Neural Network based College English Informatization Learning Environment Construction with ESP Teaching Mode

Lin Zhang[1]

[1]Sichuan Vocational College of Chemical Technology, Luzhou, 646300, China

Corresponding author: Lin Zhang, onetoonex@163.com

Abstract: Educational informatization is an inevitable direction for modern education. The college English classroom adopts a teaching mode with real-time teaching resources and digitalization, which increases the ways for teachers and students to obtain information resources. Different from traditional English, ESP English is more flexible in teaching method. The construction of college English informatization learning environment with ESP teaching mode is an inevitable trend of today's English education. In this context, the college English informatization teaching evaluation under ESP mode has become a significant topic. Based on evaluation results, the college English informatization teaching environment can be dynamically optimized. Aiming at this issue, this work proposes an evaluation method with deep learning for college English informatization teaching quality to optimize the teaching environment. This work proposes a method for evaluating the quality of college English informatization teaching under the ESP teaching mode based on a hybrid attention mechanism and an improved deep residual network, EITQENet. The feature extraction network structure of this method is improved with ResNet-50. First, it adopts a smaller convolution kernel for the input layer to ensure the resolution of the feature map. Second, it uses an improved pyramid residual block to build the main structure, and introduces a hybrid attention mechanism in the residual block. This combines channel and spatial information between feature maps, enhancing the ability to extract key features of the data. Third, add dropout and batch normalization operations to the output layer to improve the generalization ability and training efficiency. Massive experiments show designed method has high recognition accuracy on public datasets.

Keywords: College English; Informatization learning; ESP teaching mode; Neural network
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1 INTRODUCTION

The application of modern information technology such as computers and multimedia networks has become increasingly popular, prompting the emergence of information-based teaching methods and teaching methods for education. In the context of the gradually mature application of educational technology, the rise of information-based teaching has also shown a trend of innovation. Reasonable and flexible use of information-based teaching methods represented by multimedia networks and computers, and using them to assist the reform of education, is more in line with the trend and trend of the educational era. This will achieve better teaching and application results, and also make a big step forward in the construction for modern educational spirit. In college English education and teaching, educators should increase frequency for using information technology, an advanced and modern teaching method and technology. This enables the teaching content and concepts to be more fully displayed and expressed, and reflects the modern teaching concept of learner-oriented language application services and practical output, so as to improve quality for college English teaching in a more targeted manner. The information-based education model is a new development of the teaching model under information age. Under the premise of information technology support, it exists in a learning environment that integrates design theory and practice, and is a teaching model that reflects relevant teaching strategies and methods in a rich technical teaching situation. College English education and current information technology integration is an essential responsibility for universities to execute teaching reform and foster creative abilities in the face of the information society. Educators at colleges and universities must keep up with the times, continually update educational concepts, enhance advanced teaching techniques, and pay full attention and effective play to the role of technology in English curriculum reform. Modernizing college English instruction is driven by information technology, which is continually developing in a new direction toward information-based education [6], [15], [7], [28], [14].

ESP stands for English for specific purposes, which originated in the 1960s. It is centered on the needs of learners, and highlights the industry and goals. The range of skills that are in demand in today's society is wider than ever before. Students and society as a whole will suffer if traditional college English is used. College English is increasingly evolving towards ESP in order to build abilities that suit the demands of society. Following the introduction of the ESP idea, educational institutions began developing comprehensive curricula and aligning their teaching materials with societal demands. Since its inception, ESP English has grown and thrived as a classroom resource. The ESP English curriculum incorporates a range of teaching approaches as a result of informatization. Until recently, information-based education has been a popular free teaching style across the world, garnering the attention of a number of well-known universities. Although the education sector in the United States and worldwide places a high value on technology-enhanced instruction and has taken some concrete steps in this direction, ESP English instruction in colleges and institutions is still a distinct experience. However, because many colleges and institutions are unaware of the information-based English ESP courses, successful ESP English teaching results are limited [25], [3], [19], [26], [13].

