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Retraction

Retracted: Higher Education Course Evaluation Based on Deep Learning Model

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] X. Zheng, "Higher Education Course Evaluation Based on Deep Learning Model," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 8929437, 9 pages, 2022.

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Research Article

Higher Education Course Evaluation Based on Deep Learning Model

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Higher education has completed a revolutionary transition stage from traditional elite education to mass quality education, and the improvement of higher education quality has increasingly become the focus of social attention. Courses are the most basic unit of university teaching, and the quality of courses directly affects the quality of personnel training. The expansion of higher education has resulted in insufficient teaching resources and a decline in the quality of courses. Improving quality is the eternal theme of higher education reform. How to formulate scientific curriculum quality standards and objectively evaluate curriculum quality is the most concerned issue of the society. Therefore, in-depth analysis of the factors that affect the quality of the curriculum and the establishment of the curriculum quality evaluation system and method has certain practical significance for improving the quality of the curriculum. This work combines the evaluation of higher education courses with deep learning models and proposes a network MSACNN for quality evaluation of higher education courses. This work proposes to use an attention-based multiscale network to explicitly learn the relationship between the qualities of various higher education courses. By using parallel networks with different convolution kernels, it combines different scale features at the same spatial location to better learn the relationship between the quality features of higher education courses. This work conducts sufficient experiments on the higher education curriculum quality dataset, and the experimental results demonstrate that the multiscale network based on the attention mechanism exhibits superior performance. MSACNN surpasses other machine learning methods in both precision and recall metrics.

1. Introduction

After the 1980s, the world's higher education has entered an era centered on improving quality. The 21st century is a century that pays more attention to quality, and the transition from quantity to quality marks the end of an era and the beginning of an era. Quality is a proposition of an era, and whoever despises quality will pay a heavy price for it. Therefore, the quality assurance movement has been highly valued by various countries and regions since its rise in the 1980s. More than 120 countries and regions in the world have established quality assurance mechanisms. Therefore, the problem of higher education quality is no longer the problem of a country or a university but will surely become one of the major issues in the world's educational circles. With the introduction of the cost sharing theory and the establishment of the higher education charging system, the higher education consumer market was formally established. Coupled with the arrival of the popularization of higher education, how to ensure the quality of higher education has become a topic of concern not only to the higher education sector itself but also to more and more stakeholders outside the higher education sector. Therefore, many scholars have discussed from different aspects that the quality of higher education depends on the quality of teaching, scientific research, social services, and the quality of infrastructure and academic environment. However, the research on curriculum quality has not been independent and has received due attention. As we all know, curriculum plays a central role in the entire education system, and education and teaching activities are also carried out on the basis of curriculum, which is the basic embodiment of educational goals and training goals [1–5].

From the perspective of the action mechanism of the curriculum, the effect of social development and scientific progress on higher education occurs through professionalism. However, in the course of this role, the curriculum performs an essential function. In other words, in the final analysis, universities respond to the development of science and technology and social, economic, political, and cultural progress and change through courses. As society pays more and more attention to universities, people's requirements for courses will give universities more and more influence. Those who are not satisfied with a diploma will be more critical of courses, and the increasingly close relationship between university and life will rely more on courses to strengthen. Therefore, the quality assurance system of higher education courses is an integral part of the quality assurance system of higher education, and improving the quality of higher education courses has become the natural and inevitable choice of colleges and universities [6–10].

Strengthening the curriculum construction, especially the quality curriculum construction, is an extremely important part of quality engineering, which is to release the signal to people that they want the quality of the curriculum. However, in the current quality assurance system of university courses, colleges and universities lack a perfect self-assurance system and mechanisms for self-discipline, self-supervision, self-motivation, and self-development, which lead to weak internal motivation for some colleges and universities to strengthen quality management. Especially when it comes to the research on the quality assurance system of university courses at the micro level, it is not comprehensive enough, which leads to various problems in the course and teaching process. On the other hand, in the 1990s, the expansion of college enrollment raised concerns about the declining quality of college students. It can be said that it is an important subject that restricts the quality of personnel training in higher education [11–15].

