

## Research Article

# Analysis of Teaching Effect of English Classroom Mind Map Based on a Logistic Regression Model

Yan Deng  and Rui Zhu

*School of Foreign Languages, Jiangxi University of Science and Technology, Ganzhou 341000, China*

Correspondence should be addressed to Yan Deng; [yandeng@jxust.edu.cn](mailto:yandeng@jxust.edu.cn)

Received 7 January 2022; Revised 8 March 2022; Accepted 23 March 2022; Published 6 May 2022

Academic Editor: Mu Zhou

Copyright © 2022 Yan Deng and Rui Zhu. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

In order to improve the effect of English classroom teaching, this paper combines the pulse neural network to identify the teaching process of English classroom and conducts real-time supervision of classroom dynamics in combination with the actual situation. Moreover, this paper constructs an intelligent system, uses the recognition method based on the spiking neural network image to collect the real-time dynamics of classroom teaching, and combines the logistic regression model to evaluate the teaching effect. After constructing the system framework, the system process analysis is carried out. This paper combines experimental research to verify the model of this paper. The experimental research results show that the analysis model of teaching effect of mind map in English classroom based on the logistic regression model proposed in this paper has good results, which also verifies that the mind map teaching can play an important role in English classroom teaching.

## 1. Introduction

The teaching goal is the final result expected to be achieved by the teaching activity. Generally speaking, the teaching goal is a teaching result caused by a subjective wish. After the teaching activity is completed, it is a specific description of the behavioral state that the student needs to achieve [1]. In the process of English teaching, the reasonable degree of teaching objectives directly determines the teaching effect. The teaching goal of high school English courses is to develop the ability of autonomous learning and cooperative learning, form effective English learning strategies, and cultivate students' comprehensive language ability [2].

Students learn and master the basic knowledge of five aspects including pronunciation, vocabulary, grammar, functions, and topics. Knowledge is one of the important components of English ability, and it is the basis for effective use of language skills. Therefore, the effective use of mind maps in teaching can realize the organic connection between a series of related knowledge such as words, sentences, and grammar. Through the use of mind maps as a way of think-

ing for thinking and learning, it helps students to combine the actual practice of life. Moreover, in the process of drawing homework for students' real-life mind maps, it helps students to achieve effective mastery of basic theoretical knowledge [3].

Effectively master the four skills of listening, speaking, reading, and writing, and have the comprehensive ability to use these four skills. The high school English course also emphasizes that on the basis of developing students' comprehensive language ability, it focuses on improving students' ability to acquire information, deal with problems, analyze problems, and solve problems in English. Students should use a large number of special or comprehensive language practices. A comprehensive language ability lays the language foundation for actual communication. Therefore, from the perspective of learning strategies, listening, speaking, reading, and writing are not only learning content but also learning methods. Mind mapping is a graphical tool that is very convenient for language input and output, and there are nodes as the connection between knowledge. In actual teaching, applying mind maps to the four aspects of vocabulary, grammar, reading, and writing

can realize the overall improvement of students' practical use of English, information acquisition, problem analysis, and problem solving.

Let students gain a sense of satisfaction and accomplishment and have the awareness of solving practical problems. From the essence of education, learning is not only for acquiring knowledge but also for achieving awareness or emotional satisfaction. In the teaching process, teachers should guide students to transform interest into learning motivation, build self-confidence, and shape healthy personality. The purpose of high school English classroom teaching is not only to enable students to master the basic comprehensive abilities of listening, speaking, reading, and writing but also to enable students to learn from analogy to solve practical problems. English teaching can also be used as an alternative patriotism teaching, which can enhance the spirit of patriotism and the sense of national mission on the basis of further broadening the international horizon. In the process of teaching, there are often foreign cultural and historical articles. In reading teaching, using mind maps to analyze and compare the culture and history of other countries not only is a good way to learn knowledge but also can effectively improve students' thinking. The ability to solve the actual problems of the country can effectively cultivate the innovative spirit of students.

This article combines the logistic regression model to evaluate the teaching effect of English classroom mind map, which provides a theoretical reference for the subsequent reform of English classroom teaching.

## 2. Related Work

Literature [4], through the study of neurophysiological science and the classification and comparison of the connections between all things, found the radioactive phenomenon between them and analyzed the writing habits of human beings and those who have learning disabilities in humans. After training and observation, he finally created a mind map, a tool to help human thinking. Literature [5] pointed out: "This research result can be applied to information processing, that is, to summarize and synthesize research information, and can also be used to assist people in learning and research work such as thinking about complex problems and in-depth analysis of characterization information. Specifically speaking, Mind map users can comprehensively use information representation tools including pictures, graphics and words, etc., to clearly and systematically display the logical hierarchical relationship and thinking sequence relationship between concepts, and realize and improve the visualization of concept representation."

By reading the relevant literature of foreign researchers, I learned that the use of mind mapping tools in the education field will benefit both educators and learners. The most important thing is the creativity of the two in educational learning activities. Get a great improvement. With this ability of independent creation, the teaching effect of the school will be greatly improved [6]. I understand that the research scope of mind mapping by foreign scholars is getting wider

and wider and that mind mapping is applied and researched in more and more countries. Their research goals are not only limited to the basic concepts and connotations of mind maps but also more and more practical researches on the application of mind maps to subject teaching .

In these documents related to the study of mind maps, some authors mainly discussed the basic concepts and connotations of mind maps [7]. Literature [8] proposed that mind mapping is a tool that combines text and graphics. It was also pointed out that the information presented on the mind map is all related and must be drawn in a certain order. There are also many documents mainly for research on the meaning of mind mapping in foreign language classroom teaching. Researchers proposed that the use of mind mapping as a tool in foreign language classrooms to assist teaching has many benefits. In such a class, students are more efficient in language learning. Students no longer use read-only texts; they can also use mind maps to freely imagine, put forward their own unique insights, and deepen their understanding of language and text [9]. At the same time, communication between students can help them to cooperate fully. The use of this tool in foreign language classrooms is also beneficial to teachers. It can help teachers sort out their lesson preparation ideas, improve the quality and speed of teacher preparation, and help teachers formulate reasonable teaching plans. With the help of mind maps, it can also reasonably and effectively evaluate the level of knowledge learned by students [10]. There are also some documents that mainly focus on the issue of mind mapping to improve students' learning styles. Researchers believe that mind mapping, a teaching aid tool, can help students fully realize their dominant position in learning [11]. Students' learning in the classroom can no longer be passive acceptance, but active and autonomous learning. With the support of this tool, students will also actively learn to communicate with others and exchange views and opinions with each other. Their learning method is no longer single, but in multiple ways [12]. According to the research theme, when relevant experts conduct research on mind mapping, they mainly conduct research on English vocabulary, writing, reading, and oral expression [13]. In these aspects of research, we found that most of the research on mind mapping is to improve the memory of English vocabulary; secondly, there are also many researches on the use of mind mapping as a tool for English reading teaching [14]. There are also researches involved in spoken English and translation. These research themes affirm the feasibility and significance of mind mapping in English teaching [15]. These studies are mainly based on individual topics as research clues and clearly put forward that they are only studying the application of mind mapping in a certain professional aspect of English teaching and do not regard mind mapping as a complete teaching model, from the perspective of education management of the whole school. Set out to study its construction, implementation, evaluation, and management [16]. From the perspective of the English learning objects of the application of mind maps, mind maps can be used in various stages of learning such as elementary school, middle school, and university [17]. However, mind maps are mostly used in foreign