The common teaching method of information-based teaching in college ESP English is MOOC, and some colleges and universities will apply flipped teaching. MOOC teaching is different from traditional teaching. MOOC teaching can mobilize enthusiasm and set flexible course content. This makes the teaching mode more novel and supports students' personalized learning. MOOC education strives to build a new teaching mode that conforms to the actual situation. This teaching model focuses on the diversified development of students, the improvement of teachers' teaching level and the coordinated development of society. Informalization teaching takes the network as well as multimedia as the carrier, seamlessly connects a series of hardware devices, transmits learning resources through the Internet, and builds an overall learning environment around mobile devices. Information-based teaching methods are more targeted to enhance learners' knowledge reserve and application ability. The English teaching under the new form of educational development will construct teaching strategies to achieve overall goal of cultivating compound applied talents with innovative ability. This will cultivate students' English knowledge reserve and English practical application ability, so that students' English knowledge has a clearer direction. The informalization teaching mode is very different from traditional teaching. Many teachers do not have a good grasp of the information-based teaching methods. Student-teacher engagement is facilitated through information-based instruction in ESP English classrooms, which use mobile terminals to connect to the campus network via the wireless network access point. Students and teachers can achieve real-time interaction through the mobile mid-end. Students can download learning content through wireless Internet access, and send homework to teachers; teachers provide students with learning guidance through the campus wireless network. Teachers can evaluate students' learning through the Internet, and students can evaluate teachers' teaching [2], [10], [11], [20], [1].

An unavoidable tendency in today's English education is the building of college English informatization environments based on ESP teaching methods. Quality of ESP-based college English informatization instruction at universities has been an important issue of discussion in this context. Dynamically optimizing the college English information technology teaching environment is possible based on the assessment outcomes. The hybrid attention mechanism and enhanced deep residual network used in this study are proposed as a way for assessing the quality of ESP-based college English informatization instruction. This method is improved on the basis of the deep residual network ResNet-50. The input layer uses a small convolution kernel to ensure the resolution of the feature map. The main network structure uses the improved pyramid residual block stacking, and uses two 3×3 convolution kernels to fully extract the effective feature information of the data. In addition, a hybrid attention mechanism is introduced into the improved pyramid residual block to give greater weight to important information, allowing the network to learn autonomously to focus on important features. The output layer uses BN and Dropout operations to improve the training efficiency.

2 RELATED WORK

Literature [8] summarized inevitability and particularity of the tiered teaching of college oral English, and proposed a strategy for constructing the tiered teaching system of college English. From the macro and micro perspectives, it put forward new ideas for construction of oral English teaching in application-oriented undergraduate colleges. An analysis of the current scenario faced by application-oriented undergraduate schools, as well as a macro-level viewpoint on how to achieve the aim of talent training in the application-oriented undergraduate colleges, was presented in literature [32]. Literature [24] had emphasized the importance of changing the way business English was taught at undergraduate institutions. Microscopically analyzing existing issues and proposing new approaches of reform or innovation was done in accordance with the present research state. English informatization education in higher vocational schools was the topic of literature [23]. Concept shift, requirement and development relevance of integrating information technology with English instruction were explained in depth. Investigating the current state of English informatization education in higher vocational colleges enabled researchers to identify and describe the challenges that existed, as well as provide integration principles, remedies, and recommendations for students and teachers. Reference [28] briefly analyzed the research status and proposed relevant countermeasures and suggestions. However, the research on the content of the literature was not deep enough and the development is not sufficient. Literature [30] clarified a series of changes brought by educational informatization to English education, so that the public could understand the impact of the popularization of educational informatization on foreign language learning in the context of education informatization. In particular, it had an influence on thinking and learning of post-95 students, and it also made us respect vigorous promotion and application of information-based teaching in English teaching. Literature [8] deeply analyzed issues existing in focused classroom of informatization teaching, and designed and implemented the Internet classroom according to the characteristics of the student group. It integrated the concept of informatization teaching into the professional curriculum system, and the teachers' attention extended from classroom teaching to extracurricular practical teaching, with clear thinking and strong operability. Literature [34] reviewed the system construction of online education, pointed out the gap with online education, and compared online education situation. Reference [32] introduced the development and evolution of instructional design, the development background, meaning and characteristics of flipped classroom. Using practical cases to analyze the research progress of flipped classroom, there was no feasible measures for specific adjustment, and there was a lack of specific strategies for certain practical operability.

