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Retraction

Retracted: A Talent Training Model for Electrical Courses considering Diverse Constraint Models and Knowledge Recognition Algorithms

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret 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 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] F. Min, "A Talent Training Model for Electrical Courses considering Diverse Constraint Models and Knowledge Recognition Algorithms," *Advances in Multimedia*, vol. 2022, Article ID 5947573, 11 pages, 2022.

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Research Article

A Talent Training Model for Electrical Courses considering Diverse Constraint Models and Knowledge Recognition Algorithms

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In order to improve the talent training effect of electrical courses, this paper proposes a talent training model for electrical courses considering diverse constraint models and knowledge recognition algorithms. In order to obtain better performance of traditional deep learning models, it is usually necessary to increase the parameter scale of traditional deep learning models. Pretrained language models can be trained unsupervised directly using unlabeled corpora to learn vector representations of words without using labeled datasets. In addition, this paper uses the knowledge base and alias dictionary to build a knowledge graph and constructs a teaching model for electrical courses considering diverse constraint models and knowledge recognition algorithms. Through the research, it can be seen that the experimental teaching model of electrical courses proposed in this paper considering diverse constraint models and knowledge recognition algorithms has a very good effect on talent training.

1. Introduction

With the continuous development of the economy, the regional economic structure and industrial structure have begun to upgrade and transform, and the demand for high-quality technical engineering talents in the modern manufacturing industry has increased significantly. Through the analysis of the current teaching situation of electrical automation major in higher vocational colleges, it can be found that the major has various problems such as low attractiveness, low recognition, insufficient practical teaching hardware conditions, and weak social service functions. These problems all show that there is a certain distance between the talents cultivated by colleges and universities and the modernization of the electrical automation industry. In order to solve this problem, schools must work with the government and enterprises to explore a new path for the training of electrical automation professionals.

First of all, this paper analyzes the knowledge and capabilities that electrical automation engineering and technical personnel need to have from the perspective of enterprises. In the field of electrical equipment operation and maintenance, technicians need to master the basic knowledge of electrical automation, standardize the operation of various electrical equipment, and be proficient in using electrical instruments to detect and maintain electrical equipment. In the field of electrical equipment installation and commissioning, technicians need to understand electrical construction standards, be able to read drawings and drawings proficiently, and be proficient in the setting and commissioning of motors on various production lines such as asynchronous motors, synchronous motors, and servo motors [1]. In the field of electrical system development and design, technicians should be proficient in operating the hardware configuration and software debugging of programmable controllers. At the same time, it is necessary to master the hardware structure of the single-chip microcomputer and its program debugging method and parameter adjustment and combine the hardware configuration, software, and debugging of the single-chip microcomputer. For industrial enterprises, enterprises are more inclined to accept technical personnel with practical work experience, so the interns who have just left the campus are often not valued [2]. Moreover, at present, colleges and universities often attach importance to theoretical teaching, but not enough attention to practical teaching, and the updating of practical teaching content is slow, which cannot keep up with the needs of production and development of enterprises. When students graduate, they will find that some knowledge learned in school has been eliminated by enterprises, so school education is out of touch with social needs [3].

For colleges and universities, the practical teaching system should occupy a very important proportion, but due to the lack of practical teaching resources in schools and the shortage of funds, it is difficult for the development of practical teaching of electrical automation majors to achieve the desired effect [4].

Electrical engineering is the core and key discipline in the field of modern science and technology, and it is also an emerging discipline in the field of electrical information. Electrical engineering is closely related to industrial production and people's daily life, so it is developing rapidly, and related theories and technologies are relatively mature. The major of electrical engineering mainly cultivates high-quality and innovative professionals with certain scientific research, technical product development, and organizational management, so that talents have basic theoretical knowledge of engineering and related professional knowledge centered on electric energy production, transmission, and utilization and can use all the learn to solve engineering problems and build engineering systems and have good social morality and high morality, as well as comprehensive literacy to adapt to social development [5]. The main features of the electrical engineering major are the combination of strong and weak electricity, electromechanical integration, and the combination of software and hardware, which reflects the nature and characteristics of interdisciplinary. Graduates have strong adaptability and belong to "wide-caliber" majors [6].

Based on the in-depth development of electronic technology, for electrical and information students, the demand for new courses under new knowledge and new technologies is also increasing, which will inevitably reduce the number of hours of basic courses such as circuit analysis fundamentals. According to the requirements of independent colleges and universities for undergraduate talents and the college's purpose of cultivating innovative and applied talents, the teaching principles of wide caliber, solid foundation, ability, and individuality should be adopted [7]. Combined with the college's strategic concept of cultivating engineering and technical applied talents, the teaching content and teaching methods of the basic circuit analysis course for electrical and information majors are reformed, and the classic and practical chapters that are closely related to other subsequent courses are selected. Streamline outdated, poorly usable chapters [8].

Understand in theory, test in practice, and develop in innovation. The reform of education is not only a change to the teaching mode of students but also reflects the student's dominant position in essence. In a period of social turning point when economic development moves towards globalization and knowledge is gradually commodified, the diversified development of higher education, regionalization, and higherization have jointly formed three major themes of "reconstructing" the process of modern higher education [9]. Especially since the beginning of the 21st century, higher education all over the world has taken the pursuit of the diversification and rationalization of the types of undergraduate education as the trend of reform and development. Under the background of this era, in order to meet the value demands of specific social interest groups, the undergraduate teaching method focusing on practical teaching tends to become a new option in the development of higher education [10].