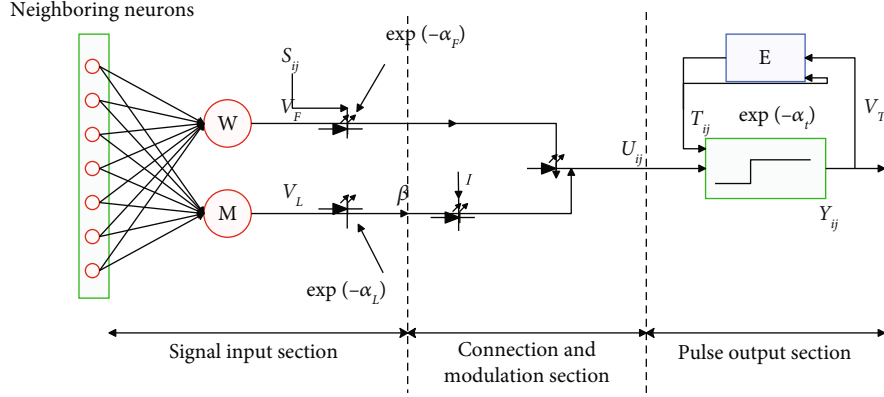


FIGURE 1: Basic structure diagram of PCNN model, quoted from the literature.

language teaching in colleges. There are few researches on the application of mind maps in English teaching to high school students and the least research on primary school students. The research in elementary school is mainly for vocabulary teaching [18]. Mind maps can be more widely used in English teaching, which is convenient for cultivating students' good language thinking from the beginning of the classroom, helping students to establish scientific thinking habits, instead of just using mind maps to help students memorize a few more English vocabulary [19].

### 3. Recognition of English Classroom Teaching Features Based on a Pulse Coupled Neural Network

This paper combines pulse-coupled neural networks to identify English classroom teaching features, which is convenient to provide data support for the subsequent teaching analysis of English classroom mind maps.

A pulse coupled neural network is a third-generation artificial neural network that is different from traditional neural networks. It is a single-layer two-dimensional locally connected feedback network proposed by the optimization and improvement of the Eckhorn model and the Rybak model. The basic model of PCNN consists of three parts: receiving domain, modulation domain, and pulse generation domain. Its structure diagram is shown in Figure 1.

The discrete equation corresponding to the pulse coupled neural network model is shown in

$$F_{ij}(n) = e^{-\alpha_F} F_{ij}(n-1) + V_F \sum_{k,l} M_{ijkl} Y_{kl}(n-1) + S_{ij}, \quad (1)$$

$$L_{ij}(n) = e^{-\alpha_L} L_{ij}(n-1) + V_L \sum_{k,l} W_{ijkl} Y_{kl}(n-1), \quad (2)$$

$$U_{ij}(n) = F_{ij}(n)(1 + \beta L_{ij}(n)), \quad (3)$$

$$E_{ij}(n) = e^{-\alpha_E} E_{ij}(n-1) + V_E Y_{ij}(n-1), \quad (4)$$

$$Y_{ij}(n) = \begin{cases} 1, & U_{ij}(n) > E_{ij}(n), \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

It can be seen from the model structure diagram that the pulse coupled neural network model is divided into three parts. Among them, formulas (1) and (2) represent the signal receiving part,  $F_{ij}(n)$  is the external stimulus, and  $L_{ij}(n)$  is the link input from the peripheral neurons. Formula (3) represents the connection modulation part. Formulas (4) and (5) represent the pulse output part, and the generated modulation signal  $U_{ij}(n)$  is compared with the threshold  $E_{ij}(n)$  to obtain the pulse signal  $Y_{ij}(n)$ . In addition, there are four types of parameters in formulas (1)–(5):

- (1) The time attenuation parameters are as follows:  $\alpha_F$ ,  $\alpha_L$ ,  $\alpha_E$ . These three parameters control the attenuation speed of the input zone  $F$ , the connection input zone  $L$ , and the threshold  $E_{ij}(n)$ , respectively.  $\alpha_E$  is particularly important, because its size directly affects the running time of PCNN. The larger the  $\alpha_E$ , the slower the decrease of  $E_{ij}(n)$ , the longer the running time of the corresponding model, and vice versa
- (2) The magnification factor are as follows:  $V_F$ ,  $V_L$ ,  $V_E$ . Among them,  $V_F$  and  $V_L$  control the size of external stimuli, while  $V_E$  affects the firing cycle of neurons
- (3) The connection coefficient is  $\beta$ .  $\beta$  is a parameter in  $U_{ij}(n)$ . The larger the value, the greater the coupling degree of the neuron to the surrounding information, and it will also affect the ignition cycle of the central neuron
- (4) The weight matrix are  $W$  and  $M$ . They, respectively, represent the connection strength between the input domain  $F$  and the connection input domain  $L$  and its surrounding neurons. The size is generally related to the distance between the neurons

When processing the image with the pulse-coupled neural network model, the pixels of the image and the neurons

of the PCNN form a two-dimensional neural network in one-to-one correspondence. First, in the signal input part, the receiving domain  $F$  receives the external stimulus  $S_{ij}$  (that is, each pixel of the image) and the feedback  $F(n-1)$  from the previous iteration, which is connected to the input domain  $L$  to receive the stimulation of surrounding neurons. The signals  $F$  and  $L$  obtained in the receiving domain enter the connection modulation part together, and the internal activity item (that is, modulated signal)  $U_{ij}(n)$  is obtained after modulation. After entering the pulse output part, the modulation signal  $U_{ij}(n)$  will be compared with the dynamic threshold  $E_{ij}(N)$  generated in the pulse generation domain. If  $U_{ij}(n) > E_{ij}(n)$ , the pulse generator will start and the neuron ignition output  $Y_{ij} = 1$ ; otherwise, the neuron nonignition output  $Y_{ij} = 0$ . After performing the same operation on each pixel, the final result  $Y$  is obtained, and the above operation is repeated until the conditions are met. According to whether neurons are interconnected, it can be divided into two working modes: uncoupled and connected and coupled.