Literature [18] put forward reform measures for college students to dislike the teaching status of English courses. Students' enthusiasm in studying English and their ability to blend their professional expertise with college English were the focus of future reform of English education, based on revising the English curriculum. It was the belief of literature [5] that all of the issues in college English teaching were represented in the curricular framework. In order to fix the existing English curriculum's difficulties, the ESP idea must be used and various phenomena in the curriculum must be carefully analyzed. It put forward some targeted measures, such as excessively compressing the public English class hours, confusing professional English and English for special purposes, and not paying attention to the practical training courses of public English. Then effectively solved these problems. Literature [22] emphasized the factors that affected the connection between public English and professional English, such as inadequate teacher training, unreasonable number of courses, and lack of professionalism in teaching materials, and proposed ways to develop professional English. Literature [21] analyzed issues according to current situation. It expounded the linking strategies of public English and professional education from three aspects: the combination of language and vocational ability, the combination of in-class English and extra-curricular English, and the combination of basic English and professional English. Literature [4] put forward the reform of English teaching from the aspect of teacher development strategy. They proposed to strengthen the communication between teachers and the industry, develop new teaching resources, build a double-teacher team, refine the teacher's industry orientation, and introduce the industry English grading system. Literature [12] believed that public English and professional should be closely integrated. Therefore, it focused on the analysis of the ways and methods of combining the two, and put forward measures such as the specialization of course content, the diversification of course evaluation methods, and the dualization of the teaching staff. Reference [16] analyzed the existing issues in English ESP teaching. It focused on the construction of ESP teaching mode and put forward some thoughts such as clarifying ESP teaching goals, strengthening teacher construction, and used network to optimize ESP teaching. Literature [27] proposed necessity of ESP teaching in English teaching by studying the theoretical basis and demand analysis of ESP courses. Literature [17] reviewed the ESP teaching mode in domestic and foreign colleges and universities from macro aspects such as meaning, teaching concept, and textbook selection, and put forward the significance of ESP teaching.

3 METHOD

An unavoidable tendency in today's English education is the building of college English informatization environments based on ESP teaching methods. Evaluation of the quality of ESP instruction in college English has been a prominent subject of study. A dynamically optimized teaching environment for college English may be created based on assessment findings, as shown in Fig. 1. A neural network-based evaluation approach for the quality of college English informatization teaching has been proposed in this study to improve the teaching environment.

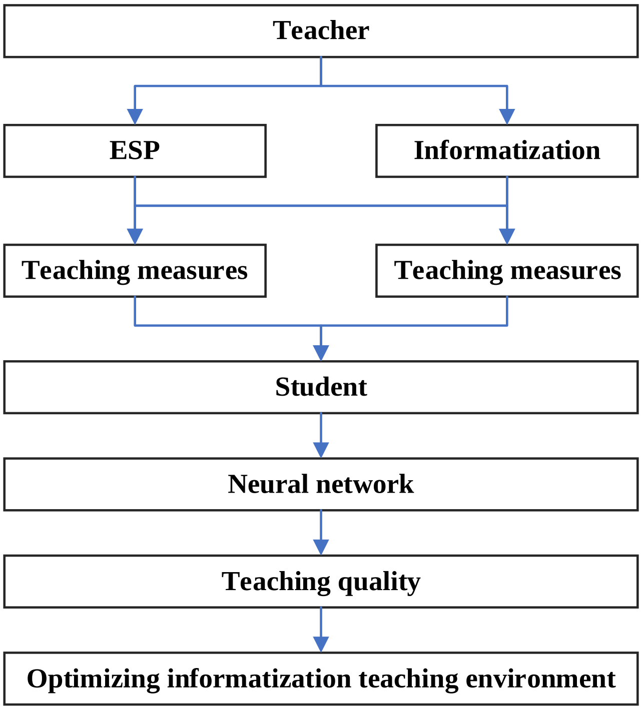

Figure 1: Optimizing teaching environment with teaching quality evaluation.

3.1 Convolutional Neural Network

CNNs typically include convolutional layers, pooling layers, BN, dropout, activation functions, and Softmax classifiers. The neural network is mainly constructed based on linear block multiplication, and a compound function is constructed by linear function and nonlinear activation function, which is used to fit the known data distribution [33]. Convolutional neural networks still use linear connections and nonlinear activation, and introduce receptive fields and weight sharing techniques to reduce parameters in traditional fully connected networks. The size for receptive field is determined with translation invariance principle, data is multiplied and accumulated in a sliding window manner to extract features. In feature extraction process, the weights involved in the same channel convolution kernel are the same, that is, weight sharing. The convolution is:

$$y_{ij} = \sum_{p=1}^{k} \sum_{q=1}^{k} x_{i+p-1,j+q-1} * w_{pq} + b \tag{3.1}$$

where k is kernel size, x is feature, w is weight, b is basis.

