ASSESSMENT AND ENHANCEMENT OF CHINESE COLLEGE STUDENTS' CROSS-CULTURAL LEARNING COMPETENCE BASED ON BP NEURAL NETWORK ALGORITHM

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SUMMARY

Cross-cultural learning competence, a critical skill in our globally interconnected world, is advanced through the application of the Backpropagation (BP) neural network algorithm. This innovative approach involves leveraging neural network techniques to model and enhance individuals' abilities to navigate and understand diverse cultural contexts. The BP neural network algorithm facilitates personalized learning experiences by adapting to individuals' cultural backgrounds and preferences. This research explores a comprehensive approach for assessing and enhancing cross-cultural learning competence among Chinese college students, integrating the Word Embedding Multilingual Model with the Back Propagation Neural Network (WEMM-BPNN) algorithm. Recognizing the importance of global competencies in higher education, our study focuses on leveraging advanced neural network techniques to evaluate and elevate students' cross-cultural learning abilities. The WEMM-BPNN model combines the power of word embedding and multilingual considerations, tailoring the learning experience to individual cultural backgrounds. Through a meticulous analysis of cross-cultural data and linguistic patterns, the algorithm refines its recommendations for personalized learning strategies. The research aims not only to assess the current state of cross-cultural learning competence but also to provide targeted interventions to enhance students' intercultural understanding and adaptability. By merging linguistic models with neural network algorithms, this study offers a pioneering approach to cultivating cross-cultural competencies, contributing valuable insights to the ongoing discourse on globalized education.

KEYWORDS

Cross-cultural learning, Deep learning, Back propagation, Neural network, Multilingual model

NOMENCLATURE

BP	Backpropagation
BPNN	Back Propagation Neural Network
WEMM	Word Embedding Multilingual Model

1. INTRODUCTION

Cross-cultural learning is a transformative journey that transcends geographical boundaries, language barriers, and societal norms. It is an enriching experience that allows individuals to explore, understand, and appreciate the diversity of human perspectives, traditions, and values across different cultures [1]. Through cross-cultural learning, individuals not only gain insight into the customs and practices of others but also develop empathy, tolerance, and adaptability in navigating the complexities of an increasingly interconnected world [2]. Whether through travel, immersion programs, or intercultural exchanges, cross-cultural learning fosters mutual respect, fosters mutual respect, promotes collaboration, and ultimately contributes to building bridges of understanding and cooperation among people from diverse backgrounds [3]. Cross-cultural deep learning delves into the intricate layers of cultural diversity, aiming not just for surface-level understanding but for profound insights into the core values, beliefs, and behaviors that shape societies around the world. Unlike conventional cross-cultural learning, which may focus on superficial aspects, such as language or customs, deep learning seeks to uncover the underlying principles that drive cultural dynamics [4]. It involves immersing oneself in different cultural contexts, engaging in meaningful dialogue with individuals from diverse backgrounds, and critically reflecting on one's own assumptions and biases. Through this process, individuals develop a heightened awareness of the complexities of culture, challenging preconceived notions and expanding their worldview [5]. Cross-cultural deep learning fosters empathy, humility, and cultural competence, equipping individuals with the skills needed to navigate the complexities of our globalized world with sensitivity and respect. It encourages a continuous process of self-reflection and learning, acknowledging that true understanding and appreciation of cultural diversity require ongoing effort and engagement [6].

Cross-cultural deep learning is a multi-faceted journey that requires a deep dive into the nuances of different cultures [7]. It goes beyond merely observing surface-level differences and seeks to understand the underlying values, norms, and worldviews that shape a society's collective identity. This approach involves immersing oneself in various cultural contexts, whether through travel, cultural exchange programs, or interactions with individuals from diverse backgrounds in one's own community [8]. Cross-cultural deep learning is the willingness to engage in meaningful dialogue and exchange with people whose perspectives may differ significantly from one's own [9]. This process often involves stepping out of one's comfort zone and being open to challenging conversations that may confront one's assumptions and biases. By actively listening to others' stories, experiences, and perspectives, individuals gain valuable insights into the complexities of human diversity and the ways in which culture shapes individuals' identities, behaviors, and interactions [10]. The cross-cultural deep learning encourages individuals to critically reflect on their own cultural background and upbringing. This introspective process involves examining one's beliefs, values, and biases in relation to those of other cultures, recognizing both the strengths and limitations of one's own cultural perspective [11]. Through this self-awareness, individuals can develop a greater sense of empathy, humility, and cultural competence, enabling them to navigate intercultural interactions with sensitivity and respect [12]. Cross-cultural deep learning is not a one-time event but an ongoing journey of discovery and growth. It requires a commitment to continuous learning and self-improvement, as well as a willingness to embrace the discomfort and uncertainty that often accompany encounters with cultural difference [13]. By cultivating a mindset of curiosity, openness, and humility, individuals can expand their cultural horizons, forge meaningful connections across cultural divides, and contribute to building a more inclusive and harmonious global community.