**3.1. No Coupling Connection.** Uncoupled connection means that the neurons between PCNNs have no connection relationship. At this time, the connection coefficient is  $\beta = 0$ , and the amplification coefficient is  $V_F = 0$  in the feedback input domain. This ensures that each neuron of PCNN runs independently during work. At this time, the corresponding mathematical model formulas (1)–(5) are transformed into

$$F_{ij}(n) = e^{-\alpha_F} F_{ij}(n-1) + S_{ij}, \quad (6)$$

$$U_{ij}(n) = F_{ij}(n), \quad (7)$$

$$E_{ij}(n) = e^{-\alpha_E} E_{ij}(n-1) + V_E Y_{ij}(n-1), \quad (8)$$

$$Y_{ij}(n) = \begin{cases} 1, & U_{ij} > E_{ij}(n-1), \\ 0, & \text{otherwise} \end{cases} \quad (9)$$

In formulas (6)–(9), the feedback input  $F$  and the dynamic threshold  $E$  are both zero in the initial state of the PCNN. Generally,  $V_E$  takes a larger value, the time  $n$  is discrete, and the neuron  $ij$  ignites, and we can get

$$U_{ij}(0) = F_{ij}(0) = S_{ij}, \quad (10)$$

$$Y_{ij}(0) = 1, S_{ij} > 0. \quad (11)$$

Substituting (11) into (8), we can get

$$E_{ij}(0) = V_E. \quad (12)$$

The neuron  $ij$  ignites at  $n = 0$  and the dynamic threshold  $E_{ij}(0) = V_E$ ,  $V_E \gg S_{ij}$  at this time. Therefore, the neuron will not ignite immediately after the zero time. It can be

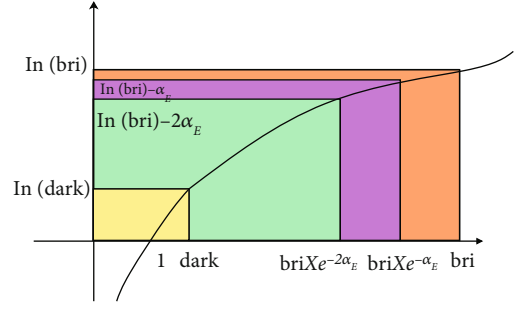


FIGURE 2: The relationship between PCNN and logarithmic transformation.

deduced that the neuron state at  $n = 1$  is as follows:

$$\begin{aligned} F_{ij}(1) &= e^{-\alpha_F} S_{ij} + S_{ij}, \\ U_{ij}(1) &= F_{ij}(1), \\ Y_{ij}(1) &= 0, \\ E_{ij}(1) &= e^{-\alpha_E} V_E. \end{aligned} \quad (13)$$

From the state value of the neuron at  $n = 0$  and  $n = 1$ , the general formula can be derived:

$$\begin{aligned} U_{ij}(1) &= S_{ij}(1 + e^{-\alpha_F} + \dots + e^{-n\alpha_F}) = V_E e^{-(n-1)\alpha_E}, \\ E_{ij}(n) &= e^{-n\alpha_E} V_E, \\ Y_{ij}(n) &= 0. \end{aligned} \quad (14)$$

From this, the first and second ignition timings can be calculated:

$$\begin{aligned} n_1 &= 1 + \frac{1}{\alpha_E} \ln \frac{V_E}{cS_{ij}}, \\ n_2 &= 1 + \frac{1}{\alpha_E} \ln \frac{V_E}{cS_{ij}} + \frac{1}{\alpha_E} \ln \frac{cS_{ij} + V_E}{c'S_{ij}}. \end{aligned} \quad (15)$$

It is deduced that the neuron ignition at time  $m$  meets the conditions:

$$n(m) = 1 + n_1 + mn_2 = 1 + \frac{1}{\alpha_E} \ln \frac{V_E}{cS_{ij}} + m \frac{1}{\alpha_E} \ln \frac{cS_{ij} + V_E}{c'S_{ij}}. \quad (16)$$

From formula (16), it can be concluded that the neuron firing cycle of PCNN is

$$T_{ij} = n(m) - n(m-1) = \frac{1}{\alpha_E} \ln \frac{((1 - e^{-(n+1)\alpha_F})/(1 - e^{-\alpha_F}))S_{ij} + V_E}{((1 - e^{-(n+1)\alpha_E})/(1 - e^{-\alpha_E}))S_{ij}}. \quad (17)$$

It can be seen from formula (17) that when there is no coupling and the surrounding neurons have no influence, the ignition cycle has a very strong relationship with the