The pooling layer is usually used after the convolution layer, and the convolution operation extracts the features in a sliding window manner. The step size of the sliding window, that is, the convolution step size, is usually pixel level. Since the regions corresponding to adjacent sliding windows are very similar, the features of adjacent regions are repeatedly extracted, and the local region features of the feature map obtained by convolution are redundant. The pooling layer can solve information redundancy in adjacent regions of the convolutional feature map. The pooling layer does not contain weights and biases, and only performs overall statistics on a certain adjacent area, and uses overall statistical features to replace features of this position in network. After maximum pooling process, maximum value in the adjacent region is given, and the maximum value is used as the feature of the region. The difference between average pooling and max pooling is that it does not just use a single maximum value as a neighbor feature. Instead, it counts the features of adjacent regions and obtains the average value, and the average value is used. Average pooling is:

$$y = \frac{1}{s*s} \sum_{i=1}^{s} \sum_{j=1}^{s} x_{ij} \tag{3.2}$$

where s is the pooling window size, x is feature.

Assuming that the distribution space of the input data is consistent with the target space, the consistency of the distribution should be kept as far as possible during the data processing. The output of layer, due to operations such as convolution, pooling, activation, etc., has a large difference between its distribution and the corresponding input distribution, and difference increases with increase of network depth. The input distribution space changes after being processed by the neural network, but the target space does not change, resulting in the inconsistency of the distribution space. The consistency of data distribution between layers in the network is beneficial for accelerating model convergence and maintaining gradient stability. During the network learning process, with the continuous optimization of the parameters of the network weight layer, the output generated by the front-layer network after each parameter adjustment will change to a certain extent in the data distribution range. The data distribution change caused by the adjustment of the network parameters of the previous layer means that each layer needs to be updated with weights. The continuous change of the data distribution is not conducive to the convergence of the network model. BN can solve inconsistent distribution in the network model. BN is calculated as:

$$x_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \varepsilon}} \tag{3.3}$$

$$y_i = \gamma x_i + \beta \tag{3.4}$$

where x_i is feature, μ is the mean, σ is variance, ε, γ, and β is parameters.

Problems such as too single distribution range of data, insufficient data samples and too strong model representation ability can easily lead to overfitting of the model. An overfitted model will lose its generalization ability and will not be useful in practical applications. Adding a Dropout layer to the network can increase the generalization performance. On the other hand, Dropout has the effect of accelerating model training, by setting the dropout rate of neurons in the network layer. It temporarily discards some neurons randomly according to a certain discarding rate, reducing parameters in the training process, so as to speed up the training of the network model. In terms of enhancing the generalization performance of the network model, by randomly discarding some neurons during the training process, each training will obtain a different network model.

Adding an activation function to the linear block transforms a linear problem into a nonlinear problem, thereby enhancing the model's ability to fit more complex data. Sigmoid activation function can fit linear functions and step functions, and Sigmoid has good derivability and nonlinear transformation ability. However, its value range is too concentrated. When input is large or small, output will be concentrated in the flat area at both ends of the curve. If the input data value is too large or too small, the flat area does not have obvious distinguishable output. Tanh activation function can fit linear functions and symbolic functions, and the Tanh activation function has similar properties to the Sigmoid activation function. Tanh activation function also has infinite derivation, but it still has the same problem as the Sigmoid activation function, which tends to cause the gradient to tend to zero. Different from the sigmoid activation function, the activation function has a mean value of zero, and there is no situation where the gradient is always positive or negative. ReLU activation function can well solve the problem of gradient saturation of the Sigmoid and Tanh activation functions. In the process of finding the gradient of the activation function, the exponential calculation is not necessary, and the computational cost is significantly lower than that of the Sigmoid and Tanh activation functions. The ReLU activation function still retains the properties of a linear function, thus avoiding the gradient saturation problem. The ReLU activation function is more computationally efficient and can effectively accelerate the convergence of the network model. Three functions are:

$$Sigmoid(x) = 1/(1 + e^{-x}) \tag{3.5}$$

$$Tanh(x) = (e^{x} - e^{-x})/(e^{x} + e^{-x}) \tag{3.6}$$

$$ReLU(x) = max\ (0, x) \tag{3.7}$$

Softmax can be used as an activation function, but is usually used as a classifier for the class output of a network model. The features are processed by fully connected layer, classification result is given by the Softmax classifier.

3.2 Deep Residual Network

As network model structure increases, model effect will continue to improve, but when network model structure increases to a certain level, the errors of training and testing will become larger. Mainly due to gradient disappearance as well as gradient explosion, the more layers of the network model structure, the more difficult it is to train. All network models with many layers are more or less affected by the problems of vanishing gradients and exploding gradients. These two problems have a great impact on the performance. Specifically, accuracy result is very unstable. The accuracy of some neural network models will be basically unchanged because the gradient is too small, and some neural network models. The accuracy of the model will be drastically reduced because the gradient is too large, and this phenomenon makes the structure of most models only have a small number of network layers.