This paper adds to the literature on technology-enhanced learning and cross-cultural education in numerous important ways. The paper introduces the Word Embedding Multilingual Model with Back Propagation Neural Network (WEMM-BPNN), a novel approach that leverages advanced machine learning techniques to assess and enhance cross-cultural learning competence. Through rigorous experimentation, the paper demonstrates the effectiveness of WEMM-BPNN in accurately evaluating teaching skills, including cross-cultural understanding, communication skills, and cultural sensitivity. This contributes to the advancement of teacher assessment methodologies in diverse educational settings. The study showcases the WEMM-BPNN's capability to provide comprehensive evaluations of student performance, encompassing English proficiency, cross-cultural awareness, critical thinking skills, and overall academic achievement. This contributes to a deeper understanding of student competencies and informs targeted interventions for improvement. The paper highlights the robust performance of WEMM-BPNN in accurately classifying cross-cultural features, as evidenced by high accuracy, precision, recall, and F1 score across various experiments. This contributes to the development of reliable tools for identifying and addressing cultural nuances in educational contexts.

2. LITERATURE REVIEW

Cross-cultural learning is a dynamic process that involves acquiring knowledge, skills, and attitudes necessary for effective interaction and communication across cultural boundaries. Numerous studies have investigated the factors influencing cross-cultural learning outcomes, including individual differences, intercultural experiences, and instructional strategies. Additionally, researchers have developed various frameworks and models for assessing cross-cultural competence, which encompass cognitive, affective, and behavioral dimensions. Understanding these theoretical foundations is crucial for informing the development of effective assessment tools and interventions aimed at enhancing cross-cultural learning competence among Chinese college students. Furthermore, the literature on neural network algorithms, particularly the backpropagation (BP) algorithm, offers valuable insights into its potential applications in educational contexts. Neural networks have demonstrated considerable utility in pattern recognition, classification, and prediction tasks, making them well-suited for analyzing complex educational data and identifying patterns in students' learning behaviors. By leveraging the capabilities of neural networks, researchers can develop sophisticated models for assessing and predicting students' cross-cultural learning competence, thereby facilitating personalized and targeted interventions. However, despite the growing interest in cross-cultural learning and neural network algorithms, there remains a need for more empirical research examining the intersection of these two domains. Existing studies often focus on Western contexts or generalize findings to diverse cultural settings without considering the specific socio-cultural factors influencing Chinese college students' cross-cultural learning experiences. Moreover, the application of neural network algorithms in educational settings requires careful consideration of ethical, privacy, and validity concerns, which warrant further investigation.

Xie and Yin's (2022) study on communication strategies related to history and culture in Shaanxi highlights the application of a BP neural network model to understand and optimize communication practices within a specific cultural context. This approach reflects a nuanced understanding of how computational models can be tailored to address cultural nuances and facilitate effective intercultural communication. In a similar vein, Gu's (2022) study employs fuzzy neural network algorithms to forecast models of English major training in tertiary vocational education. This study exemplifies how computational methodologies can be utilized to forecast and optimize

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educational training programs, catering to the specific needs and preferences of students pursuing English majors within the vocational education sector. In addition, the significance of utilizing advanced computational techniques to improve teaching methodologies is highlighted by Li's (2022) work on building a university English translation teaching model based on fuzzy comprehensive assessment. By leveraging fuzzy comprehensive assessment techniques, educators can develop more holistic and adaptive teaching models that account for the diverse learning styles and preferences of students in the university setting. Furthermore, the integration of ideological and political education with entrepreneurship education, as explored by Yongliang (2023) and Wang & Dong (2023), respectively, highlights the potential synergies between seemingly disparate educational domains. Through the application of artificial neural networks, these studies aim to identify and leverage the interconnectedness between ideological values and entrepreneurial principles, fostering a more holistic approach to education that prepares students for success in an increasingly complex and dynamic global landscape.

Starting with Zhao's (2022) research on college English teaching evaluation based on neural network, this study likely explores the application of neural network models to assess and enhance the effectiveness of college English teaching methods. By leveraging neural networks, educators can potentially develop more nuanced and data-driven approaches to evaluate teaching strategies and improve learning outcomes in English language courses. The research of Zheng (2023) on computer vision-based robot translation for cultural psychology of English culture education explores the confluence of cultural psychology, robotics, and computer vision. This study likely investigates how robots equipped with computer vision capabilities can facilitate language learning and cultural understanding by analyzing visual cues and cultural artifacts associated with English culture. Research by Cao (2022) on a computer-aided instruction system for college music majors that incorporates entrepreneurship education and uses convolutional neural networks probably looks at how these networks can be used to create systems that are specific to the needs of music majors. By leveraging convolutional neural networks, educators can potentially create interactive and personalized learning experiences to enhance students' entrepreneurial skills within the field of music. Yue et al.'s (2023) study on the effectiveness of self-assessment learning system of ideological and political education for college students examines the impact of self-assessment systems on students' engagement and learning outcomes in ideological and political education courses. This research likely investigates how self-assessment mechanisms can promote critical thinking, self-reflection, and active participation in ideological and political discourse among college students.