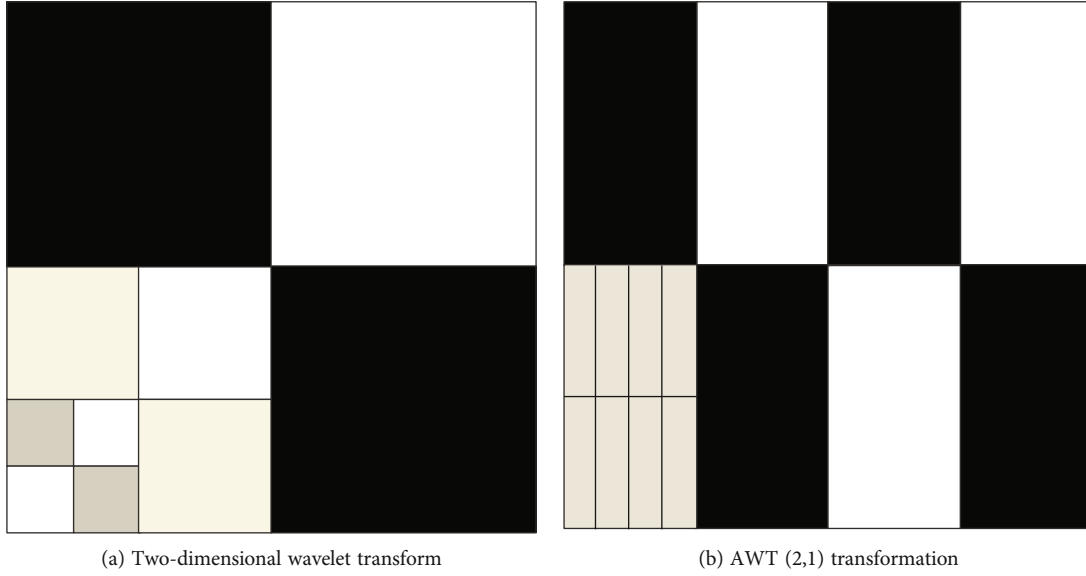


FIGURE 3: Comparison of two-dimensional wavelet transform and AWT transform.

external stimulus  $S_{ij}$ . The larger the  $S_{ij}$ , the shorter the ignition period, and the smaller the  $S_{ij}$ , the longer the ignition period.

**3.2. Coupling Connection.** The coupling connection of PCNN is the key to transfer information between neurons, as shown in formulas (1)–(5). It uses the link input  $L$  to modulate the feedback input  $F$ . We assume that there are two interconnected neurons  $ij$  and  $kl$ , where  $S_{ij} > S_{kl}$ , and other parameters are the same. If two neurons fire at the same time at  $t = 0$ , the firing cycle of the neuron mentioned above; that is, from formula (17), the second point of neuron  $ij$  will precede neuron  $kl$  after the second point. At this time, as a coupling neuron of neuron  $kl$ , neuron  $ij$  transmits ignition information to neuron  $U_{kl}$  through modulation signal  $U_{kl}$ , that is,

$$U_{kl} = S_{kl}(1 + \beta L_{kl}). \quad (18)$$

If  $U_{kl} > S_{ij}$ , it can be calculated that neuron  $kl$  will pre-ignite. It is obtained that the coupled neuron  $kl$  of neuron  $ij$  will ignite with the ignition of neuron  $ij$  when it satisfies

$$S_{kl} \in \left[ \frac{S_{ij}}{1 + \beta L_{kl}}, S_{ij} \right]. \quad (19)$$

In image processing, there are generally 9 neuron couplings around a neuron, and the neurons meeting the capture conditions will be fired in advance. For  $\beta$  and  $L$ , the larger the value, the wider the capture range.

In order to make digital image enhancement more convenient and effective, the pulse-coupled neural network model is simplified, and its discrete mathematical description is

$$F_{ij}(n) = S_{ij}(n), \quad (20)$$

$$L_{ij}(n) = e^{-\alpha_L} L_{ij}(n-1) + V_L \sum_{k,l} W_{ijkl} Y_{kl}(n-1), \quad (21)$$

$$U_{ij}(n) = F_{ij}(n)(1 + \beta L_{ij}(n)), \quad (22)$$

$$E_{ij}(n) = e^{-\alpha_E} E_{ij}(n-1) + V_E Y_{ij}(n-1), \quad (23)$$

$$Y_{ij}(n) = \begin{cases} 1, & U_{ij}(n) > E_{ij}(n), \\ 0, & \text{?} \end{cases} \quad (24)$$

The image pixels are stretched through logarithmic transformation to achieve the effect of image enhancement. The output of the pulse coupled neural network also has a logarithmic transformation relationship, as shown in Figure 2.

Among them, the abscissa is the gray value of the image pixel, and the ordinate is the corresponding logarithmic result.  $\text{bri}$  is the largest pixel value, and its corresponding dark is the smallest pixel value. Assuming that the initial value of  $E_{ij}$  is  $E_{ij}(0) = \text{bri}$ , the neuron  $ij$  is in a state of no ignition at the beginning, and the output is 0. After the first iteration of PCNN, the threshold  $E_{ij}(1) = \text{bri} \times e^{-\alpha_E}$  at time 1 can be obtained from formula (23). At this time, all neurons with gray values are between  $\text{bri} \times e^{-\alpha_E}$  and  $\text{bri}$  ignite. At this time, the firing excitation of neurons is set to  $\ln(\text{bri})$ . Next, perform the second iteration, and we can get  $E_{ij}(2) = \text{bri} \times e^{-2\alpha_E}$ . The ignition gray value range of the neuron becomes between  $\text{bri} \times e^{-2\alpha_E}$  and  $\text{bri} \times e^{-\alpha_E}$ , and the gray excitation value of this segment of neuron ignition is denoted as  $\ln(\text{bri}) - \alpha_E$ . It keeps iterating until the smallest gray value dark of the entire image is also ignited. In this way, we can define the gray-scale excitation value of neuron ignition at different moments as the image that has been

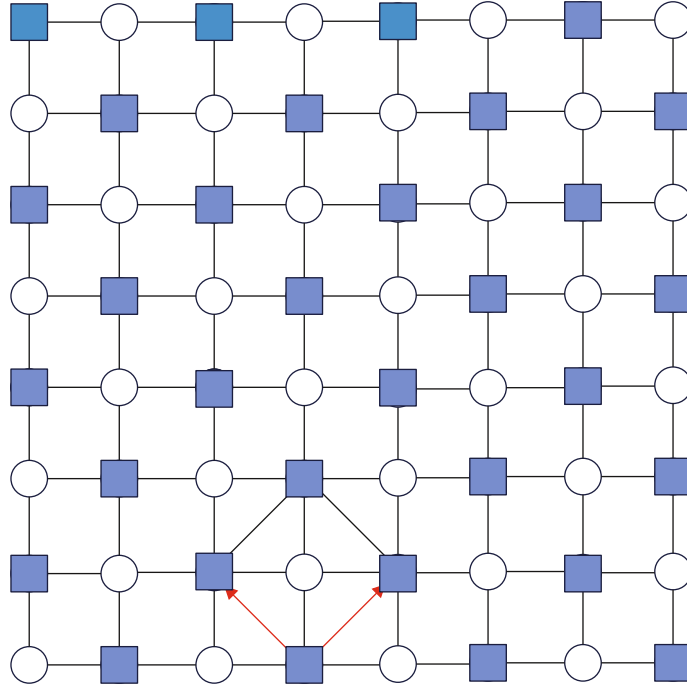


FIGURE 4: Schematic diagram of integer lattice decomposition.