To sum up, the research on the model of higher education curriculum quality assurance system is not only a theoretical problem but also a practical problem. Because it not only includes how to develop high-quality courses to achieve the goal of talent training but also includes how to ensure the realization of high-quality courses and achieve sustainable improvement and development of courses. This requires theoretical guidance and reflection, and more importantly, summarizing successful experience and failure lessons in practice. Therefore, on the basis of summarizing the existing research results of domestic and foreign scholars, it is undoubtedly of great theoretical and practical significance to conduct further in-depth research on the mode of higher education curriculum quality assurance system.

The unique contributions of the paper include:

(i) Development of a deep learning model entitled as MSACNN to evaluate the quality of higher education courses

(ii) The development of an attention-based multiscale network to understand the relationship among the quality attributes of the higher education courses

(iii) Parallel networks with different convolutional kernels are used to combine various scale features at the same spatial location. This helps in achieving more clarity in understanding the relationship of the quality attributes of the higher education courses

The organization of the paper is as follows: Section 2 presents detailed review of related studies followed by the methodology in Section 3. Section 4 discusses the results and Section 5 presents the conclusion of the study.

2. Related Work

Literature [16] proposed that the evaluation of teaching quality includes eight dimensions: learning value, teaching enthusiasm, organizational clarity, group interaction, interpersonal harmony, knowledge breadth, test scores, and homework volume dimensions, which cover 32 evaluation indicators. Reference [17] proposed that the evaluation consists of multiple choice and written comments. Multiple choice includes a full evaluation of the course as well as evaluation of instructors and teaching assistants. Written comments include comments on the course structure, classroom organization, teaching content, teaching effectiveness, teachers' attitudes toward students, and examination methods. Literature [18] proposed that the evaluation form consists of 23 quantitative evaluation indicators, 3 background feature questions, and 4 narrative questions. The quantitative indicator consists of four parts: the presentation of the course, the discussion of the course, the assignments and evaluation of the course, and the overall four parts of the course, and students respond by choosing 6 different options. Literature [19] proposes that the course evaluation includes five parts: the overall effect of the course, homework burden, teacher teaching, evaluation of discussion class or experimental class, and evaluation of teaching assistants and research assistants. At the same time, it also requires students to write specific opinions on teachers' teaching quality, structure, clarity of expression, attitude towards students, reading materials assigned, homework, examinations, elective requirements, and directions for improvement. Literature [20] proposed that curriculum evaluation is an important part of educational evaluation. It is a process of making judgments on the actual or potential value of school curriculum, constantly improving the curriculum, and achieving value-added education. It includes the evaluation of the curriculum plan, the evaluation of the curriculum standards and teaching materials, and the evaluation of the effect of the curriculum implementation. Literature [21] proposes that curriculum evaluation is the process of judging the value or characteristics of relevant issues such as curriculum plans, activities, and results by certain methods and approaches. Literature [22] divides course evaluation into dynamic evaluation and static evaluation. From a dynamic point of view, curriculum evaluation is the evaluation of the entire implementation process of the curriculum, in order to test the pros and cons, and constantly update to improve the quality. From a static point of view, curriculum evaluation is the evaluation of curriculum plans, teachers' teaching, and students' academic performance. Literature [23] proposes that the evaluation of teachers' curriculum quality is a comprehensive evaluation activity with teachers and their teaching activities as the evaluation object and students, peers, and teaching administrators as the evaluation subjects. Literature [24] pointed out that the improvement of teaching quality in colleges and universities depends on teaching work in accordance with teaching laws. It also depends on the scientific syllabus and high-level, high-quality, distinctive teaching materials. Literature [25] pointed out that factors such as teachers, students, teaching management, teaching conditions, and textbooks are the specific reasons that lead to the decline of the teaching quality of basic courses. Among them, teachers are the first among several influencing factors, followed by students themselves, teaching management and so on.