At present, the teaching purpose of most colleges and universities is based on the discipline, separate teaching, and assessment of theoretical knowledge and practical operation and implement staged training, single subject assessment, etc. In this case, students will be in the learning process. After completing the theoretical knowledge of electrical operation, because the corresponding practical operation training was not arranged in time, the practical operation training was delayed, so that students could not remember and understand the professional knowledge more deeply. In addition, in terms of teaching methods, colleges and universities mostly adopt collective and unified teaching methods. Whether it is theoretical knowledge, operational practice, or professional examinations, colleges and universities have not analyzed and studied more suitable teaching plans for different situations of students, and some, in colleges and universities, the theoretical teachers and practical teachers of electrical operation and control majors are not the same teacher, and the two teachers will not discuss and communicate during teaching, but each carry out teaching according to their own teaching plans [11]. At the same time, in terms of teaching and assessment methods, most colleges and universities still pay too much attention to the final test scores of students and regard the test scores as the only criterion for judging the strength of a student's professional ability. In this way, the score alone cannot reflect the true nature of the students. The ability and level of electrical operation will also damage the self-confidence of students to a certain extent [12]. In addition to the above problems, the teaching mode of colleges and universities still has teachers as the center, rather than students as the main body of teaching, which leads to the failure of the original intention of colleges and universities to be based on higher ability and thus makes the students cultivated by colleges and universities unable to reflect. It is difficult for students to find employment, and at the same time, the professional counterpart rate will also drop significantly, hindering the better development of colleges and universities in the future [13].

For students majoring in electrical operation and control, colleges and universities should strengthen off-campus cooperation to integrate with enterprises when teaching. The real training environment can effectively cultivate students' professional skills and emergency response. Or change the on-campus training into a simulated enterprise training, whether it is the clothing worn by the students or the management method, the unified management of the enterprise is adopted, and then a real enterprise production environment is simulated to help students carry out practical operations [14]. Through the above methods, students can feel the real job position, and it is conducive to improving the teaching quality and effectiveness of colleges and universities and also greatly narrows the gap between colleges and universities and enterprises, and facilitating the integration of higher education institutions and enterprises [15].

Teachers occupy a very important position in the teaching process. Therefore, in the integrated teaching mode, the professional level of teachers should reach the level of electrical operators, so that they can go down to the workshop to provide real guidance and help students improve their professional level. In order to improve the professional level of teachers, colleges and universities should regularly conduct relevant training and assessment for teachers or invite professionals in electrical operation to hold lectures, so as to continuously improve the professional level of teachers, so that teachers' teaching methods are more practical, which is beneficial to students' future higher development [16].

When carrying out teaching, in addition to explaining the knowledge and operation of electrical operation and control, teachers should also play the role of supervisors and act as managers in the enterprise to integrate teaching and enterprise management. In addition, teachers should analyze the management mode of the enterprise, apply it to teaching, and then divide several students into groups according to the regulations of the enterprise production workshop. At the same time, each group selects a group leader to be responsible for the work progress of the entire group and safety [17]. In this way, it is divided into layers like the management of the enterprise, and the work responsibilities of each person are clearly defined. Doing so not only allows students to be exposed to the corporate culture as early as possible but also improves students' professional skills and resilience in practice. In addition, after the practice, teachers should ask students to talk about their own experience and summarize the gains brought by this practical training [18].

In order to improve the talent training effect of electrical courses, this paper proposes a talent training model for electrical courses considering diverse constraint models and knowledge recognition algorithms, which provides a reference for the subsequent talent training of electrical courses.

2. Diverse Constraint Models and Knowledge Recognition Algorithm

CNN models used in computer vision have the characteristics of sparse interaction and parameter sharing. Among them, the sparse interaction can well extract the local features of the image and then combine these local features to form more complex features. Parameter sharing can reduce the number of parameters of the model, greatly simplify the difficulty of training the model, and improve the efficiency of the model. Therefore, the TextCNN model inherited from the CNN model inherits these characteristics well, which can well extract the local features of discrete text sequences and further combine them into more complex overall features, while greatly improving the training efficiency.

The structure of the TextCNN model is shown in Figure 1. It can be seen from the figure that the model structure is firstly the input layer, then the convolutional layer, the pooling layer, and finally the fully connected layer.