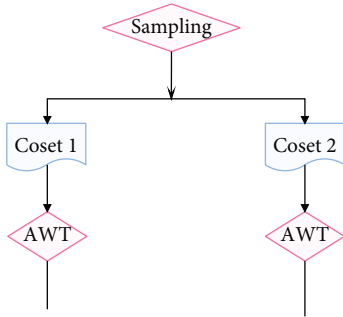


FIGURE 5: Directionlet transformation structure diagram.

enhanced, as in

$$\text{enh}S_{ij} = \ln(\text{bri}) - \alpha_E(k-1). \quad (25)$$

In the formula,  $\text{enh}S_{ij}$  is the gray value of the enhanced image, and  $k$  is the ignition moment of neuron  $ij$ . Formula (25) is logarithmic, and each ignition moment of neuron  $ij$  has a one-to-one correspondence with the enhanced image value. In fact, we have assumed that the input of each neuron is not affected by the previous output of surrounding neurons, which means that formula (25) is the logarithmic transformation value of the grayscale image. However, due to the influence of  $\alpha_E(k-1)$ , the result is different from the true logarithmic relationship.

The traditional wavelet transform is isotropic; that is, the same number of transformations is performed on the horizontal and vertical directions at the same scale. However, when dealing with two-dimensional images, the ideal results

cannot be obtained. Anisotropic wavelet (AWT) refers to the transformation of horizontal and vertical directions at different times under the same scale. For example, in an AWT,  $n_1$  one-dimensional wavelet transforms are performed in the horizontal direction, and  $n_2$  one-dimensional wavelet transforms are performed in the vertical direction. If  $n_1 = n_2$ , it is the original isotropic; if  $n_1 \neq n_2$ , it is anisotropic wavelet transform. The extensibility of  $v$  is determined by its opposite sex rate  $\rho = n_1/n_2$ .

Figure 3(a) is a general two-dimensional wavelet transform; the number of transformations in the horizontal and vertical directions is the same. However, the AWT (2,1) transform in Figure 3(b) performs two one-dimensional wavelet transforms in the horizontal direction and only one one-dimensional wavelet transform in the vertical direction.

The so-called integer lattice refers to a set of points composed of two sets of linearly independent vectors  $d_1$  and  $d_2$  to form an integer lattice  $\Lambda$ , and  $d_1$  and  $d_2$  must be integers,  $\Lambda \in \mathbb{Z}^2$ . The formula is expressed as

$$\Lambda = \{c_1 d_1 + c_2 d_2 | c_1, c_2 \in \mathbb{Z}\}. \quad (26)$$

However,  $\Lambda$  can be represented by a non-unique generator matrix  $M_\Lambda$ , and it can be set up as

$$M_\Lambda = \begin{bmatrix} a_1 & b_1 \\ a_2 & b_2 \end{bmatrix} = \begin{pmatrix} d_1 \\ d_2 \end{pmatrix}, a_1, a_2, b_1, b_2 \in \mathbb{Z}, c = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix}. \quad (27)$$

Then,  $\Lambda$  can be expressed as  $\Lambda = cM_\Lambda$ . This means that

$\Lambda$  can be determined by  $M_\Lambda$  and the entire plane  $Z^2$  can be divided into  $|\det M_\Lambda|$  (the absolute value of the  $M_\Lambda$  determinant) cosets about the lattice  $\Lambda$ . Each coset corresponds to a displacement vector  $S_k = (S_{k1}, S_{k2})$ ,  $k = 0, 1, 2 \dots, |\det(M_\Lambda)| - 1$ . When performing the Directionlet transformation, the transformation direction is the  $d_1$  direction with a slope of  $r_1 = b_1/a_1$ , and the queue direction is the  $d_2$  direction with a slope of  $r_2 = b_2/a_2$ . Various combinations of  $d_1$  and  $d_2$  directions are different, so that different sampling matrices are obtained. Therefore, image information of anisotropic images with different directions is obtained.

For the Directionlet transformation of the image, the first choice is to use the sampling matrix  $M_\Lambda$  to sample the image to obtain  $|\det(M_\Lambda)|$  cosets. Then, these cosets undergo an anisotropic wavelet transform in the transform direction and the queue direction, that is, AWT. In this way, the Directionlet sparse representation of the image can be obtained, and the wavelet transform will not produce dense wavelet coefficients due to its same direction and limited direction. This is of great help to our subsequent processing work.

Next, this paper uses Figure 4 to advance one to explain how cosets are decomposed.

As shown in Figure 4, the sampling matrix is selected as

$$M_\Lambda = \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix}, \quad (28)$$

and the slope of the transformation direction is  $r_1 = 1$ , and the slope of the queue direction is  $r_2 = -1$ , which means that the transformation is performed along the  $\pm 45^\circ$  direction. The whole grid space is divided into two cosets of black point and white point, the displacement vector of black point is  $S_0 = [0, 0]$ , and the displacement vector of white point is  $S_1 = [0, 1]$ . The structure diagram of the entire Directionlet transformation is shown in Figure 5.

The time attenuation constant is  $\alpha_L, \alpha_E$ , the amplification factor is  $V_L, V_E$ , the connection factor is  $\beta$ , and the weight matrix is  $W$ . The meanings and functions of these parameters have been introduced in the section of this paper, so I will not discuss them here.

In the pulse-coupled neural network image enhancement in this paper, because all the gray values are required to be fired only once, the final enhanced image is determined by its ignition time  $k$ . Therefore, the threshold amplification factor  $V_E$  must be large enough so that after the neuron  $ij$  is ignited, it will not reignite for a long time (at least until the neuron with the smallest external stimulation, that is, the pixel with the smallest gray value has also ignited).