Reference [26] treats all the factors that affect the quality of courses as a system. The level of teachers, teaching methods, and teaching evaluation are the soft factors in the system. Teaching materials, experimental equipment, teaching methods, etc. are the hard factors in the system. Literatures [27, 28] believe that the main factors affecting curriculum quality are curriculum concept, curriculum resources, and curriculum management. Literature [29] adopted the method of distributing questionnaires to students and factor analysis and concluded that the three indicators that students thought had the greatest impact on teaching quality were the quality of the syllabus, the integration of materials by teachers, and the effect of teachers on explaining concepts. Finally, these indicators are summarized into four aspects: teaching preparation, teaching organization, teaching effect, and homework and feedback. Literature [30] believes that the content of curriculum evaluation should include curriculum planning, teaching reform, teaching and educating people, teaching staff, teaching material construction, teaching status, and teaching effect evaluation. Literature divides the elements of curriculum evaluation into internal elements and external elements. Internal elements include course objectives and content, course teaching resources, teaching methods and techniques, and teaching effects. External factors mainly include teaching conditions and teaching environment, teachers' quality and level, and curriculum management system. Reference [31] believes that the design of indicators should start from the perspective of learners and increase the specific content of intuitive evaluation. It includes the students' gains after learning the course, the effect of teachers' teaching design and implementation, the use of teaching materials, and the relationship between teachers and students in the classroom. Reference [32] analyzes the teaching evaluation index system and actual evaluation effect of famous colleges and universities at home and abroad. It divides the evaluation indicators of course teaching in research universities into students' overall impression of teachers' classroom teaching, teachers' teaching, and students' overall evaluation of the course. Literature [33] believes that the content of college curriculum evaluation must cover all the teaching process, including teaching team, teaching content, teaching methods and means, teaching conditions, teaching effect and characteristics, and policy support. Reference [34] takes the national quality curriculum evaluation index system as a reference and constructs a curriculum quality evaluation index system including curriculum resources, teaching conditions, teaching organization, and teaching effect. Literature [35] believes that the curriculum evaluation system can be constructed from the aspects of teaching staff, curriculum objectives, teaching conditions, teaching content, teaching organization, and teaching effect and curriculum characteristics. Literature [36] believes that the evaluation indicators of inquiry-based teaching courses should be changed from routine to diversified. Therefore, when constructing the evaluation index system, it covers students' classroom performance indicators, students' work evaluation indicators, and teachers' classroom performance evaluation indicators. The study in [37] used a hybrid two-dimensional CNN model to predict the student's academic performance. The one-dimensional data was transformed into two-dimensional image data in order to test the performance of the model. The comparison of the model with state-of-the-art techniques justified the superiority of the model. The study in [38, 39] analyzed the influence coefficient of different learning behavior data based on learning concentration. The study designed and used a terminal data acquisition tool to gather information pertaining to device perception in the learning environment of the learners. It also collected the learners' touch screen operation-related data based on virtual simulation experiment, and then the neural network model was implemented to process the sensor data. This enabled the understanding of learners' behavior, learners' activity state, and also factors relevant to learners' concentration

3. Method

This work combines the evaluation of higher education courses with a deep learning model and proposes a deep learning model for the quality evaluation of higher education courses. This work proposes to use an attention-based multiscale network to explicitly learn the relationship between the qualities of various higher education courses. By using parallel networks with different convolution kernels, it combines different scale features at the same spatial location to better learn the relationship between the quality features of higher education courses.

3.1. Convolutional Neural Network. The artificial neural network before the advent of deep learning is to extract the features of the data and then map the features to the feature vector values. In contrast, deep learning uses an end-to-end design concept to map inputs to ideal features through autonomous network learning. That is to say, deep learning no longer involves the step of manual feature extraction, and feature extraction is done by the network itself. The reason why deep learning has grown in popularity in recent years is also because of its ability to represent complex sets of functions in a simple way. The deep learning model used in this work is CNN.

Convolutional layers are used to select features of the input data from different perspectives. The input of this layer is the output of the previous layer of network, and the output of the convolutional layer is the result of calculating the dot product between the feature map of the previous layer and the convolution kernel. Calculating the dot product operation of the network output of this layer can be described as sliding the convolution kernel over the entire feature map with a certain step size and repeating this operation continuously to ensure that the feature map of each channel has completed the dot product with the convolution kernel. This method of calculating the same parameters for different positions of the input feature map reflects one of the characteristics of convolutional neural networks—weight sharing. The parameters of the convolution kernel are often two-dimensional vectors. If multiple convolution kernels are connected in series, a three-dimensional matrix will be formed. The new one dimension belongs to the number of channels, where the number of channels is equal to the number of convolution kernels.