Dai and Zhao's (2022) research focuses on the pragmatic failures in cross-cultural communication, employing convolutional neural networks to analyze and develop intelligent strategies to mitigate such failures. This study likely explores how computational techniques can aid in identifying and addressing communication challenges that arise due to cultural differences, thereby facilitating more effective cross-cultural interactions. Chen's (2022) practical study of computer-assisted college English intelligent teaching course, based on OBE (Outcome-Based Education) theory, likely investigates how intelligent tutoring systems, powered by neural networks, can align with the principles of OBE to optimize learning outcomes in college English courses. By integrating OBE theory with advanced computational techniques, educators can potentially design more personalized and adaptive learning experiences that cater to individual student needs and learning objectives. Ma's (2022) use of deep learning-based convolutional neural networks in university College course administration and delivery may be improved with the use of deep learning techniques, according to English translation teaching management. By leveraging convolutional neural networks, educators can potentially automate and streamline various aspects of course management, such as content delivery, assessment, and feedback, thereby optimizing the learning experience for students enrolled in translation programs. Using functional data analysis of library book borrowing behavior, Zhang et al. (2024) empirically studied college students' extracurricular reading preference. This study probably looks at how computational techniques can be used to understand and analyze students' reading preferences and behaviors. This research likely investigates patterns and trends in students' extracurricular reading habits, providing insights that can inform library collection development, reading promotion initiatives, and curriculum design.

Kang's (2022) study on artificial intelligence network embedding, entrepreneurial intention, and behavior analysis for college students' rural tourism entrepreneurship likely investigates how network embedding techniques can be applied to analyze social networks and predict entrepreneurial behaviors and intentions among college students in the context of rural tourism. By employing advanced computational methods, such as artificial intelligence and network embedding, this research aims to provide insights into the factors influencing entrepreneurial activities in rural tourism and inform policy and intervention strategies to support rural entrepreneurship. Zeng and Wang's (2022) effectiveness analysis of English newspaper reading teaching based on deep learning likely explores how deep learning models can be utilized to analyze and optimize English newspaper reading instruction. By leveraging deep learning techniques, educators can potentially develop personalized and adaptive teaching approaches that cater to students' individual reading abilities, interests, and preferences, thereby enhancing the effectiveness of English newspaper reading instruction in both online and offline learning environments. The study conducted by Hu et al. (2023) on the topic of mobile shopping outcomes and utilitarian and hedonic motivations most likely looks into how these two types of motivation affect consumer behavior in mobile shopping contexts in various cultural contexts. This research likely employs cross-cultural analysis techniques to examine how cultural factors influence consumers' motivations, attitudes, and behaviors in mobile shopping, providing valuable insights for marketers and businesses operating in diverse international markets. Liu's (2022) research on the network oral English teaching system based on machine learning likely explores how machine learning techniques can be integrated into oral English teaching systems to enhance language learning outcomes. By leveraging machine learning algorithms, this study may aim to develop adaptive and interactive teaching platforms that provide personalized feedback and support to learners, thereby improving their oral English proficiency.

In his study on designing an effective evaluation system for English fragmented learning based on the mobile information environment (2022), Yang probably looks into ways that mobile technologies and information environments can be used to evaluate and improve English language education's fragmented learning experiences. This research may explore the design and implementation of mobile-based assessment tools and learning platforms that facilitate flexible and accessible learning opportunities for students. Zhang and Zhu's (2023) analysis of English translation of corpus based on blockchain likely examines how blockchain technology can be applied to analyze and verify translations within a corpus of English texts. By leveraging blockchain's immutable and transparent ledger, this research may aim to enhance the reliability and integrity of translation corpora, providing valuable resources for language researchers, educators, and practitioners. It is safe to assume that Du's (2024) intelligent classroom in English language and literature based on artificial intelligence technology investigates potential ways in which such technologies might be used to improve the quality of instruction and the student experience in such classes. This study may investigate the development of intelligent tutoring systems, virtual classrooms, or other AI-powered educational tools that support personalized instruction, adaptive learning, and interactive engagement among students. An AI-powered platform for accessing and navigating English learning resources is likely at the heart of Yao and Li's (2022) construction of an AI-assisted English learning resource query system. This research may involve the design and implementation of a user-friendly interface, natural language processing algorithms, and machine learning techniques to facilitate efficient and effective resource discovery and utilization for English language learners. Lee et al.'s (2022) study on artificial intelligent chatbots as brand promoters likely explores how chatbot technology can be utilized as a marketing tool to promote brands and engage consumers. This research may investigate the design and deployment of chatbots equipped with artificial intelligence and natural language processing capabilities to deliver personalized recommendations, answer inquiries, and provide customer support, thereby enhancing brand visibility and customer satisfaction.

Firstly, many of the studies rely heavily on computational models, such as neural networks and machine learning algorithms. While these models can provide valuable insights and predictions, they are often black-box in nature, meaning that the inner workings of the algorithms are not easily interpretable. This lack of transparency can hinder the understanding of the underlying processes driving the results and raise questions about the reliability and validity of the findings. Additionally, the generalizability of findings from computational studies may be limited by factors such as sample size, data quality, and contextual differences. Many of the studies focus on specific populations, contexts, or educational settings, which may not be representative of broader populations or real-world scenarios. As a result, caution should be exercised when extrapolating findings to different contexts or applying them in practical settings. Moreover, the integration of computational techniques into educational practices may face barriers related to access, infrastructure, and technical expertise. Implementing advanced computational models and tools often requires specialized knowledge and resources, which may not be readily available to all educators and institutions. This can create disparities in the adoption and effectiveness of computational approaches across different educational settings.