Specifically, for a given sentence, $\mathbf{x}_i \in \mathbb{R}^d$ represents the i-th word vector in the sentence, and the word vector dimension is d. If it is assumed that the maximum length of the sentence is n, and if the sentence length is less than n, the sentence length is supplemented to n, then, for each sentence, it can be expressed as

$$x_{i:n} = x_1 \oplus x_2 \oplus \cdots \oplus x_n \quad (1)$$

Among them, $\oplus$ represents the concatenation operator, and $x_{i:i+j}$ represents the sequence of words from position i to position j in the sentence. $w \in \mathbb{R}^{hd}$ represents the convolution kernel in the convolution operation, where d is the word vector length, and h is the window length of the convolution kernel at each run. If c_i represents a feature vector generated from a text sequence $x_{i:i+h-1}$, then c_i is computed as follows:

$$c_i = f(w x_{i:i+h-1} + b) \quad (2)$$

Among them, b is the bias term, and f is the nonlinear function. It should be noted here that the size of each convolution kernel varies. Only in this way can the convolution kernel capture the most important features of each length in the range of text sequences of different lengths. The idea of this approach is similar to the n-gram model. By moving the convolution kernels through the sentence in front-to-back order, a feature vector will be produced:

$$c = [c_1, c_2 \cdots c_{n-h+1}] \quad (3)$$

Among them, $c \in \mathbb{R}^{n-h+1}$. For each feature vector generated, in order to retain the most obvious features, a maximum pooling operation $\widehat{c} = \max\{c\}$ is performed. That is, the maximum value in each set of vectors is retained, so that the retained local features are the most important local features for the sentence. Finally, the feature vectors after max pooling are spliced to get z:

$$z = [\widehat{c}_1, \widehat{c}_2, \cdots, \widehat{c}_n] \quad (4)$$

Finally, the above feature vector z is fed into a fully connected layer to get the classification result y:

$$y = w \cdot z + b \quad (5)$$

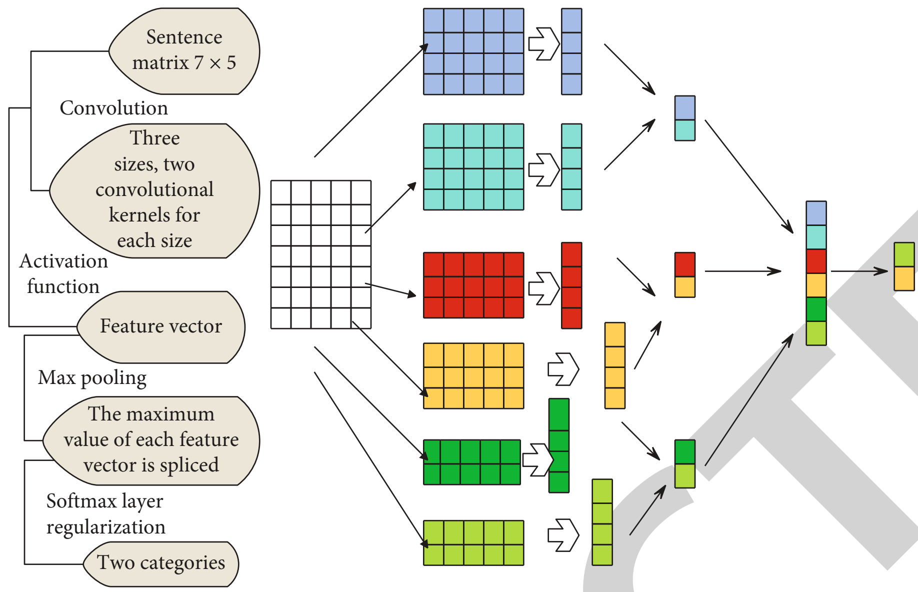

Figure 1: TextCNN model structure.

Finally, in order to enhance the generalization ability of the model and reduce overfitting, dropout is introduced into the model. The final formula for calculating y is

$$y = w \cdot z^{\circ} r + b \tag{6}$$

Among them, $^{\circ}$ is the multiplication operator, and r is a random vector. In this experiment, the TextCNN model with random loss will be used as the final comparison model.

The structure of the RNN model is shown on the left side of Figure 2, and the right side is the expanded structure of the RNN model.

Specifically, $t-1tt+1$ represents the time sequence, x represents the input text sequence, and s_t represents the memory of the RNN model at time t, which is obtained by the following formula:

$$s_t = f(W \cdot s_{t-1} + U \cdot x_t) \tag{7}$$

Among them, W represents the weight matrix input by the model, $U \cdot x_t$ represents the weight matrix corresponding to the input text sequence x_t at this time, and U represents the weight matrix corresponding to the output S. At the start time, $t = 1$. At this time, $s_0 = 0$, and weight matrices W, V, and U are randomly initialized, and then, the following calculations are performed:

$$\begin{aligned} h_1 &= Ux_1 + Ws_0, \\ s_1 &= f(h_1), \\ o_1 &= g(Vs_1). \end{aligned} \tag{8}$$

Among them, $f(\,)$ and $g(\,)$ are activation functions, and the weight matrices W, V, and U remain unchanged. As time t progresses, the final output of formula (8) is:

$$\begin{aligned} h_t &= Ux_{t-1} + Ws_{t-1}, \\ s_t &= f(h_t), \\ o_t &= g(Vs_t). \end{aligned} \tag{9}$$

It can be seen from the above formula that while modeling the features of each word sequence, the RNN model also models the preceding features of the word sequence, so the RNN model fully considers the sequential features of the text sequence. Through the introduction of the TextCNN model in the previous section, we know that the TextCNN model can model the local features of text sequences. The TextRCNN model combines the advantages of the above two models, which can not only capture the local features of text hunting but also model the order of text sequences.

The model structure of TextRCNN is shown in Figure 3. In terms of model structure, the TextCNN model is mainly composed of convolutional layers and pooling layers, while the TextRCNN model replaces the convolutional layer in the TextCNN model with a bidirectional RNN model.