Correspondingly, the time attenuation coefficient  $\alpha_E$  of the threshold value needs to be small enough to ensure that the attenuation speed of the threshold value  $E_{ij}(n)$  is slow enough, so that different gray levels of the image have different output results at different ignition moments. If the attenuation coefficient is very small, it will cause a lot of redundancy in the system, so we can set

$$\alpha_E \leq \ln(\text{bri} | (\text{bri} - 1)). \quad (29)$$

$\beta$  controls the relationship between input and external stimuli. The larger the value, the more the neuron is affected by nearby neurons and the easier it is to be captured. Therefore, the more complex the image of a certain area, the less the influence of the central neuron should be, and the simpler the area image, the greater the influence of the surrounding neurons and the neurons should be captured in advance. This will also avoid the problems of overcapture in areas with small differences and undercapture in areas with large differences due to the same connection coefficient  $\beta$ . Therefore, the standard deviation will be used as the  $\beta$  value in this paper, that is,

$$\beta = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_{ij} - \mu)^2}. \quad (30)$$

The standard deviation is the quantity that reflects the degree of spatial dispersion within a certain group. Here, it represents the difference between a neuron and its neighboring neurons. As shown in formula (30),  $N$  represents the total number of neurons in a certain neighborhood of the image,  $x_{ij}$  represents the gray value of each neuron in this neighborhood, and  $\mu$  is the average gray value of the neurons in the neighborhood. The larger the value of  $\beta$ , the greater the difference between neurons in the neighborhood. Therefore, a larger connection coefficient is required to make it captured. The smaller the value of  $\beta$ , the neighborhood can be captured without the need for such a large connection coefficient.

The weight matrix  $W$  represents the degree of connection between the neuron and surrounding neurons. Generally, we set its size as the reciprocal of the square of the Euclidean distance of the neuron, that is,

$$W = \begin{bmatrix} \frac{1}{2} & 1 & \frac{1}{2} \\ 1 & 0 & 1 \\ \frac{1}{2} & 1 & \frac{1}{2} \end{bmatrix}. \quad (31)$$

This article will use image contrast ( $C$ , Contrast), peak signal-to-noise ratio (PSNR, Peak Signal-to-Noise-Rate) and information entropy  $H$  as the evaluation criteria to judge the enhancement effect. The formula for image contrast is

$$C = \sqrt{\frac{\sum_{(x,y)} (I(x,y) - \nu)^2}{x \times y}}. \quad (32)$$

Among them,  $I(x, y)$  represents the gray value of a certain pixel of the image,  $\mu$  is the average gray value of the image, and  $x$  and  $y$  are the pixel values of the image. The peak signal-to-noise is shown in

$$\text{PSNR} = 10 \times \log \left( \frac{255^2}{\text{MSE}} \right). \quad (33)$$

MSE is the mean square error, that is, the average of the

TABLE 1: Image enhancement evaluation indicators of different algorithms.

Index	Algorithm			
	Lena original image	Logarithmic enhancement	Wavelet transform enhancement	Algorithm enhancements in this paper
Contrast $C$	274.60	326.86	544.62	624.53
Peak signal-to-noise ratio PSNR	40.11	40.06	40.03	40.153
Information entropy $H$	6.638	6.479	7.175	7.348

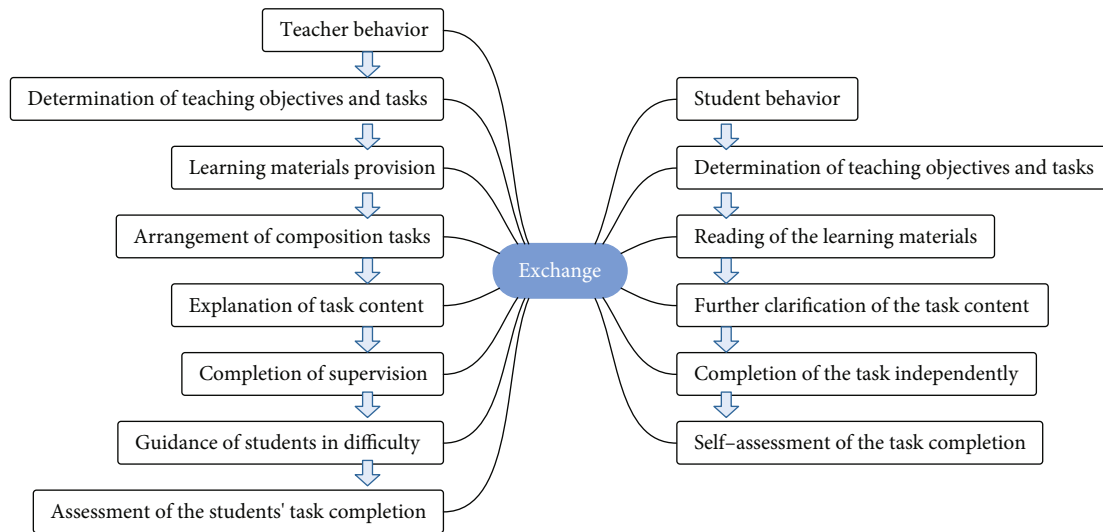


FIGURE 6: The design of the teaching process of personal mind map.

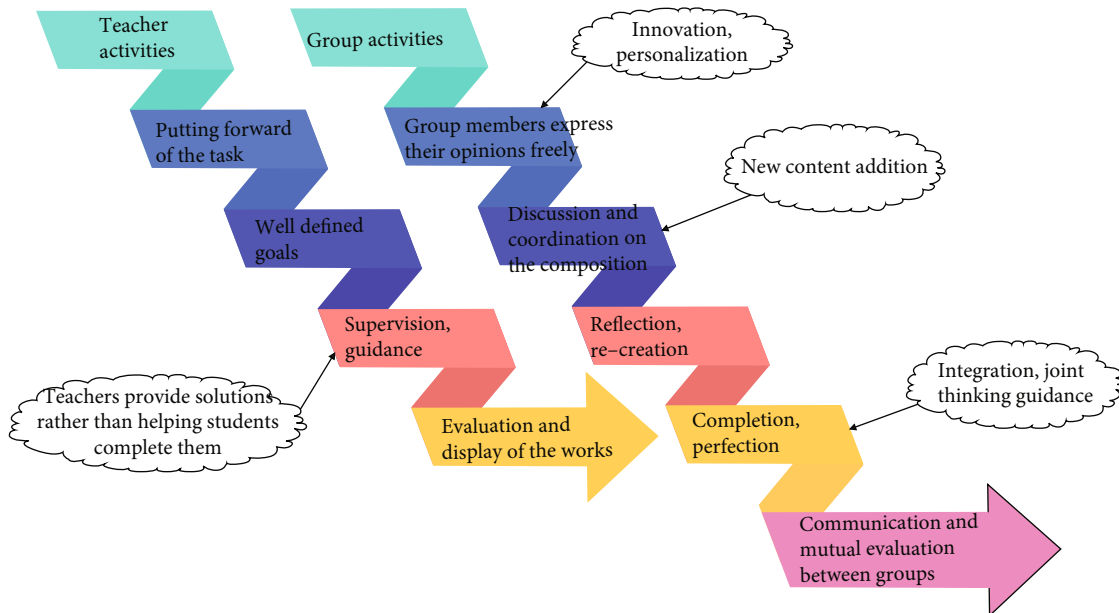


FIGURE 7: The strategy of drawing collective mind maps.