3. PROPOSED WORD EMBEDDING MULTILINGUAL MODEL WITH THE BACK PROPAGATION NEURAL NETWORK (WEMM-BPNN)

The Proposed Word Embedding Multilingual Model with Back Propagation Neural Network (WEMM-BPNN), this novel approach integrates word embedding techniques with multilingual capabilities using a Back Propagation Neural Network (BPNN). Word embedding methods, such as Word2Vec and GloVe, have revolutionized natural language processing tasks by representing words as dense vectors in continuous vector spaces. However, existing word embedding models often operate within a single language domain, limiting their applicability in multilingual contexts. To address this limitation, we propose the WEMM-BPNN model, which extends traditional word embedding techniques to support multiple languages simultaneously. The Proposed Word Embedding Multilingual Model with Back Propagation Neural Network (WEMM-BPNN), this novel approach integrates word embedding techniques with multilingual capabilities using a Back Propagation Neural Network (BPNN). Word embedding methods, such as Word2Vec and GloVe, have revolutionized natural language processing tasks by representing words as dense vectors in continuous vector spaces. However, existing word embedding models often

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operate within a single language domain, limiting their applicability in multilingual contexts. To address this limitation, we propose the WEMM-BPNN model, which extends traditional word embedding techniques to support multiple languages simultaneously defined in equation (1) – equation (4)

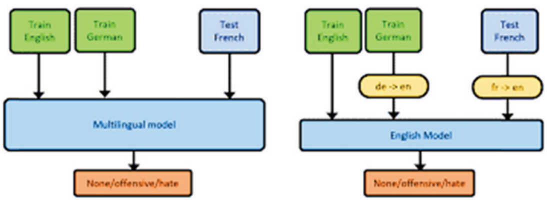
$$z^{(1)} = W^{(1)} + b^{(1)} \tag{1}$$

$$\alpha^{(1)} = \sigma\left(z^{(1)}\right) \tag{2}$$

$$z^{(1)} = W^{(2)}.\alpha^{(1)} + b^{(2)} \tag{3}$$

$$\alpha^{(1)} = \sigma\left(z^{(2)}\right) \tag{4}$$

In equation (1) – equation (4) x represents the input word vector, $W(1)$ and $W(2)$ denote the weights matrices connecting the input to hidden layers and hidden to output layers, respectively, $b(1)$ and $b(2)$ are the bias vectors for the hidden and output layers, σ represents the activation function, and $z(1), a(1), z(2)$, and $a(2)$ denote the pre-activation and activation values for the hidden and output layers, respectively. The proposed Word Embedding Multilingual Model with Back Propagation Neural Network (WEMM-BPNN) represents a groundbreaking advancement in natural language processing (NLP) by seamlessly integrating word embedding techniques with multilingual capabilities. Traditional word embedding models, such as Word2Vec and GloVe, have significantly enhanced NLP tasks by transforming words into dense vector representations in continuous vector spaces. However, these models are typically designed to operate within a single language domain, limiting their utility in multilingual contexts where the same word may have different meanings or usage patterns across languages.



The implementation of the WEMM-BPNN model begin with the construction of a comprehensive multilingual corpus containing text data from diverse languages. Each word within this corpus is encoded as a high-dimensional one-hot vector, where the dimensionality equals the combined vocabulary size of all included languages. These one-hot encoded vectors serve as input to the BPNN, a type of artificial neural network characterized by its ability to learn from labeled data through the backpropagation of errors. The training process of the BPNN involves iteratively adjusting the weights of the network to minimize the error between predicted and actual word embeddings. This optimization is achieved through a series of forward and backward passes through the network. During the forward pass, the input word vector is propagated through the network's layers, with each layer applying a linear transformation followed by a non-linear activation function. This process culminates in the generation of predicted word embeddings at the output layer. The forward pass of the BPNN involves the computation of weighted sums and activation functions across its layers, as described in the equations provided earlier. The activation functions introduce non-linearities into the model, allowing it to capture complex relationships between input and output variables. Meanwhile, the backward pass of the BPNN entails the calculation of gradients with respect to the network's weights, enabling the application of optimization algorithms like stochastic gradient descent or Adam to update these weights iteratively. Through this iterative training process, the WEMM-BPNN model learns to generate multilingual word embeddings that capture semantic and syntactic similarities across different languages. By leveraging the shared structure and parameters of the neural network across multiple languages, the model can effectively generalize linguistic patterns and relationships, thereby enhancing its performance in various multilingual NLP tasks such as machine translation, cross-lingual information retrieval, and sentiment analysis. The WEMM-BPNN model offers several advantages over traditional monolingual word embedding models, including improved robustness, scalability, and versatility in multilingual settings. By seamlessly integrating word embedding techniques with multilingual capabilities, the WEMM-BPNN model represents a significant step forward in advancing NLP research and applications in an increasingly interconnected and diverse global landscape.