Both the pooling layer and the convolutional layer are the basic components for building a convolutional neural network. The output of this layer is obtained by downsampling the input data, and the pooling layer often used by researchers has average pooling. The unique properties of pooling layers can be described in the following aspects. The first is position invariance. In the deep model, the setting of this layer makes the network only focus on the feature itself and ignore the small changes in the feature position, which makes the change of the feature position without affecting the performance of the network. The second is feature dimensionality reduction. Since the input data of the pooling layer undergoes a series of calculations, the output data dimension is generally less than or equal to the input data dimension, which reduces the amount of network computation and parameters. The third is to prevent overfitting to ensure that the model has good stability.

The emergence of activation layers is mainly to solve the problem of weak expressive ability of the multilayer linear models. Commonly used nonlinear activation functions are Sigmoid and ReLU, but the most commonly used activation function is the ReLU function. Because the ReLU activation function adopts a piecewise linear expression, it can solve the problem of gradient disappearance caused by the Sigmoid function, and it can also speed up the calculation speed of the network. Secondly, the unilaterality of ReLU is more in line with the characteristics of biological neurons, which greatly improves the expressive ability of the deep network models. ReLU is essentially a piecewise function. When the feature is used, the gradient of the ReLU function is 1; otherwise, the gradient of the ReLU function is 0.

$$\mathrm{ReLU}(x) = \max(x, 0). \tag{1}$$

In a deep neural network, changing the underlying parameters of the network will cause the parameters of the entire network to change. This makes the model difficult to train and the model converges more slowly. Therefore, batch normalization layers (BN) were developed to weaken the correlation and coupling between layers in deep neural networks. Batch normalization in a deep neural network framework helps in resolving challenges pertinent to internal covariate shift. It enables flowing of the data between intermediate layers of the model using higher learning rate. Thus, the neural network functions with enhanced speed and stability by adding extra layers to the DNN. The batch normalization layer first pulls the distribution of the input features back to a standard normal distribution with zero mean and low variance. Normalizing the input of the hidden layer of the network solves the problem of vanishing gradients and speeds up the network convergence. The normalized data will reduce the expressive power to a certain extent and perform a learnable linear transformation on the input with zero mean and low variance.

$$\begin{aligned} \mu &= \frac{1}{B}\sum_{i=1}^{B} x_{i,} \\ \sigma^2 &= \frac{1}{B}\sum_{i=1}^{B} (x_i - \mu)^2, \\ x_i' &= \frac{x_i - \mu}{\sqrt{\sigma^2 + \varepsilon}}, \\ y_i &= \alpha x_i' + \beta. \end{aligned} \tag{2}$$

3.2. Spatial Channel Attention Module Analysis. For the evaluation data of different courses, the network can fully consider the importance of each course when designing and carry out different levels of learning on this basis. This chapter proposes to use the attention mechanism because its convolutional network can adaptively learn the weights between different courses, which are very important for course quality data with extremely wide data distribution. Spatial attention allows individuals to process visual information selectively by prioritization of an area in the visual field. A particular region of space within a visual field is selected for attention and the relevant information within this region is emphasized and processed. It basically includes selection of a stimulus based on its spatial location. The region held by the entity is selected, wherein further cognitive processing is conducted. Thus, the SCA in this context would help in analyzing attention level and concentration level of various higher education courses. Whether it is a one-dimensional convolutional neural network or a two-dimensional convolutional neural network, it often pays equal attention to the features of the hidden layer of the entire network, and the convolution kernel parameters are shared among the features. The spatial attention mechanism can adaptively learn the parameter matrix of the one-dimensional convolutional layer or the two-dimensional convolutional layer, focusing on the quality characteristics of higher education courses that require in-depth learning, thereby improving the