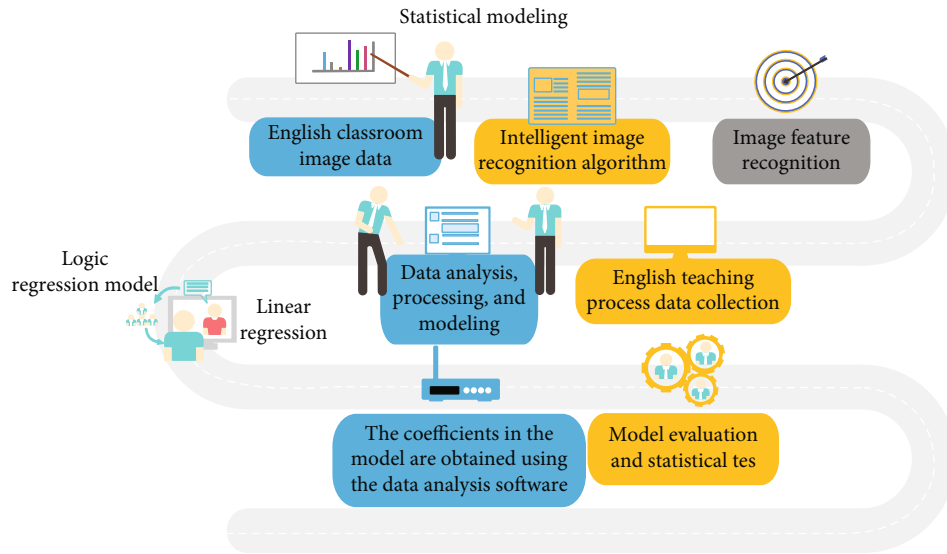


FIGURE 8: An analysis model of the English classroom mind mapping teaching effect based on the logistic regression model.

TABLE 2: The effect of feature recognition in English classroom teaching.

Number	Teaching feature recognition	Number	Teaching feature recognition	Number	Teaching feature recognition
1	94.51	20	94.06	39	93.09
2	91.61	21	92.31	40	93.20
3	88.55	22	95.78	41	93.15
4	91.95	23	87.95	42	88.21
5	88.07	24	95.62	43	93.87
6	93.84	25	90.12	44	91.84
7	92.28	26	92.49	45	92.29
8	87.31	27	88.48	46	88.48
9	95.51	28	93.80	47	95.00
10	93.27	29	90.90	48	89.54
11	92.72	30	91.55	49	89.41
12	88.39	31	91.20	50	95.35
13	92.86	32	92.04	51	88.78
14	91.96	33	94.51	52	95.99
15	88.92	34	89.89	53	87.49
16	93.73	35	88.76	54	94.64
17	92.73	36	88.70	55	90.53
18	90.40	37	89.73	56	89.12
19	88.66	38	89.27		

squared errors of each data. The formula for the information entropy of the image is

$$H_1 = - \sum_{i=0}^{255} P_i \ln P_i. \quad (34)$$

$P_i$  is the probability of a certain gray value of the image. Table 1 shows the data results of these three evaluation indicators in the enhanced images of different algorithms.

It can be seen from the table that although logarithmic enhancement increases the contrast, the information entropy decreases. Although the wavelet transform method has achieved certain results, the peak signal-to-noise ratio drops slightly. The algorithm in this paper has achieved the greatest enhancement in contrast and information entropy, and there is no drop in the peak signal-to-noise ratio. Therefore, it can be judged that the algorithm in this paper is better than the other two algorithms.

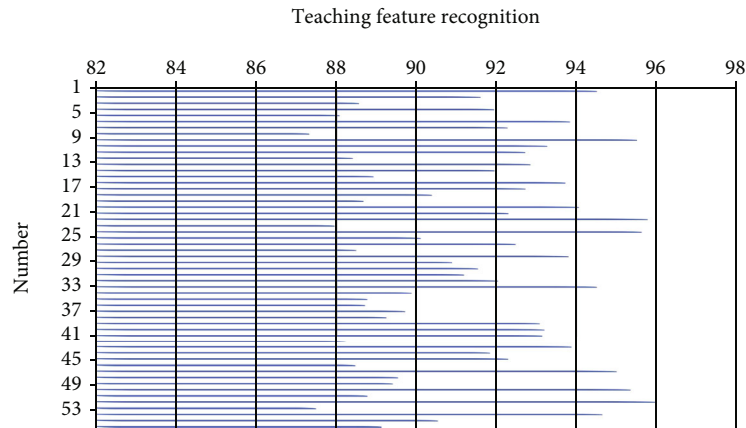


FIGURE 9: Statistical diagram of the effect of real-time feature extraction in English class.

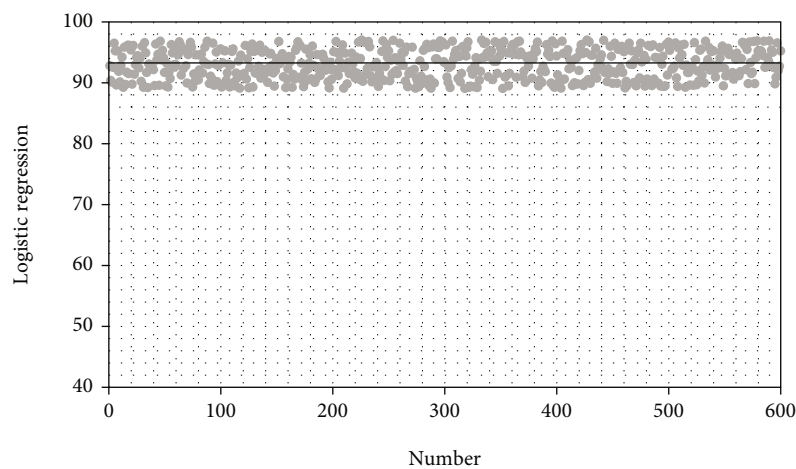


FIGURE 10: The effect evaluation of the analysis model of teaching effect of mind map in English classroom based on the logistic regression model.