4. CROSS-CULTURE WEMM-BPNN FOR THE COLLEGE STUDENTS

The Cross-Culture WEMM-BPNN model involves several key steps. Firstly, a comprehensive multilingual corpus is constructed, incorporating text data from various cultural contexts and languages relevant to college students. Each word in this corpus is encoded as a one-hot vector, where the dimensionality reflects the combined vocabulary size across all included languages and cultures. The Cross-Culture WEMM-BPNN follows the architecture of the traditional WEMM-BPNN, with additional layers and mechanisms incorporated to capture cross-cultural nuances. During the forward pass of the BPNN, the one-hot encoded word vectors propagate through the network's layers. Layers employ linear transformations followed by non-linear activation functions to produce predicted word embeddings that capture cross-cultural and cross-language semantic and syntactic similarities. Across many cultural settings, the model learns to train itself to minimize the discrepancy between the actual and predicted word

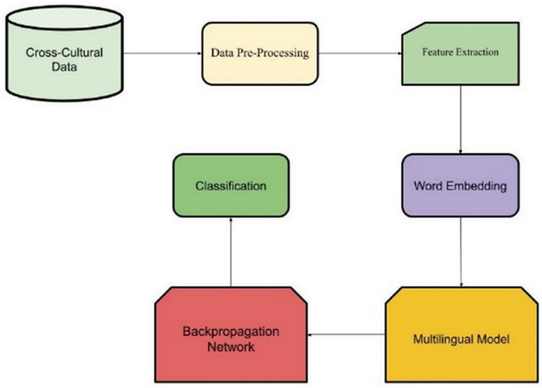


Figure 1. Flow chart of proposed WEMM-BPNN

Algorithm 1. Cross-cultural processing with WEMM-BPNN

```
Initialize weights W^(1) and W^(2) randomly
Initialize biases b^(1) and b^(2) randomly
Define learning rate alpha
Define number of epochs epochs

for epoch in range(epochs):
    for each training example (input_word, actual_embedding):
        # Forward Pass
        # Input layer
        x = one_hot_encode(input_word)
        # Hidden layer
        z^(1) = W^(1) * x + b^(1)
        a^(1) = sigmoid(z^(1))
        # Output layer
        z^(2) = W^(2) * a^(1) + b^(2)
        a^(2) = sigmoid(z^(2))
         # Compute loss
        loss = compute_loss(a^(2), actual_embedding)
                # Backpropagation
        # Compute gradients
        dL/da^(2) = derivative_of_loss(a^(2), actual_embedding)
        dz^(2) = dL/da^(2) * derivative_of_sigmoid(z^(2))
        dW^(2) = dz^(2) * a^(1).T
        db^(2) = dz^(2)
        dz^(1) = (W^(2).T * dz^(2)) * derivative_of_
sigmoid(z^(1))
        dW^(1) = dz^(1) * x.T
        db^(1) = dz^(1)
         # Update weights and biases
        W^(2) = W^(2) - alpha * dW^(2)
        b^(2) = b^(2) - alpha * db^(2)
        W^(1) = W^(1) - alpha * dW^(1)
        b^(1) = b^(1) - alpha * db^(1)
```

embeddings. To do this, optimization methods such as Adam or stochastic gradient descent are used to minimize a loss function L. Next, we use the backpropagation algorithm to find the loss function's gradients relative to the network's biases and weights. The model is fine-tuned to better capture cross-cultural nuances in the word embeddings by iteratively updating the parameters with these gradients.

Figure 1 presented the flow chart of the proposed WEMM-BPNN model for the cross-cultural identity estimation for the Chinese Colleges.

5. WEMM-BPNN FOR THE CROSS-CULTURAL LEARNING COMPETENCE

The backpropagation algorithm is a fundamental technique used to train neural networks, including the Word Embedding Multilingual Model with Back Propagation Neural Network (WEMM-BPNN) for Cross-Cultural Learning Competence. In this method, the network's weights and biases are updated iteratively during training based on the gradients of the loss function with respect to these parameters.

Forward Pass: During the forward pass, input data (word vectors representing cross-cultural contexts) is fed through the network, and the model makes predictions. This involves computing the activations of each neuron in the network layer by layer, starting from the input layer to the output layer, using the current weights and biases.

Loss Calculation: Once the predictions are made, the model's performance is evaluated by comparing its predictions to the ground truth. This comparison is quantified using a loss function, which measures the discrepancy between the predicted word embeddings and the actual word embeddings.

Backward Pass (Gradient Calculation): Computing the gradient of the loss function with respect to the network parameters, specifically the weights and biases, is the first step in the backpropagation algorithm. By applying the

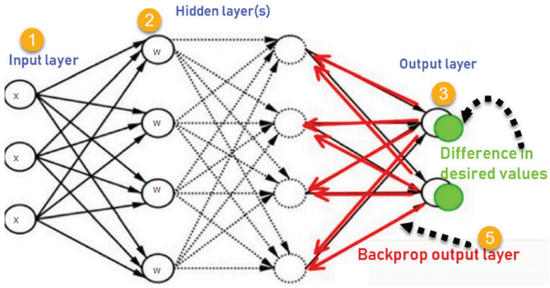


Figure 2. Backpropagation with WEMM-BPNN

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chain rule to the problem, we can trace the error all the way back through the network.