Specifically, if it is assumed that a text sequence is written in left-to-right order, the left text sequence refers to the previous text, and the right text sequence refers to the subsequent text. If $c_l(w_i)$ represents the left context of character w_i, and $c_r(w_i)$ represents the right context of character w_i, then $c_l(w_i)$ and $c_r(w_i)$ are calculated as

$$\begin{aligned} c_l(w_i) &= f\left(W^l c_l(w_{i-1}) + W^{sl} e(w_{i-1})\right), \\ c_r(w_i) &= f\left(W^l c_r(w_{i-1}) + W^{sl} e(w_{i-1})\right) \end{aligned} \tag{10}$$

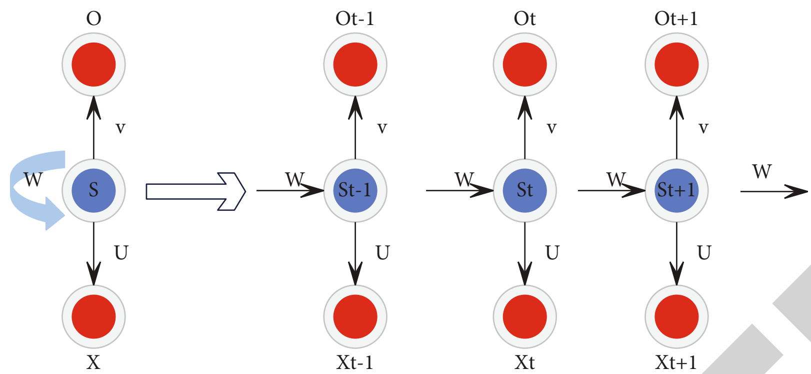

FIGURE 2: RNN model structure.

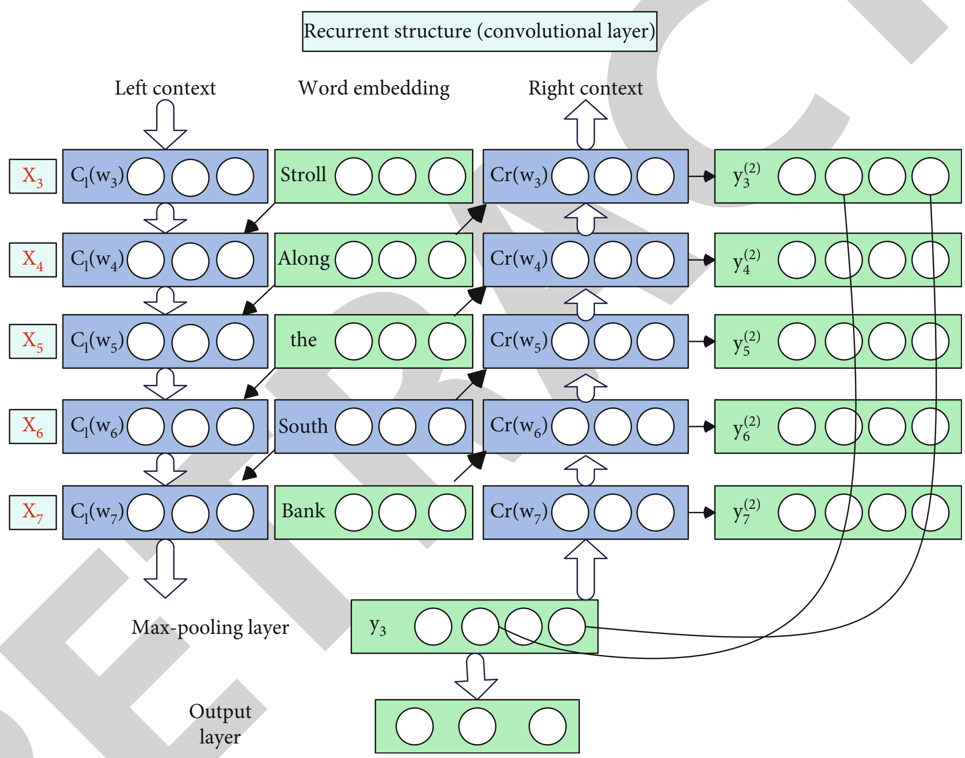

FIGURE 3: TextRCNN model structure.

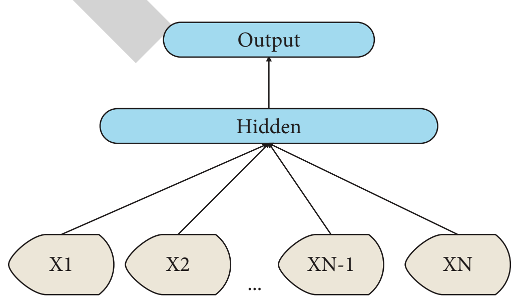

FIGURE 4: FastText model structure.

Among them, $e(w_{i-1})$ is the character vector of character w_{i-1}, and $c_l(w_{i-1})$ is the text to the left of character w_{i-1}. For each text sequence, the left text sequence $c_l(w_1)$ corresponding to the leftmost character uses the same shared initialization parameters, and the right side is the same, denoted as $c_r(w_n)$, where n represents the length of the text sequence. W^l is a matrix used to convert the left-hand text sequence of the current word to the next word. W^{sl} is also a matrix that combines the semantic vector of the current character with the left-hand text sequence of the next character. $W^r W^{sr}$ is the same as W^{sr}. $f()$ is the nonlinear activation function.