ResNet model applies the Residual block structure to solve degradation, as demonstrated in Fig. 2. Residual block relies on cross-connection to pass residual module input information to deeper layers of neural network through cross-layer shortcuts, instead of passing information along the main path like other convolutional neural networks.

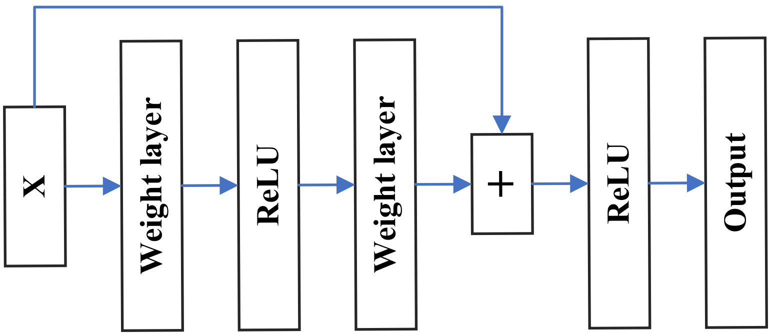

Figure 2: Residual block.

The basic deep residual network structure used in the experiments in this chapter is ResNet-50, which has four block module groups. Each block module group has 3, 4, 6, and 3 block sub-module groups, and each block sub-module group has three convolution layers. ResNet-50 has two basic blocks named conv block and identity block. The size of the input and output feature maps of the former is different, so they cannot be connected in series. A convolution layer is added to the skip connection to make the feature maps equal in size and then added. The function of this block is to change feature map. The size of the latter is the same as the output, which is connected in series. The function of this module is to deepen the depth of the network.

3.3 Hybrid Attention Mechanism

The essence of the attention mechanism is to obtain a set of weight coefficients through the autonomous learning ability. And mechanism of emphasizing the regions of interest in the network learning process and suppressing the irrelevant regions in a dynamically weighted manner. In the method of this chapter, the hybrid attention mechanism CBAM will be introduced into the improved deep residual network to enhance the recognition ability of the model. CBAM is an attention mechanism with spatial and channel in Fig. 3. CBAM includes a spatial attention mechanism and a channel attention mechanism. It performs autonomous learning of attention in space and channel in these two modules, which can not only save network parameters but also save the computing power required for training.

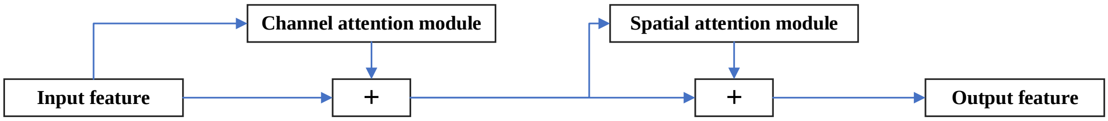

Figure 3: CBAM attention.

The purpose of the channel attention module is to draw attention to the relationships between the feature map's various channels, which can then be used to determine the relative relevance of each channel via network self-learning and then apply varying weight coefficients to each. This draws attention to the most vital aspects while obscuring the less important ones. The spatial dimension of the input feature map must be reduced in order to accurately calculate the channel's attention. Average pooling is a typical technique for combining spatial data. Maximizing the amount of data in a pool is a way to draw attention to specific characteristics in the incoming data. The two poolings are so combined in this instance. Two feature maps are generated from the input feature map by performing global max pooling and global average pooling. The two-layer neural network's output features are then added one by one to the feature maps that were created. After activating the sigmoid, the final channel attention weight feature map may be generated. These two maps are then multiplied one by one to provide input characteristics for the spatial attention module, which uses them.

$$M_c(F) = \sigma(MLP(AvgPool(F)) + MLP(MaxPool(F))) \tag{3.8}$$

where F is input feature.