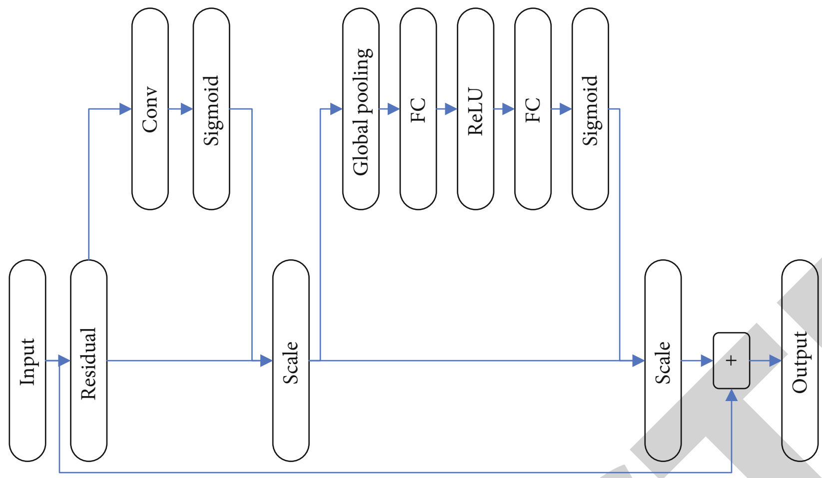

FIGURE 1: SCA pipeline.

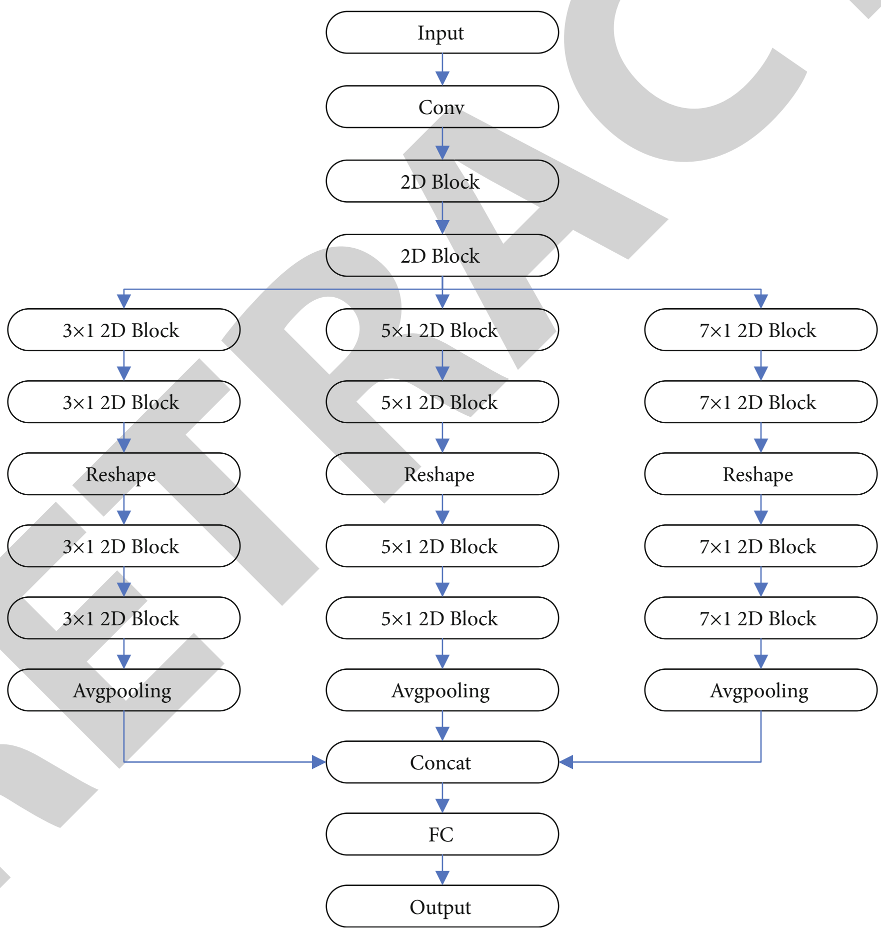

FIGURE 2: MSACNN pipeline.

performance of the model. Spatial attention is calculated as

$$\begin{aligned} z_s &= \text{Sigmoid}(WV), \\ V' &= a * V. \end{aligned} \tag{3}$$

The channel attention mechanism can complete the gradient update of the channel weight vector and obtain the importance of each feature channel in an end-to-end manner, so as to focus more on learning useful features and suppress features that are useless or of little use for the current task. Specifically, the weight of the channel attention mechanism can be continuously updated together with the gradient of the network, the effective feature weight will continue

TABLE 1: The course quality feature.