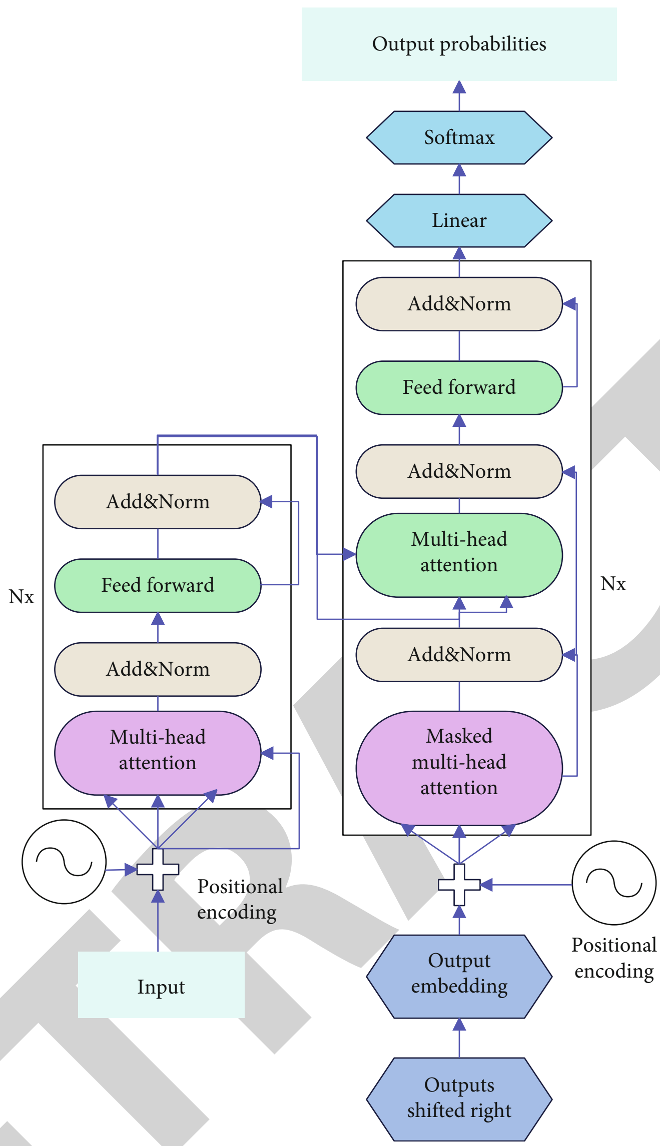

Figure 5: Transformer structure diagram.

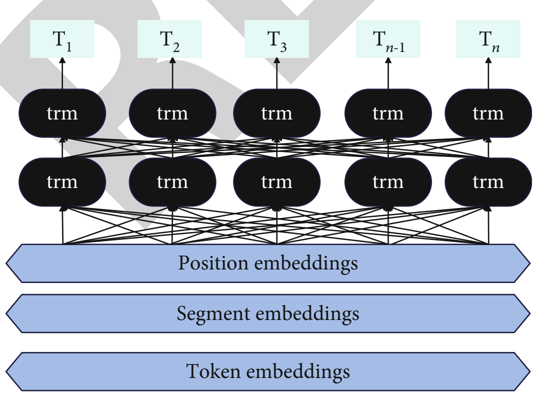

Figure 6: BERT model structure.

For any character w_i, with the context representation $c_l(w_i)$, $c_r(w_i)$, the feature vector of character w_i is defined as the concatenation with $c_r(w_i)$:

$$x_i = [c_l(w_i) ; e(w_i) ; c_r(w_i)] \tag{11}$$

Through this splicing method, the ambiguity contained in the character w_i can be reduced. Then, the character vector x_i is calculated by the following formula to obtain y_i and sent to the next layer:

$$y_i^{(2)} = \tan\text{h}\left(W^{(2)}x_i + b^{(2)}\right) \tag{12}$$

In the pooling layer, for each $y_i^{(2)}$, a one-dimensional

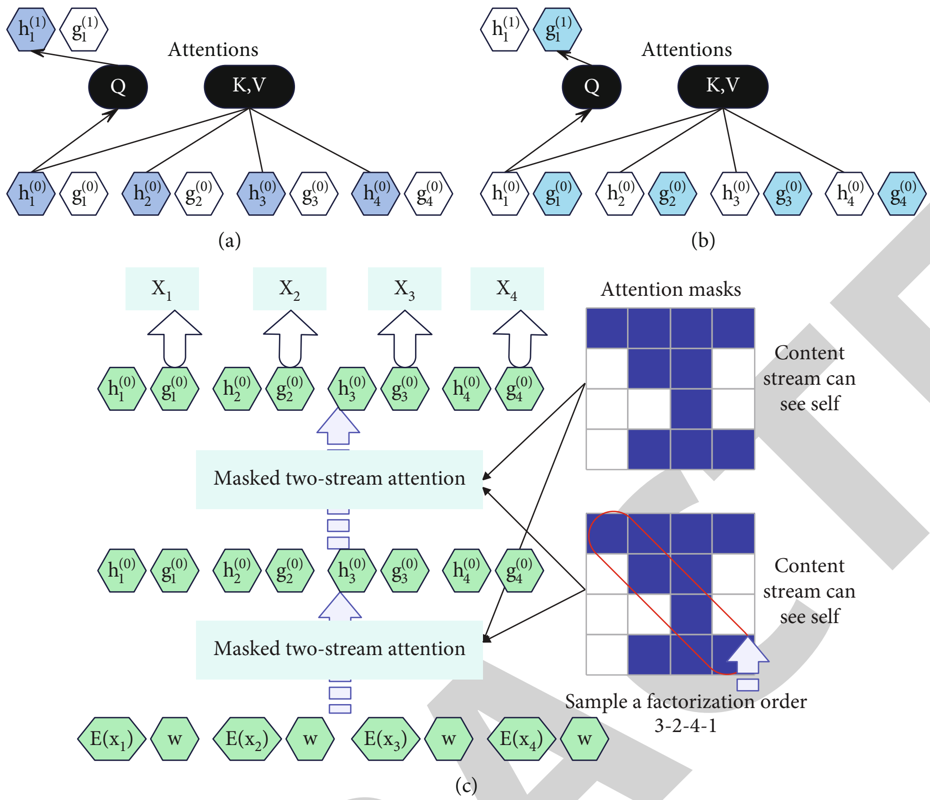

FIGURE 7: The structure of the dual-stream attention mechanism.

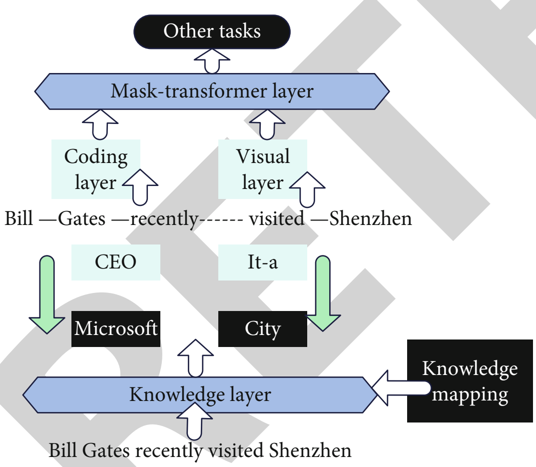

FIGURE 8: *K*-BERT model structure.

max pooling operation is used to obtain $y_i^{(3)}$, so that the k-th element in $y_i^{(3)}$ is the largest element among the k-th elements of $y_i^{(2)}$:

$$y_i^{(3)} = \max_{i=1}^{n} y_i^{(2)} \tag{13}$$

After that, the result is input into a fully connected layer to get the text representation, and the final output is obtained by the following formula:

$$\begin{aligned} y^{(4)} &= W^{(4)} y^{(3)} + b^{(4)}, \\ p_i &= \frac{\exp\left(y_i^{(4)}\right)}{\sum_{k=1}^{n} \exp\left(y_k^{(4)}\right)} \end{aligned} \tag{14}$$

The TextCNN model uses convolution kernels of different sizes to capture different local features of text sequences, but even this is difficult to capture text features at long distances. Compared with TextCNN model, TextRCNN has better performance in capturing long-distance dependent features. Therefore, this experiment will also try to test the performance of the TextRCNN model under the short question corpus.

The reason why FastText can greatly reduce the training time while the accuracy is not weaker than TextCNN and TextRCNN is that the FastText model has two important optimizations: hierarchical softmax and N-gram.

The FastText model uses hierarchical softmax to perform small-scale softmax for different categories, which can avoid the huge time-consuming problem of uniform softmax for all categories. The time complexity of softmax decreases from (n) to $O(\log(n))$, as shown in Figure 4.

The transformer model structure is shown in Figure 5. Compared with traditional deep learning models, the transformer model has made many improvements. First, the transformer model has a deeper layer structure thanks to