Spatial attention a complement to the channel attention module, and its primary purpose is to draw attention to the most informative area. This module uses average and maximum pooling operations throughout the channel to compute spatial attention. Convolution is then used to create a spatial attention weight feature map from the concatenation of these features. The feature map generated by the channel attention module is sent into the spatial attention module. The first step is to conduct the global maximum pooling and the global average pooling operations on each channel of the input feature map in order to produce two feature maps. Convolution is used to decrease the dimension of the feature maps to one channel once they have been spliced together. Then, using the sigmoid function, the spatial attention weight feature map is generated. In order to create a feature map with spatial attention, the weight feature map and the input feature map are multiplied element by element.

$$M_c(F) = \sigma(Conv(AvgPool(F); MaxPool(F))) \tag{3.9}$$

3.4 EITQENet for English Informalization Teaching Quality Evaluation

The backbone structure of the feature extraction network used in the experiments in this chapter is improved on the basis of the ResNet-50. The first layer input is a convolution with a stride of 2 and a convolution kernel size of 7×7. However, the size of the preprocessed experimental data in this chapter is 112×112, which is a relatively small data compared to other tasks. If want high-quality feature maps and more expressive feature vectors, you'll need to utilize an operation with a stride of 1 and a kernel size of 3 x 3 to replace a convolution operation that was previously employed. Improve the model's capacity to generalize and speed up training by adding BN and Dropout procedures to its output layer. To replace the ReLU activation function in the network structure with the PReLU activation function, just a few new parameters are required. When the model is able to fit more accurately, the danger of overfitting is reduced. The residual unit's Building Block is the heart of the residual network. This chapter employs the modified pyramid residual block structure to develop the backbone structure of the network in order to maximize the performance of the network model structure and increase the ability of the feature vector to express itself. The structure depicted in Fig. 4 is initially created by activating PReLU rather than ReLU. This is followed by setting stride 2 in the second convolutional layer to construct the network's backbone.

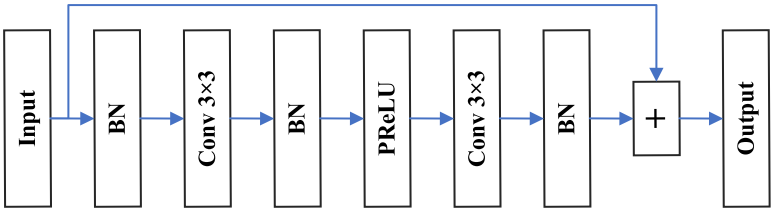

Figure 4: The improved structure.

The hybrid attention mechanism CBAM is introduced into the improved residual unit, using the self-learning mechanism of attention, combining channel attention and spatial attention, network can pay more attention to key feature information. This enhances the expressiveness of the feature vector extracted by the network, making the extracted feature information more discriminative. The proposed EITQENet structure is demonstrated in Table 1.

Layer	*Parameter*
Conv1	*Conv 3×3*
Conv2_x	*(Conv 3×3 + CBAM) × 2*
Conv3_x	*(Conv 3×3 + CBAM) + (Conv 3×3 + CBAM) × 3*
Conv4_x	*(Conv 3×3 + CBAM) + (Conv 3×3 + CBAM) × 12*
Conv5_x	*(Conv 3×3 + CBAM) + (Conv 3×3 + CBAM) × 3*
Output	*BN + Dropout + FC + BN*

Table 1. EITQENet structure.

The network constructs the characteristics of college English informatization teaching quality under the ESP teaching mode as feature data with a size of 112×112. First, the convolution operation is performed through the convolution kernel to generate feature map. Then, residual block of hybrid attention mechanism CBAM is introduced to perform the convolution extraction feature operation to obtain the feature map. Finally, a 512-dimensional feature vector is obtained through the output layer.

4 EXPERIMENT AND ANALYSIS

4.1 Dataset and Evaluation Index

This work collects data to evaluate quality for English informatization teaching under ESP teaching mode. with evaluation, teaching measures can be adjusted by feedback, so as to construct a college English informatization learning environment with ESP teaching mode. The data used in this work contains 30,291 training samples and 12,037 test samples. The data characteristics of each sample are shown in Table 2, which needs to be processed into 112×112 two-dimensional data. The experimental environment used in this work is Inter Core i9-7900X CPU, GeForce GTX1080Ti GPU, the operating system is Ubuntu 20.04, and the programming language is Python.

Index	*Feature*
a_1	*Learning attitude*
a_2	*Teaching attitude*
a_3	*Study method*
a_4	*Teaching method*
a_5	*Learning interest*
a_6	*Classroom performance*
a_7	*Communicative competence*
a_8	*Test score*

Table 2: The detailed data feature.

The evaluation indicators used are accuracy and precision, which are calculated as:

$$Accuracy = (TP + TN)/(TP + FN + FP + TN \tag{4.1}$$

$$Precision = TP/(TP + FP) \tag{4.2}$$

4.2 Network Loss Experiment

To evaluate the training convergence of the network, this paper analyses the loss of the network. The experimental results are demonstrated in Fig.