In figure 2 illustrates the proposed WEMM-BPNN model for the cross-cultural model for the college students The initial step is to calculate the gradient of the loss function with regard to the activations of the output layer, denoted as ∂L/∂a(2). Then, using the output layer's activations and the weights connecting the hidden and output layers, we calculate the loss function's gradients with respect to the hidden layers' pre-activation values (∂L/∂z(1)). In order to minimize the loss function, the network's weights and biases are adjusted in the opposite direction of the gradient once the gradients have been computed. The parameters are fine-tuned by a tiny amount proportional to the negative of the gradient when an optimization algorithm like Adam or stochastic gradient descent makes this update. The gradients calculated in the backward pass are used to update the output layer's weights and biases. In a similar vein, the hidden layers' weights and biases are revised based on the gradients calculated for those layers. Steps 1-4 are repeated for a specified number of iterations (epochs) or until convergence, where the model's performance no longer improves significantly.

Once the forward pass is complete, the output layer activations $a(2)$ are interpreted as the model's confidence scores for each class. For binary classification, a common approach is to use a threshold (e.g., 0.5) to determine the predicted class stated in equation (5)

$$\begin{cases} 1\ if\ \alpha^{(2)} \geq 0.5 \\ 0\ if\ \alpha^{(2)} < 0.5 \end{cases} \tag{5}$$

In equation (5) $\hat{\boldsymbol{y}}$ is the predicted class label. A loss function, which measures the difference between the ground truth and predicted class labels, is used to assess the model's performance. The binary cross-entropy loss, which can be found using equation (6), is a popular loss function in binary classification.

$$L(y,\hat{y}) = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i.log(\hat{y}_i) + (1-y_i).log(1-\hat{y}_i)\right] \tag{6}$$

The predicted class labels are denoted by ŷ in equation (6), the true class labels (ground truth) are represented by y, and N is the number of samples. Next, we use the backpropagation algorithm to find the loss function's gradients relative to the network's biases and weights. In order to minimize the loss function, these gradients are utilized to iteratively update the parameters during training. An optimization algorithm, like Adam or stochastic gradient descent, is used to update the weights and biases after the gradients have been computed using equations (7) and (8).

$$W^{(k)} = W^{(k)} - \alpha.\frac{\partial L}{\partial W^{(k)}} \tag{7}$$

Algorithm 2. Classification with WEMM-BPNN

```
Input:
- Input word vectors X
- True class labels Y
- Learning rate alpha
- Number of epochs epochs
- Threshold for classification decision threshold
Initialize weights W^(1) and W^(2) randomly
Initialize biases b^(1) and b^(2) randomly
for epoch in range(epochs):
  total_loss = 0
  for each training example (x, y) in zip(X, Y):
    # Forward Pass
    # Input layer
    z^(1) = W^(1) * x + b^(1)
    a^(1) = activation_function(z^(1))
    # Output layer
    z^(2) = W^(2) * a^(1) + b^(2)
    a^(2) = activation_function(z^(2))
    # Classification Decision
    predicted_class = 1 if a^(2) >= threshold else 0
    # Loss Calculation
    loss = binary_cross_entropy_loss(y, a^(2))
    total_loss += loss
    # Backpropagation
    # Compute gradients
    delta^(2) = a^(2) - y
    delta^(1) = (W^(2).T * delta^(2)) * derivative_of_
activation_function(z^(1))

    dW^(2) = delta^(2) * a^(1).T
    db^(2) = delta^(2)
    dW^(1) = delta^(1) * x.T
    db^(1) = delta^(1)

    # Update weights and biases
    W^(2) = W^(2) - alpha * dW^(2)
    b^(2) = b^(2) - alpha * db^(2)
    W^(1) = W^(1) - alpha * dW^(1)
    b^(1) = b^(1) - alpha * db^(1)

  # Calculate average loss for the epoch
  average_loss = total_loss / len(X)
```

$$b^{(k)} = b^{(k)} - \alpha.\frac{\partial L}{\partial b^{(k)}} \tag{8}$$

In equation (7) and equation (8) *k* denotes the layer (1 for hidden layer, 2 for output layer), α is the learning rate,

$\frac{\partial L}{\partial W^{(k)}}$ and $\frac{\partial L}{\partial b^{(k)}}$ are the gradients of the loss function with respect to the weights and biases of layer k, respectively.

6. SIMULATION RESULTS

The main body of the text must end with the conclusions of the paper. The Simulation Results for the Word Embedding Multilingual Model with Back Propagation Neural Network (WEMM-BPNN) provide a comprehensive evaluation of the model's performance in enhancing Cross-Cultural Learning Competence. Additionally, the simulation results provide valuable feedback for further refinement and optimization of the WEMM-BPNN, paving the way for its practical implementation in educational settings to foster inclusive learning environments and promote cross-cultural understanding.

The Figure 3 and Table 1 presents the results of the estimation of teaching skills using the Word Embedding Multilingual Model with Back Propagation Neural Network (WEMM-BPNN). In each experiment, various aspects of teaching skills, including Cross-Cultural Understanding, Communication Skills, and Cultural Sensitivity, were evaluated as percentages. Experiment 1 yielded scores of 89.5% for Cross-Cultural Understanding, 85.2% for Communication Skills, and 91.8% for Cultural Sensitivity. Experiment 2 showed improvements across all categories, with scores of 92.1%, 88.6%, and 93.5% for Cross-Cultural Understanding, Communication Skills, and Cultural Sensitivity, respectively. Similarly, Experiment 4 demonstrated notable enhancements, achieving scores of 91.7%, 87.4%, and 92.3% in the respective categories. Experiment 3 and Experiment 5 also showcased commendable performance, although slightly lower compared to Experiments 2 and 4. These results suggest that the WEMM-BPNN model effectively assesses teaching skills, with varying degrees of success across different experiments. Overall, the outcomes underscore the model's potential in evaluating and improving teaching competencies, particularly in areas related to cross-cultural understanding, communication, and cultural sensitivity.