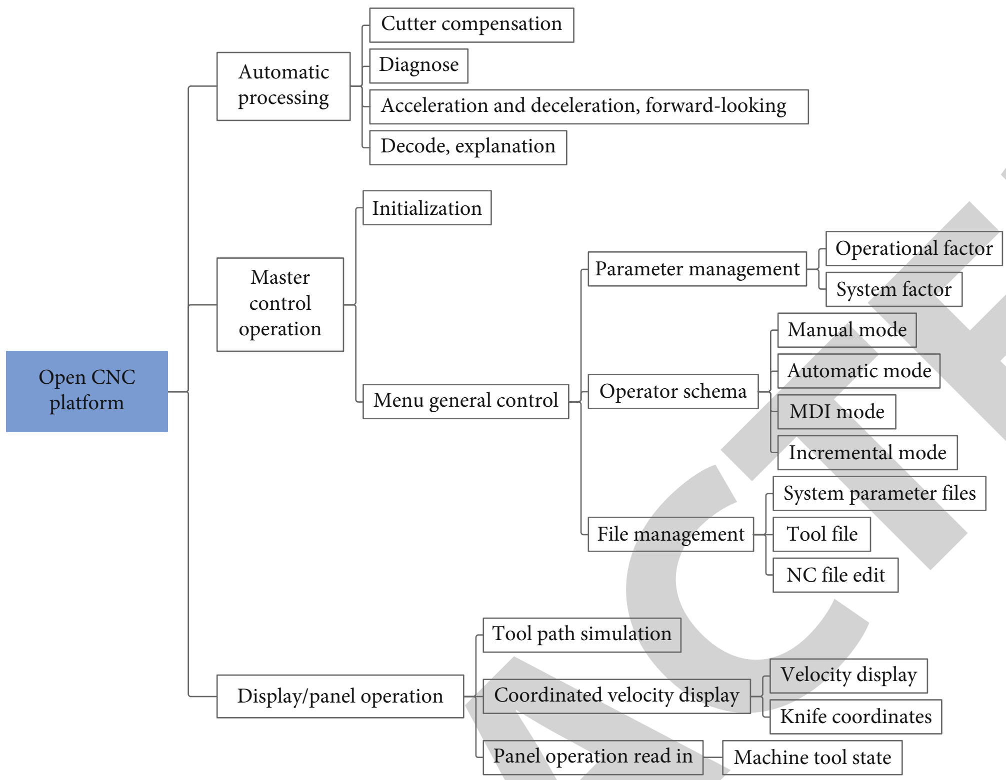

Figure 9: System function diagram.

the introduction of the residual network, which enables the transformer model to better extract text features.

The BERT model is built based on the transformer model, and the model structure is shown in Figure 6. BERT uses a bidirectional transformer to model text sequences, which enables the BERT model to have many of the advantages of the transformer model described above. At the same time, because it is a bidirectional model, this allows the model to better pay attention to the context of the text sequence. The difference from the transformer model is that the BERT model does not directly add the word vector and the position encoding like the transformer, but splices the two. In addition, in order to fully adapt to different downstream tasks, the BERT model also introduces sentence encoding, so that the model can distinguish different sentences. The vector input by the final BERT model is the splicing vector of the token vector, the sentence vector, and the position vector.

In order to allow the BERT model to better model text sequences, generate word vectors containing richer semantic features, and better support downstream tasks, BERT is pretrained under two new unsupervised tasks.

In order to further enhance the processing ability of the XLNet model for long texts, the model introduces the transformer-XL mechanism. When the segmented long text is calculated in segments, the calculation result of the previous text is stored in the memory, and the text features calculated by the previous text are added when the current text is calculated. This further strengthens the model's ability to understand long texts. However, the location information of each piece of text will cause ambiguity in the understanding of the model. The reason is that for position i, the model cannot distinguish between the position of this text i and the position of the previous text i. To solve this problem, the model introduces relative position encoding. It does not directly add the word vector and the position vector in the input like the transformer model, but determines the relative position according to the position distance between the current position and the predicted word during the model calculation process. This solves the problem that the model understands the ambiguity of different text segment positions. Figure 7 shows the structure of the dual-stream attention mechanism.

The K-BERT model enhances the model's understanding of background knowledge in a specific field and its semantic understanding of short text sequences by introducing knowledge graphs into the model. The model structure is shown in Figure 8.

Compared with the BERT model, the K-BERT model mainly modifies the input. Specifically, for the input text sequence, the knowledge layer and the knowledge graph are first integrated to form a sentence tree structure. Because the model can only recognize sequence structure, soft-position encoding of the sentence tree is required. At the same time, a visible matrix is introduced to make the text sequences on different branches of the sentence tree invisible to each other, so as to reduce the influence of the semantic information in the knowledge graph on the main text sequence.