#### 4. Analysis of the Teaching Effect of Mind Map in English Class Based on a Logistic Regression Model

In the teaching process, different teaching media and teaching methods are used because of the different topics selected, and different mind map drawing processes are formed. There are two main strategies for mind map construction: personal mind map drawing strategy and collective mind map drawing strategy. The two drawing strategies, the teacher's activity and the student's activity process, are, respectively, introduced in the form of a flowchart below. The personal mind map is drawn as shown in Figure 6.

In this model, there are two parts: teacher activities and group activities, as shown in Figure 7.

This article uses the third part of the image recognition method based on the pulse neural network to identify the classroom teaching process, collect the real-time dynamics of classroom teaching, and evaluate the teaching effect with the logistic regression model. The analysis model of the English classroom mind mapping teaching effect based on the logistic regression model is shown in Figure 8.

After constructing the above intelligent model, this paper evaluates the feature recognition effect of intelligent English classroom teaching in this paper through the simulation platform, and the results are shown in Table 2 and Figure 9.

The above research shows that the English classroom feature recognition based on spiking neural network proposed in this paper has a good effect. On this basis, this paper evaluates the analysis model of the English classroom mind mapping teaching effect based on the logistic regression model. The results obtained through logistic regression are shown in Figure 10.

From the above research, the analysis model of teaching effect of mind map in English classroom based on the logistic regression model proposed in this paper has good results, which also verifies that the mind map teaching can play an important role in English classroom teaching.

#### 5. Conclusion

As an effective thinking technology and cognitive tool, the mind map can not only guide and extend the thought

process but also record the thought process and carry out a clearer visual expression. At the same time, when establishing an individual's self-knowledge network, it is also conducive to the exchange and transmission of personal knowledge and information and affects the individual's cognition. From the previous discussion, we know that English learning is not only a language activity but also a thinking activity. Moreover, it is a procedural activity in which learners use their background knowledge, language skills, and thinking skills to communicate through words or oral language. This article combines the logistic regression model to evaluate the teaching effect of mind map in English classroom. The research results show that the analysis model of teaching effect of mind map in English classroom based on the logistic regression model proposed in this paper has good results, which also verifies that the mind map teaching can play an important role in English classroom teaching.

### Data Availability

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

### Conflicts of Interest

The authors declare no competing interests.

### Acknowledgments

This study is sponsored by Jiangxi University of Science and Technology.

### References

- [1] J. C. Richards, "Teaching English through English: proficiency, pedagogy and performance," *RELC Journal*, vol. 48, no. 1, pp. 7–30, 2017.
- [2] L. Susanty, Z. Hartati, R. Sholihin, A. Syahid, and F. Y. Liriwati, "Why English teaching truth on digital trends as an effort for effective learning and evaluation: opportunities and challenges: analysis of teaching English," *Linguistics and Culture Review*, vol. 5, no. S1, pp. 303–316, 2021.
- [3] A. S. Fatimah, S. Santiana, and Y. Saputra, "Digital comic: an innovation of using Toondoo as media technology for teaching English short story," *English Review: Journal of English Education*, vol. 7, no. 2, pp. 101–108, 2019.
- [4] B. Ayçiçek and T. Yanpar Yelken, "The effect of flipped classroom model on students' classroom engagement in teaching English," *International Journal of Instruction*, vol. 11, no. 2, pp. 385–398, 2018.
- [5] N. Guzachchova, "Zoom technology as an effective tool for distance learning in teaching English to medical students," *Бюллетень науки и практики*, vol. 6, no. 5, pp. 457–460, 2020.
- [6] M. S. Hadi, "The use of song in teaching English for junior high school student," *English Language in Focus (ELIF)*, vol. 1, no. 2, pp. 107–112, 2019.
- [7] A. Mahboob, "Beyond global Englishes: teaching English as a dynamic language," *RELC Journal*, vol. 49, no. 1, pp. 36–57, 2018.
- [8] H. Sundari, "Classroom interaction in teaching English as foreign language at lower secondary schools in Indonesia," *Advances in Language and Literary Studies*, vol. 8, no. 6, pp. 147–154, 2017.
- [9] A. Gupta, "Principles and practices of teaching English language learners," *International Education Studies*, vol. 12, no. 7, pp. 49–57, 2019.
- [10] B. S. Abdelshaheed, "Using flipped learning model in teaching English language among female English majors in Majmaah University," *English Language Teaching*, vol. 10, no. 11, pp. 96–110, 2017.
- [11] T. A. Ashraf, "Teaching English as a foreign language in Saudi Arabia: struggles and strategies," *International Journal of English Language Education*, vol. 6, no. 1, pp. 133–154, 2017.
- [12] O. Tarnopolsky, "Principled pragmatism, or well-grounded eclecticism: a new paradigm in teaching English as a foreign language at Ukrainian tertiary schools?," *Advanced Education*, vol. 5, no. 10, pp. 5–11, 2018.
- [13] N. I. Sayakhan and D. H. Bradley, "A nursery rhymes as a vehicle for teaching English as a foreign language," *Journal of University of Raparin*, vol. 6, no. 1, pp. 44–55, 2019.
- [14] D. A. W. Nurhayati, "Students' perspective on innovative teaching model using Edmodo in teaching English phonology: "a virtual class development"," *Dinamika Ilmu*, vol. 19, no. 1, pp. 13–35, 2019.
- [15] A. B. Rinekso and A. B. Muslim, "Synchronous online discussion: teaching English in higher education amidst the covid-19 pandemic," *JEES (Journal of English Educators Society)*, vol. 5, no. 2, pp. 155–162, 2020.
- [16] A. S. N. Agung, "Current challenges in teaching English in least-developed region in Indonesia," *SOSHUM: Jurnal Sosial Dan Humaniora*, vol. 9, no. 3, pp. 266–271, 2019.
- [17] M. A. Saydaliyeva, E. B. Atamirzayeva, and F. X. Dadaboyeva, "Modern methods of teaching English in Namangan state university," *International Journal on Integrated Education*, vol. 3, no. 1, pp. 8–9, 2020.
- [18] L. B. Kelly, "Preservice teachers' developing conceptions of teaching English learners," *TESOL Quarterly*, vol. 52, no. 1, pp. 110–136, 2018.
- [19] A. Coşkun, "The application of lesson study in teaching English as a foreign language," *İnönü Üniversitesi Eğitim Fakültesi Dergisi*, vol. 18, no. 1, pp. 151–162, 2017.