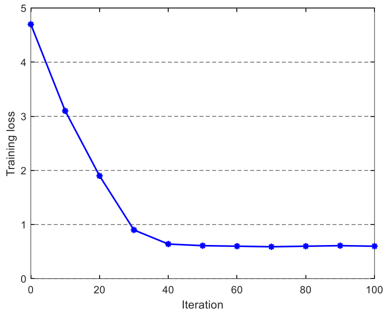

Figure 5: The training loss of EITQENet.

The loss gradually decreases as the network is trained. At about 50 iterations, loss reaches a convergence value. This shows EITQENet can fit better on training set.

4.3 Comparison Experiment

To verify reliability of EITQENet, it is compared with other machine learning methods. The compared methods include BP, CNN, and ResNet, and the experimental results are illustrated in Fig. 6.

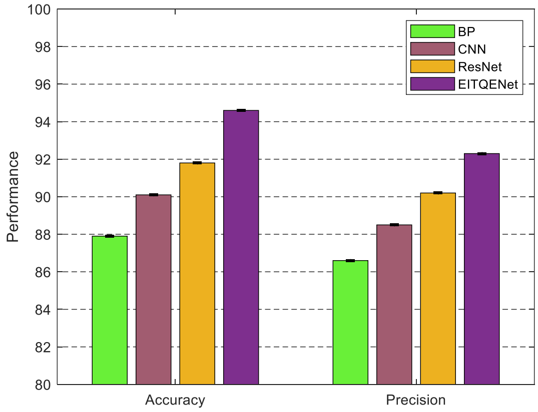

Figure 6. Comparison with other evaluation methods.

From the data in the figure, EITQENet can obtain the highest accuracy and precision. Compared with the best performing ResNet network, 2.8% accuracy improvement and 2.1% precision improvement can also be obtained.

4.4 Pyramid Residual Block Experiment

This work uses the pyramid residual block (PRB) structure to build EITQENet. To verify effectiveness for this strategy, it is compared with network performance without the pyramid residual block structure. To ensure reliability and keep the other parameters unchanged, the experimental results are demonstrated in Table 3.

Method	*Accuracy*	*Precision*
Without PRB	*94.7*	*91.1*
With PRB	*94.6*	*92.3*

Table 3: Evaluation on pyramid residual block.

Compared with not using PRB structure, after using this strategy, EITQENet can obtain 1.9% accuracy improvement and 1.2% precision improvement respectively. It can be seen that this module can improve the representation ability of features.

4.5 CBAM Mechanism Experiment

This work uses the CBAM attention mechanism to build EITQENet. To verify effectiveness, it is compared with network performance without the CBAM structure. To ensure reliability and keep the other parameters unchanged, experimental results are demonstrated in Fig. 7.

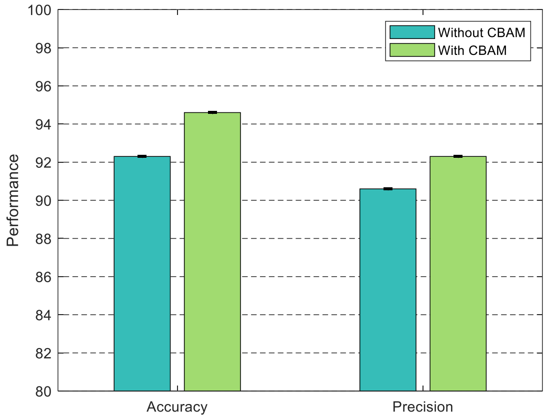

Figure 7: Evaluation on CBAM module.

Compared with not using CBAM structure, after using this strategy, EITQENet can obtain 2.3% accuracy improvement and 1.7% precision improvement respectively. This shows that this module can make the network focus on more important features.

4.6 Batch Size Experiment

In deep learning network training, the batch size is variable. To verify the influence of different parameters on network performance and select the best batch size parameter, this work conducts experiments on different parameters, and the results are demonstrated in Table 4.

Batch size	*8*	*16*	*32*	*64*	*128*
Accuracy	*92.5*	*94.1*	*94.6*	*94.2*	*91.9*
Precision	*91.2*	*91.5*	*92.3*	*91.7*	*90.1*

Table 4: Evaluation on batch size.

Different evaluation performances can be obtained by choosing different batch sizes. When the parameter is set to 32, the best performance can be obtained. And as it increases further, the performance actually decreases.