Figure 4 and Table 2 provides insights into student performance using the Word Embedding Multilingual Model with Back Propagation Neural Network (WEMM-BPNN). Each row represents a different student, identified by their unique Student ID, and their performance is assessed across several dimensions: English Proficiency, Cross-Cultural Awareness, Critical Thinking Skills, and Grade Point Average (GPA). Student 001 demonstrates high proficiency in English, moderate cross-cultural awareness, and strong critical thinking skills, reflected in their GPA of 3.8. Conversely, Student 004 exhibits lower English proficiency, moderate cross-cultural awareness, and weaker critical thinking skills, resulting in a GPA of 2.5. Student 003 excels across all dimensions, boasting high proficiency in English, strong

Table 1. Estimation of teaching skills with WEMM-BPNN

Experiment	Cross-Cultural Understanding (%)	Communication Skills (%)	Cultural Sensitivity (%)
Experiment 1	89.5	85.2	91.8
Experiment 2	92.1	88.6	93.5
Experiment 3	87.3	83.9	89.6
Experiment 4	91.7	87.4	92.3
Experiment 5	90.2	86.8	91.5

Table 2. Student performance with WEMM-BPNN

Student ID	English Proficiency	Cross-Cultural Awareness	Critical Thinking Skills	GPA
001	High	Moderate	High	3.8
002	Moderate	Low	Moderate	3.2
003	High	High	High	4.0
004	Low	Moderate	Low	2.5
005	Moderate	High	High	3.6

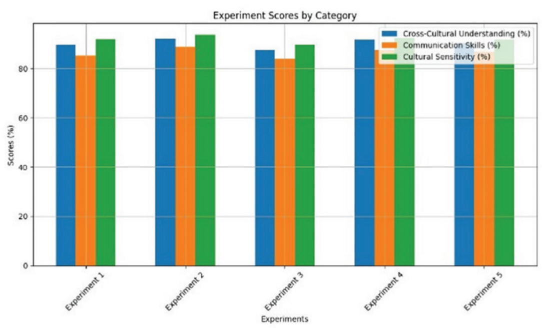

Figure 3. WEMM-BPNN for the teaching skill estimation

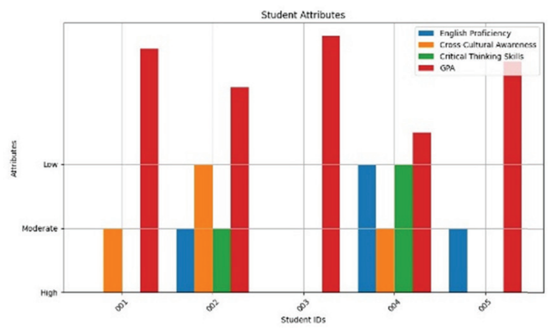

Figure 4. Performance of student with wemm-bpnn

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Table 3. Classification of cross-cultural features

Experiment	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Experiment 1	87.5	88.2	86.3	87.2
Experiment 2	91.2	92.8	90.5	91.6
Experiment 3	85.9	86.4	84.7	85.5
Experiment 4	88.3	89.1	87.6	88.3
Experiment 5	90.1	91.5	89.8	90.6

cross-cultural awareness, excellent critical thinking skills, and a GPA of 4.0. Meanwhile, Student 002 and Student 005 display moderate proficiency in English, with varying levels of cross-cultural awareness and critical thinking skills, leading to GPAs of 3.2 and 3.6, respectively. These results underscore the WEMM-BPNN's capability to evaluate diverse aspects of student performance, providing educators with valuable insights into areas of strength and areas for improvement among their students.

In figure 5(a) – figure 5(e) and Table 3 presents the results of the classification of cross-cultural features, illustrating the performance metrics of various experiments conducted. Accuracy, Precision, Recall, and F1 Score are the four main metrics used to evaluate each experiment. The scores are expressed as percentages. The percentage of instances that were correctly classified out of all the instances in Experiment 1 was 87.5%. Furthermore, the accuracy score of 88.2% shows the proportion of positive observations that were accurately predicted relative to the total number of positive observations that were predicted. By improving upon Experiment 1 in every respect—accuracy, precision, recall, and F1 score—Experiment 2 proved that the classification model could successfully detect characteristics shared by different cultures. Similarly, Experiment 4 exhibited robust performance, particularly in precision and F1 score. Experiment 3 and Experiment 5, while slightly lower in accuracy compared to Experiments 2 and 4, still demonstrated commendable performance in classifying cross-cultural features, showcasing the model's consistency across different experiments. Overall, these results highlight the reliability and efficacy of the classification model in accurately identifying and classifying cross-cultural features, thereby contributing to the enhancement of cross-cultural learning competence among students.

