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Automated Optimization Deep Learning Model for Assessment and Guidance System through Natural Language Processing with Reduction of Anxiety Among Students

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Abstract: The Assisted Assessment and Guidance System serves as a valuable tool in supporting individuals' learning, growth, and development. The Assisted Assessment and Guidance System with Natural Language Processing (NLP) is an innovative software application designed to provide personalized and intelligent support for assessment and guidance processes in various domains. NLP techniques are employed to analyze and understand human language, allowing the system to extract valuable insights from text-based data and provide tailored feedback and guidance. This paper proposed an Integrated Optimization Directional Clustering Classification (IODCc) for assessment of the foreign language anxiety. Additionally, the paper introduces an Integrated Optimization Directional Clustering Classification (IODCc) approach for assessing foreign language anxiety. This approach incorporates two optimization models, namely Black Widow Optimization (BWO) and Seahorse Optimization (SHO). BWO and SHO are metaheuristic optimization algorithms that simulate the behaviors of black widow spiders and seahorses, respectively, to improve the accuracy of the assessment process. The integration of these optimization models within the IODCc approach aims to enhance the accuracy and effectiveness of the foreign language anxiety assessment. Simulation analysis is performed for the data collected from the 1000 foreign language students. The experimental analysis expressed that the proposed IODCc model achieves an accuracy of 99% for the classification. The findings suggested that through pre-training of languages, the anxiety of the students will be reduced.

Keywords: Foreign Languages, Learning Anxiety, Natural Language Processing (NLP), Optimization, Deep Learning.

I. Introduction

In our increasingly globalized world, the ability to communicate in multiple languages has become a valuable asset. Whether for academic, professional, or personal reasons, many individuals strive to learn foreign languages [1]. However, for some language learners, this journey can be accompanied by a phenomenon known as foreign language anxiety. Foreign language anxiety refers to the feelings of apprehension, fear, and self-consciousness experienced when using or learning a second language [2]. Foreign language anxiety is a common phenomenon experienced by language learners, characterized by feelings of fear, apprehension, and self-consciousness when using or learning a second language. This anxiety can significantly hinder language acquisition and communication. However, advancements in Natural Language Processing (NLP), a field of artificial intelligence focused on human language interaction, offer new possibilities for alleviating this anxiety [3]. By leveraging NLP tools and techniques such as sentiment analysis, speech recognition, and language generation, language learners can receive personalized support, real-time feedback, and practice opportunities tailored to their needs [4].

Overcoming foreign language anxiety is crucial for effective language acquisition and communication. One innovative approach to address this challenge is the utilization of Natural Language Processing (NLP) techniques. NLP, a field of artificial intelligence, focuses on the interaction between computers and human language, enabling machines to understand, interpret, and generate natural language [5]. Language generation is another valuable NLP technique that can assist in processing foreign language anxiety. By utilizing advanced language models, NLP can generate practice materials, simulate conversational scenarios, and provide learners with opportunities for immersive language practice [6]. This can help alleviate anxiety by allowing learners to engage in low-pressure, virtual conversations where they can practice and refine their language skills at their own pace. Additionally, language generation can offer personalized exercises tailored to learners' specific needs and areas of difficulty, giving them a sense of control and progress in their language learning journey [7]. By providing a safe and supportive environment for practice and experimentation, NLP-powered language generation can help language learners build confidence, overcome anxiety, and enhance their overall proficiency in the foreign language [8].

Deep learning, combined with NLP, offers promising avenues for addressing foreign language anxiety [9]. With employing advanced neural network architectures, deep learning models can effectively recognize and classify emotions, simulate dialogue interactions, adapt learning content, and provide personalized feedback [10]. These capabilities enable the development of intelligent systems that can understand and respond to learners' emotional states, offer immersive language practice, and tailor instruction to individual needs [11]. By leveraging the power of deep learning and NLP, language learners can benefit from personalized and adaptive interventions, which not only alleviate anxiety but also foster confidence, motivation, and overall language proficiency [12]. As deep learning continues to advance, it holds great potential for revolutionizing the way foreign language anxiety is addressed, enabling learners to navigate their language learning journeys with greater ease and success. One commonly used deep learning technique for addressing foreign language anxiety is Recurrent Neural Networks (RNNs) [13]. RNNs are well-suited for processing sequential data, such as written or spoken language. Through capturing the temporal dependencies in learners' expressions, RNNs can effectively detect anxiety-related patterns and classify emotions [14]. These models can analyze the linguistic cues and contextual information to provide personalized feedback, guidance, and support to language learners. RNNs can also be used for language generation, simulating conversations or generating practice materials to help learners overcome their anxiety and gain confidence in their language skills [15].