4.7 Dropout Strategy Experiment

This work uses the Dropout strategy to build EITQENet. To verify effectiveness for this strategy, it is compared with network performance without the Dropout strategy. To ensure reliability and keep the other parameters unchanged, the experimental results are demonstrated in Fig. 8. Compared with not using Dropout strategy, after using this strategy, EITQENet can obtain 2.6% accuracy improvement and 2.2% precision improvement respectively. This shows that Dropout can improve the robustness and effectiveness of the model.

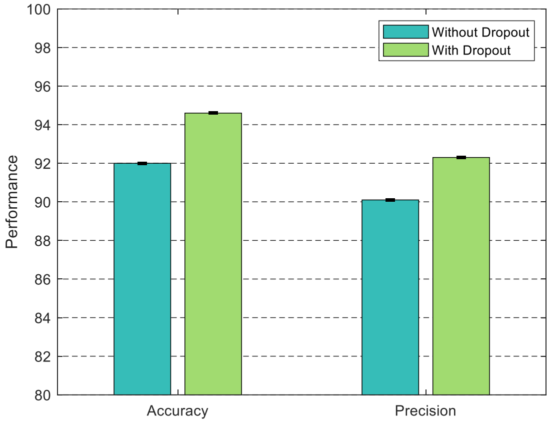

Figure 8: Evaluation on Dropout strategy.

4.8 BN Strategy Experiment

This work uses the BN strategy to build EITQENet. To verify effectiveness for this strategy, it is compared with the network performance without the BN strategy. To ensure reliability and keep the other parameters unchanged, the experimental results are demonstrated in Fig. 9.

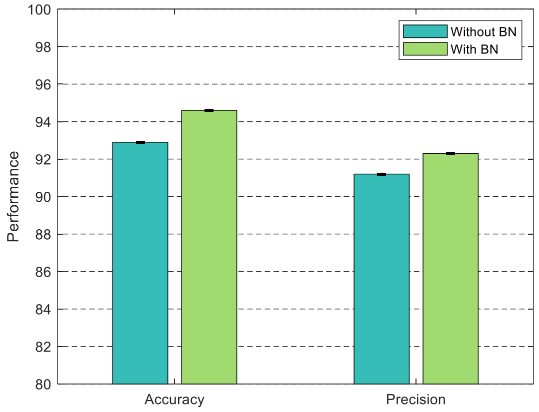

Figure 9: Evaluation on BN strategy.

Compared with not using BN strategy, after using this strategy, EITQENet can obtain 1.7% accuracy improvement and 1.1% precision improvement respectively. This shows that BN can improve the robustness for the model.

4.9 PReLU Strategy Experiment

This work uses the PReLU strategy to build EITQENet. To verify the effectiveness of this strategy, it is compared with the network performance with the ReLU strategy. To ensure the reliability of the experiment and keep the other parameters unchanged, the experimental results are demonstrated in Table 5.

Activation function	*Accuracy*	*Precision*
ReLU	*93.2*	*91.7*
PReLU	*94.6*	*92.3*

Table 5: comparison of relu and prelu.

Compared with using ReLU strategy, after using PReLU activation, EITQENet can obtain 1.4% accuracy improvement and 0.6% precision improvement respectively. This shows that PReLU can improve the model performance.

5 CONCLUSION

Information technology is widely used in college English classrooms, gradually forming the phenomenon of educational informatization. The college English ESP teaching course with informalization has really changed the traditional classroom teaching by guiding students to form a new teaching mode. It makes a substantial subversion of ESP English teaching, which stimulates students' initiative in learning, forms a harmonious classroom atmosphere, greatly reduces students' learning pressure. In this context, the quality valuation for college English informatization teaching with ESP is a significant topic. Based on evaluation results, the college English informatization teaching environment can be dynamically optimized. Aiming at this issue, this work proposes an evaluation method for the quality of college English informatization teaching with deep learning to optimize teaching environment. This work proposes an evaluation method for college English informatization teaching quality under ESP teaching mode with hybrid attention mechanism and improved residual network. The network structure of this method is reasonably improved on ResNet-50. The input layer uses a small convolution kernel to ensure the resolution of the feature map. The main network structure uses the improved pyramid residual block stacking, and uses two 3×3 convolution kernels to fully extract the effective feature information of the data. And introduce a hybrid attention mechanism CBAM in the improved pyramid residual block, which combines channel attention and spatial attention to give more weight to important information on the feature map. This allows the network to learn autonomously to focus on important features and suppress unimportant features. The output layer uses BN and Dropout operations to improve the training efficiency and the generalization ability. Through a series of experiments, it is proved that this method has good results on the data set.

Lin Zhang, https://orcid.org/0009-0006-2247-4727

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