Index	Feature
x_1	Teacher professional background
x_2	Teacher's academic level
x_3	Teacher's teaching attitude
x_4	Teaching content
x_5	Teaching method
x_6	Course resource
x_7	Teaching achievement
x_8	Student satisfaction

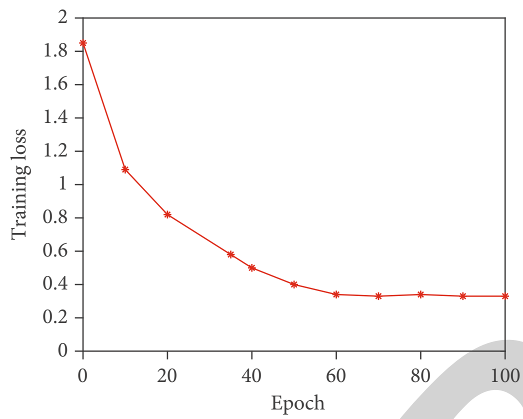

FIGURE 3: Training loss of MSACNN.

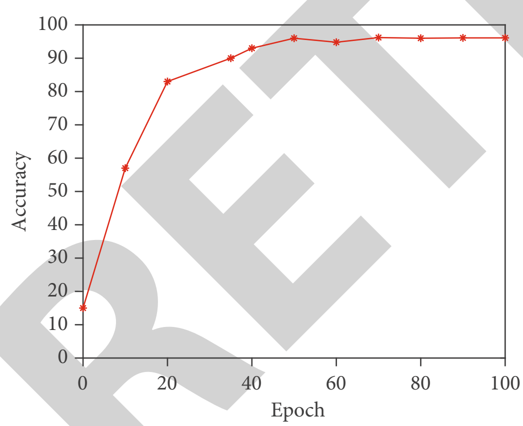

FIGURE 4: Training accuracy of MSACNN.

to increase, and the useless feature weight will continue to decrease, so that the network will converge. The channel attention mechanism can be embedded into the network as an independent module, thus affecting the training of the network.

Specifically, the channel attention mechanism can be divided into two processes: compression and excitation. The first step is to perform feature compression in the spatial dimension, compressing each one-dimensional or two-dimensional convolutional feature of the network into a corresponding real number. This weight is similar to the global receptive field with the feature, which can respond to the global distribution on the feature channel, and the dimension of the weight vector output matches the number of input feature channels.

$$z_c = \frac{1}{\mathrm{HW}} \sum_{i=1}^{H} \sum_{j=1}^{W} u_{ij}. \tag{4}$$

The second step is to generate weights for all feature channels through the parameters of the fully connected layer. The parameters are used to explicitly learn the correlation between feature channels and infer the weight vector. The role of these two fully connected layers is to fuse the information between the feature channels, and the weight vector after excitation is the parameter that is really used to characterize the importance of each channel in the feature. Because the learning is performed by first nonlinear layer and then fully connected layer, gradient can be backpropagated and end-to-end training can be achieved. During the excitation process, the statistics of the channel information are generated by the fully connected layer to generate the feature weight, which is equivalent to mapping the feature to the target channel and finally activates it.

$$a = \mathrm{Sigmoid}(W_2(\sigma(W_1(z)))). \tag{5}$$

In terms of the implementation order of spatial attention and channel attention, this paper chooses the space first and then the channel and defines the spatial channel attention module as SCA. The weights learned by SCA are weighted on a channel-by-channel basis to the previous features, enabling remapping of features in the channel dimension. The structure of SCA is illustrated in Figure 1.

3.3. MSACNN Architecture. The essence of convolution is to use the convolution kernel to perform linear operations on the local area of the feature map to extract sample features. Corresponding to the quality data of higher education courses, the larger the convolution kernel, the more signals the convolution can perceive. The multiscale network input layer data is 200×8 two-dimensional data. It then uses a 50×1 convolution kernel for convolution operations and a large number of 15×1 convolution kernels for feature extraction to achieve refined feature selection for course quality data. After that, in the same spatial position, the features of different scales are combined, and the convolution kernels of other sizes can ensure the diversity of features.

