MSE loss function is used to calculate the cross-entropy loss function. If the desired output is a random variable and you want to classify anything, the cross-entropy loss function is preferable to the mean square error loss function when you compare both. As

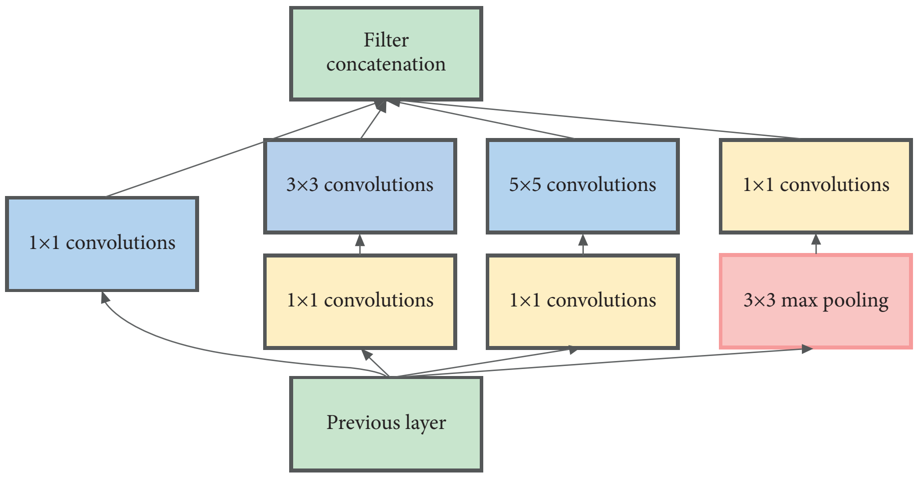

Figure 4: Structure of improved CNN.

an example, the following mathematical formula is considered:

$$J = -\sum_{i=1}^{K} I\left(\overline{y}_i = k\right)\log\frac{e^{x_k^T c_k}}{\sum_{k=1}^{K} e^{x_k^T c_k}}, \tag{7}$$

where i is the i^{th} sample, k means belonging to the kth category, and y_i is the ith real label.

We used mean square error (MSE) and accuracy (ACC) to judge the physical fitness prediction performance model.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(o_{\text{true}} - o_{\text{predict}}\right). \tag{8}$$

The tests were carried out on a computer that was set up with Windows 10, an AMD Raider 7–5800 H processor, and 64 GB of RAM. Testing was also done on the PyCharm platform and the Python programming language and it was carried out using the TensorFlow deep learning framework.

Increased network model depth results in greater effectiveness in describing its properties; yet, as the number of layers in a network model increases, both the gradient explosion and the degradation problem become more visible. It is used to train the network in the experimental process, and the dynamic learning rate is used to do so; the learning step is set to 0.001, and the decay rate is 0.9. Due to the fact that the model is based on the convolutional neural network model, the parameter design is equivalent to that of the convolutional neural net.

Following the convolution layer's parameters (3, 3, 1), (5, 5, 1), and (11, 1), the multiscale sampling module includes three parallel channels for feature extraction from the input 2D feature map, according to the parameters (3, 3, 1), (5, 5, 1), and (11) in the convolution layer. For feature extraction, a 33 convolution kernel with step size 1 is used; for feature extraction, a 55 convolution kernel with step size 1 is connected in series; and for feature extraction, an 11 convolution kernel with a step size of 1 is used. Convolutional layers (1, 1, 1) and (3, 3, 2) in the Inception module are constructed using the same architecture as in the previous layers, but the step size of each convolutional kernel is increased by two steps for each

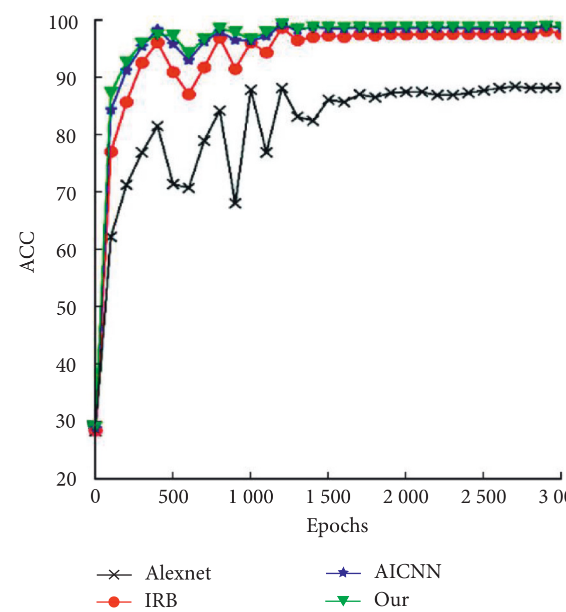

Figure 5: Comparison of our method with AlexNet, IRB, and AICNN.

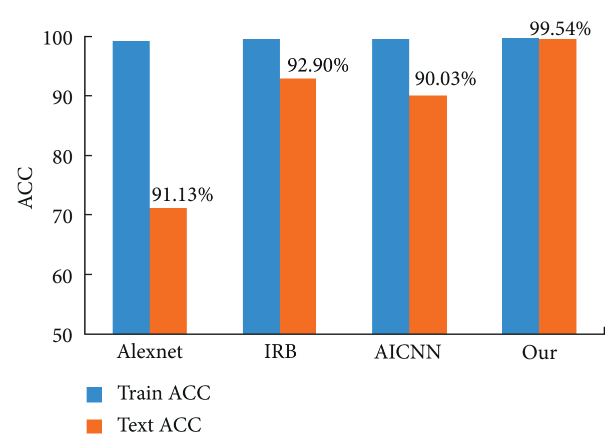

Figure 6: Final ACC of our method, AlexNet, IRB, and AICNN.

layer. A comparison of our approach with AlexNet, IRB, and AICNN is shown in Figure 5.

As shown in Figures 5 and 6, the suggested technique in this study has considerable benefits over other approaches when it comes to joint injury diagnostic accuracy, with a diagnosis accuracy of 99.54 percent when compared to other methods. In particular, a jump connection module and a multiscale feature extraction module are included in the approach described in this work, which allows for complete extraction of information from fault data, resulting in an increase in fault diagnosis accuracy of up to 50% over previous methods.

6. Conclusions and Future Works

Taijiquan has been proposed as a treatment for knee osteoarthritis. With the growth of Taijiquan's popularity in recent years in China and all over the world, there has been an increase in reports about knee joint injuries in elderly practitioners. In this study, we proposed an improved CNN technique for early warning diagnosis of joint injury risk in Taiji sports, which is based on the Inception network structure and adds an attention mechanism. A multiscale feature extraction module has been designed to extract features from the input data through multichannel convolutional layers of different scales in order to ensure maximum extraction of effective information from joint injury data was designed in this research. The fusion convolutional layer in the multiscale feature extraction module, a channel attention mechanism module introduced in order to achieve adaptive enhancement of effective information and suppression of interferential information was proposed in the CNN approach. It was seen that the channel attention mechanism module that was designed to achieve adaptive enhancement of effective information and suppression of interferential information was effective in developing the early warning model for knee joint injuries. It can be seen through the experimental validation that, when compared to a large number of deep network models, the technique given in this research has a higher accuracy rate than the alternatives. Future work in this area can be done to study the effectiveness of the early warning model for knee joint injuries for larger datasets. New models for the analysis and classification of knee joint injuries faced by Taiji practitioners can be developed to aid medical experts in the early treatment of damaged joints.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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