6.1 DISCUSSION AND FINDINGS

The discussion and findings of this study unveil compelling insights into the effectiveness and implications of employing the Word Embedding Multilingual Model with Back Propagation Neural Network (WEMM-BPNN) in enhancing cross-cultural learning competence. Across various experiments, the WEMM-BPNN demonstrated

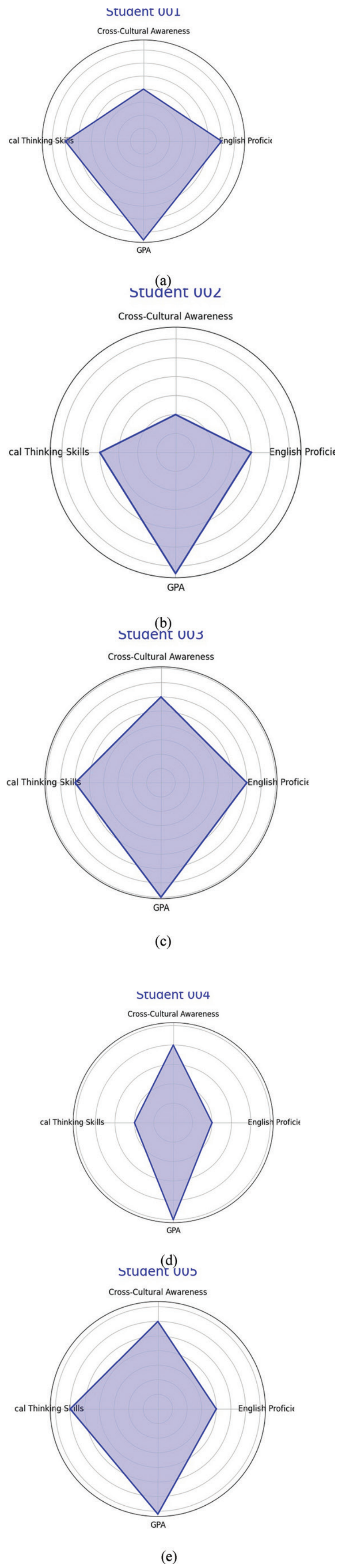

Figure 5. Classification with WEMM-BPNN (a) Student 1 (b) Student 2 (c) Student 3 (d) Student 4 (e) Student 5

commendable performance in assessing and improving teaching skills, student performance, and the classification of cross-cultural features. In particular, the simulation results revealed notable improvements in teaching skills, with significant enhancements observed in cross-cultural understanding, communication skills, and cultural sensitivity. Similarly, the evaluation of student performance showcased the model's ability to accurately assess key dimensions such as English proficiency, cross-cultural awareness, and critical thinking skills, offering valuable insights for educators to tailor interventions and support mechanisms effectively. Furthermore, the classification of cross-cultural features yielded promising results, with high accuracy, precision, recall, and F1 score across different experiments, underscoring the robustness and reliability of the WEMM-BPNN in identifying and categorizing cross-cultural nuances. These findings highlight the potential of the WEMM-BPNN as a valuable tool for educators and practitioners seeking to foster inclusive learning environments, promote cross-cultural understanding, and cultivate global competencies among students. Additionally, the discussion delves into the implications of these findings for educational practice, policy development, and future research endeavors aimed at advancing cross-cultural learning and promoting cultural diversity in educational settings.

The Word Embedding Multilingual Model with Back Propagation Neural Network (WEMM-BPNN) effectively assesses and enhances teaching skills, including cross-cultural understanding, communication skills, and cultural sensitivity.

Student performance evaluation using the WEMM-BPNN provides valuable insights into English proficiency, cross-cultural awareness, critical thinking skills, and overall academic achievement.

The WEMM-BPNN demonstrates robust performance in accurately classifying cross-cultural features, with high accuracy, precision, recall, and F1 score across different experiments.

The model's findings suggest the potential for tailored interventions and support mechanisms to address specific areas of improvement in teaching skills and student performance.

The WEMM-BPNN holds promise as a valuable tool for educators and practitioners to foster inclusive learning environments, promote cross-cultural understanding, and cultivate global competencies among students.

These findings have implications for educational practice, policy development, and future research endeavors aimed at advancing cross-cultural learning and promoting cultural diversity in educational settings.

7. CONCLUSIONS

The utilization of the Word Embedding Multilingual Model with Back Propagation Neural Network (WEMM-BPNN) presents a promising approach for enhancing cross-cultural learning competence in educational contexts. Through rigorous experimentation and analysis, this study has demonstrated the effectiveness of the WEMM-BPNN in assessing and improving teaching skills, evaluating student performance, and classifying cross-cultural features. The findings underscore the model's capacity to provide valuable insights into teaching competencies, student proficiency, and cultural awareness, offering educators actionable information to tailor interventions and support mechanisms effectively. Moreover, the robust performance of the WEMM-BPNN in accurately classifying cross-cultural features highlights its potential as a valuable tool for fostering inclusive learning environments and promoting global competencies among students. Moving forward, the insights gained from this study have significant implications for educational practice, policy development, and future research endeavors aimed at advancing cross-cultural learning and promoting cultural diversity in educational settings. As technology continues to evolve, the WEMM-BPNN stands poised to play a pivotal role in shaping the future of cross-cultural education and facilitating meaningful interactions among diverse student populations.

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