Concatenating the outputs of multiple convolution kernels of different sizes, on the one hand, increases the width of the features in the channel dimension, and on the other hand, the convolution layer convolution kernels with different sizes can increase the adaptability of the network to features of different scales. Features of different scales in the data are extracted by using three convolution kernels of different sizes: 3×1, 5×1, and 7×1. Finally, the extracted multiscale features are fused, which greatly improves the

Table 2: Comparison of the various methods.

Method	Accuracy	Recall
BP	87.2	85.3
VGG	90.1	88.3
ResNet	91.5	90.2
MSACNN	93.8	91.9

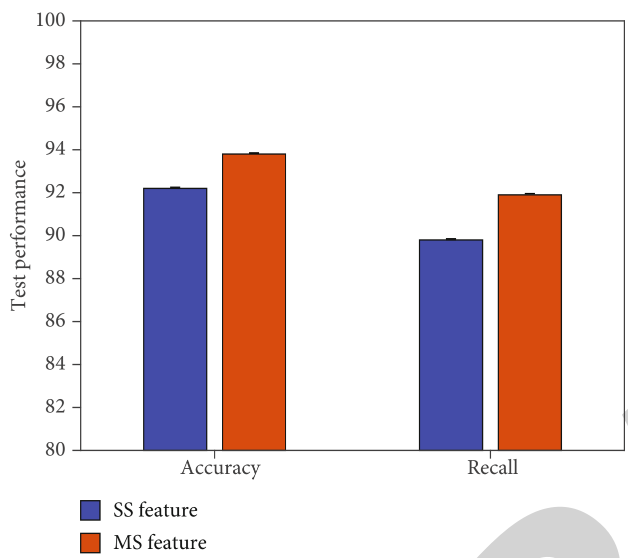

Figure 5: Multiscale feature analysis.

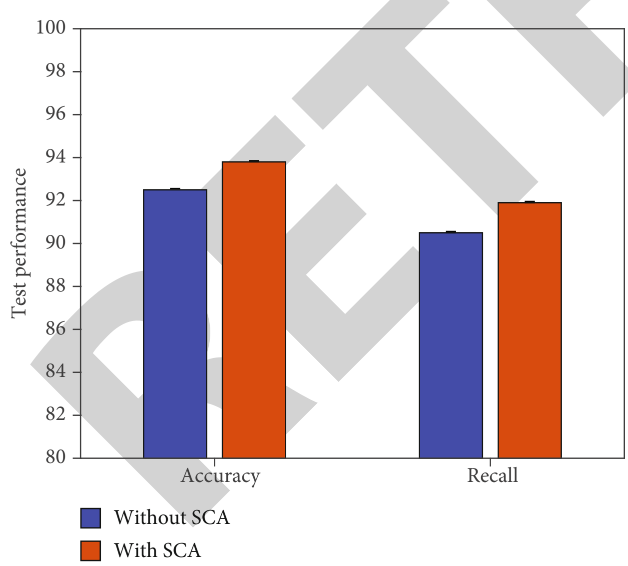

Figure 6: SCA attention analysis.

Table 3: Comparative analysis of the activation functions.

Activation function	Accuracy	Recall
Sigmoid	91.2	89.7
Tanh	91.6	90.2
ReLU	93.8	91.9

network performance. The structure of the MSACNN model is shown in Figure 2.

The input layer dimension is 200×8 higher education course quality data. The kernel size used by the convolutional layer is 50×1, the stride is set to 2, and the number of channels is 32. The first layer consists of three basic blocks, each of which is a classic residual network structure. The size of the two-dimensional convolution kernel used is 15×1, the number of channels is 32, and the stride is set to 2. The second layer belongs to three parallel networks, and each network branch contains six basic blocks. The size of the two-dimensional convolution kernel used by each network branch from left to right is 3×1, 5×1, and 7×1, and the number of channels is 32, which is repeated 4 times. The function of reshape is to convert the features between different leads extracted by last layer into one-dimensional data, which is convenient for subsequent use of one-dimensional convolution. The third layer transforms the input data from two-dimensional to one-dimensional, and each network branch contains twelve basic blocks. The one-dimensional convolution kernel sizes used by each network branch from left to right are 3×1, 5×1, and 7×1, and the number of channels is 256. The step size is set to two every three basic blocks, and the feature downsampling is performed four times. AvgPooling is used to reduce feature dimension. The concat layer concatenates the feature vectors after dimension reduction. The fully connected layer outputs the predicted probability of each quality evaluation level.