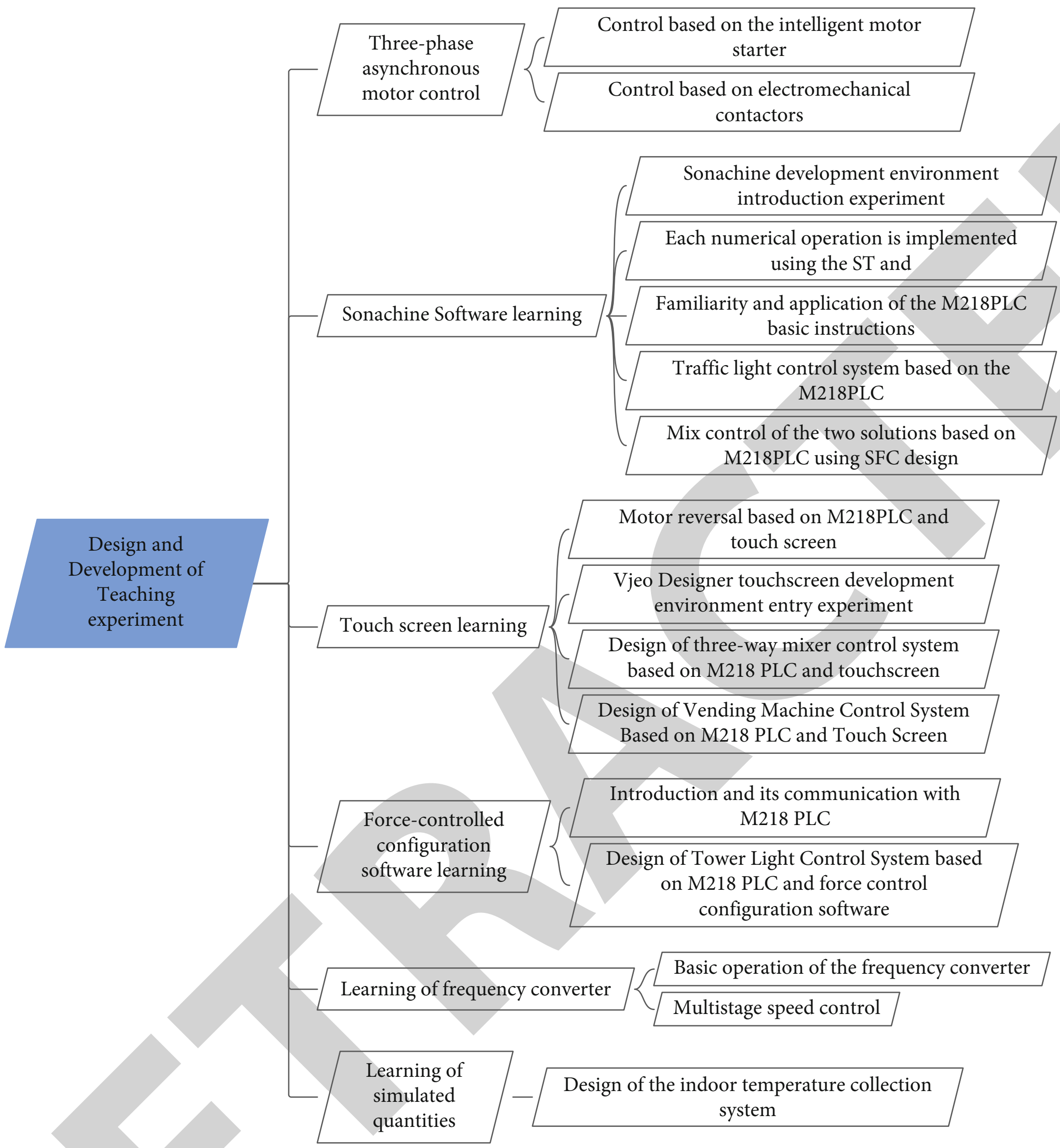

Figure 10: Diagram of teaching experiment system.

The models do not affect each other during training and use an attention mask similar to XLNet, which is called the visibility matrix.

3. Electrical Teaching Test Platform considering Diverse Constraint Models and Knowledge Recognition Algorithms

The system function diagram of the machine tool in this paper is shown in Figure 9. Two aspects need to be considered when dividing modules according to function diagrams. One is to ensure as much as possible the irrelevance between modules, the modules have clear functions, and there are communication interfaces between them. In addition, the other is that the size of the basic module should be appropriate. If it is too large, it will increase the difficulty of modifying and replacing the original module, and it is not conducive to the reuse of the module, thereby reducing the openness.

The electronic automation experiment platform is mainly used in the course teaching experiment of programmable logic controller for undergraduates and can also be used in course design, graduation design, and innovation experiment. According to the requirements of PLC course teaching experiment, this section tentatively designs and develops several teaching experiments to form a teaching experiment system, as shown in Figure 10.

On the basis of the above research, the effect of the experimental teaching system of electrical courses considering various constraint models and knowledge recognition algorithms is verified, and the effect of talent training is counted. The quantitative data is shown in Table 1.

It can be seen from the above research that the experimental teaching model of electrical courses considering various

Table 1: Validation of talent training effect of the experimental teaching model of electrical courses considering various constraint models and knowledge recognition algorithms.

Number	Effect statistics
1	85.07
2	81.57
3	83.70
4	85.28
5	77.00
6	83.29
7	85.73
8	83.22
9	85.69
10	80.05
11	76.55
12	76.54
13	78.52
14	79.46
15	78.64
16	81.05
17	78.34
18	78.19
19	77.69
20	84.32
21	82.09
22	80.93
23	78.38
24	77.87
25	79.56
26	80.30
27	79.87
28	81.25
29	76.74
30	78.49
31	83.34
32	83.72
33	79.83
34	76.78
35	85.51
36	85.05
37	77.64
38	82.76
39	80.03
40	83.26
41	85.36
42	81.31
43	76.31
44	85.90
45	80.18
46	82.35
47	78.48
48	84.98
49	80.63
50	82.23
51	82.58
52	85.97
53	77.74
54	79.57
55	83.08
56	76.42
57	81.77

constraint models and knowledge recognition algorithms proposed in this paper has a very good effect on talent training.

4. Conclusion

The flexible and open design idea of the experimental platform is considered from the essence of the experiment. The original purpose of the experiment is to get the same or different effect as expected by running the hardware combination you want, so as to achieve the purpose of learning and understanding, rather than just watching the phenomenon of the experiment like a demonstration system. In order to restore the essence of the experiment, the design of this experimental platform follows the flexible and open design idea, and the port of the device is kept open as much as possible. When there is a need or an idea, the control system can be flexibly set up. This paper proposes a talent training model for electrical courses that takes into account various constraint models and knowledge recognition algorithms. Through the research, it can be seen that the experimental teaching model of electrical courses proposed in this paper considering various constraint models and knowledge recognition algorithms has a very good effect on talent training.

Data Availability

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

Conflicts of Interest

The author declares no competing interests.

Acknowledgments

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