Structurally, the parallel multiscale network differs only in the size of the convolution kernel, which is similar to repeating the structure of the residual network three times. However, in the same spatial location, combining the features of different scales to learn the feature information of the quality of higher education courses, which is equivalent to the multiscale network sampling the data multiple times and making more effective use of the original data features.

4. Experiment

4.1. Dataset. This work collects course evaluation data from different universities to form a training data set and a test data set. Each data sample consists of the quality characteristics of ten different courses, and the quality characteristics of each course are the same. The specific information is shown in Table 1. The performance metrics used in this work are precision and recall.

4.2. MSACNN Training Analysis. This work first analyzes the training process of MSACNN, mainly analyzes the change of loss and accuracy rate during the training process. The results are demonstrated in Figures 3 and 4.

With the deepening of training, the training loss gradually decreases, and the training accuracy gradually increases. When the training reaches about 60 epochs, the two basically no longer change significantly, and MSACNN has converged at this time.

4.3. Comparison of Different Method. This work compares MSACNN with other machine learning methods to verify the feasibility of this method for higher education curriculum evaluation. The compared methods include BP, VGG, and ResNet, results are illustrated in Table 2.

As can be seen from the data in the table, MSACNN can obtain the highest precision and recall rates, which are 93.8% and 91.9%, respectively. Compared with other methods, different degrees of performance improvement can be obtained.

4.4. Multiscale Feature Analysis. This work uses convolution kernels of different scales to extract features of different scales. In order to verify the reliability of multiscale features, it is compared with single-scale features. The comparison results are demonstrated in Figure 5.

As can be seen from the data in the figure, compared with single-scale features, the performance improvement of 1.6% and 2.1% can be obtained after using the multifeature strategy, respectively. This shows that multiscale features can effectively improve feature discrimination.

4.5. SCA Attention Analysis. This work proposes the SCA attention module to realize the importance of discrimination of features. To verify the superiority of the SCA strategy, the performances without and with SCA were compared, and the results are illustrated in Figure 6.

As can be seen from the data in the figure, after using the SCA attention module, the performance of MSACNN can be improved to a certain extent. This verifies that SCA is beneficial to the feature extraction process and improves feature robustness.

4.6. Activation Function Analysis. In deep learning, there are many choices for the activation function of the network. This work compares the network performance corresponding to the different activation functions, and the experimental results are demonstrated in Table 3.

As can be seen from the data in the table, the accuracy rate and the recall rate corresponding to Sigmoid are the lowest, and the performance corresponding to Tanh is slightly higher. When the ReLU activation function is used, the best precision and recall can be obtained.

5. Conclusion

After the 1980s, the world's higher education will enter an era centered on improving quality. As universities are increasingly moving from the fringes of economic society to the center of economic society, the quality of higher education is not only an issue of universities but has become one of the major issues of a country and even the whole world. As a response and continuation to the quality of higher education, the research on the quality assurance system of higher education is in the ascendant. The effect of social development and scientific progress on higher education mainly occurs through professionalism. However, in the course of this role, the curriculum performs an essential function. At present, facing the call of the era of knowledge economy, the challenge of market competition mechanism, the arrival of popularization of higher education, and the unfolding of higher education system reform, the whole society is torturing the quality of higher education. This work combines the evaluation of higher education courses with a deep learning model and proposes a deep learning model for the quality evaluation of higher education courses. This work proposes to use an attention-based multiscale network to explicitly learn the relationship between the qualities of various higher education courses. By using parallel networks with different convolution kernels, it combines different scale features at the same spatial location to better learn the relationship between the quality features of higher education courses. The experimental results show that the multiscale network based on the attention mechanism exhibits superior performance, surpassing other machine learning methods in both precision and recall indicators.

Data Availability

The datasets used during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The author declares that he has no conflict of interest.

Acknowledgments

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