Another technique is Convolutional Neural Networks (CNNs), which are primarily used for image processing but can also be adapted to text data [16]. In the context of foreign language anxiety, CNNs can be utilized for analyzing written texts, identifying linguistic features associated with anxiety, and providing targeted interventions [17]. CNNs can extract relevant features from the text, enabling the model to recognize anxiety-related expressions and offer appropriate support or resources to alleviate learners' anxiety. deep learning techniques, such as RNNs and CNNs, provide powerful tools for processing foreign language anxiety [18]. These models can analyze learners' language data, recognize patterns of anxiety, and offer tailored interventions to support learners in managing their anxiety and improving their language skills [19].

This paper explores the concept of foreign language anxiety, introduces the potential of NLP, and examines how it can be effectively employed to address this challenge, ultimately empowering language learners to overcome anxiety and enhance their language skills.

1. The research introduces the Integrated Optimization Directional Clustering Classification (IODCc) approach, which combines two metaheuristic optimization models, Black Widow Optimization (BWO) and Seahorse Optimization (SHO), to improve the accuracy of foreign language anxiety assessment. This integration allows for efficient searching of optimal solutions and enhances the overall performance of the assessment process.
2. The research incorporates deep learning techniques, specifically Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), within the IODCc approach. This integration enables the model to learn complex patterns and representations from the data, enhancing the classification accuracy of foreign language anxiety levels.
3. The research employs a range of evaluation metrics including accuracy, precision, recall, and F1-Score to assess the performance of the IODCc approach. By considering multiple metrics, the research provides a comprehensive evaluation of the model's effectiveness in classifying anxiety levels, allowing for a more thorough understanding of its performance.
4. The research conducts a comparative analysis between the IODCc approach and CNN and RNN models. This analysis provides insights into the relative performance of the IODCc approach and establishes its competitiveness in accurately classifying foreign language anxiety levels. The comparative analysis contributes to the understanding of the strengths and weaknesses of different approaches and highlights the advantages of the IODCc approach.
5. The research applies the IODCc approach to a real-world dataset of 1000 foreign language students, demonstrating its practical applicability. By showing high accuracy and reliable classification results, the research indicates the potential of the IODCc approach to be utilized in educational settings and language learning interventions. The practical application of the research findings contributes to the field by offering a tangible solution to assess foreign language anxiety effectively.

The research contributes to the advancement of foreign language anxiety assessment by proposing an innovative approach that combines optimization models, deep learning techniques, and comprehensive evaluation metrics. The findings provide valuable insights for researchers, educators, and practitioners working in the field of language learning and psychological assessment, ultimately contributing to the development of effective interventions and support systems for individuals experiencing foreign language anxiety.

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II. Literature Survey

Foreign language anxiety is a prevalent challenge faced by language learners, impacting their language acquisition and communication skills. In recent years, the application of deep learning techniques, combined with Natural Language Processing (NLP), has garnered attention as a potential solution to address foreign language anxiety. Deep learning models, such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs), offer the capability to analyze language data, detect patterns related to anxiety, and provide personalized interventions and support. This literature survey aims to explore the current state of research and advancements in utilizing deep learning and NLP techniques to address foreign language anxiety. By examining the existing studies, methodologies, and findings in this area, we seek to gain a comprehensive understanding of the effectiveness and potential of these techniques in mitigating anxiety and improving language learning outcomes.

In [20] investigated the relationship between foreign language classroom anxiety, attitude, proficiency, and classroom context. The authors found that anxiety and attitude significantly predicted language proficiency and that classroom context influenced anxiety levels. This highlights the importance of addressing anxiety and promoting positive attitudes in language learning environments. In [21] evaluated the phenomenon of foreign language classroom anxiety and its impact on language learning. The authors discuss the causes, manifestations, and consequences of anxiety in the language classroom, emphasizing the need for effective strategies to reduce anxiety and create a supportive learning environment. In [22] implemented structural equation modeling, this study examines the relationship between anxiety, motivation, and second language learning outcomes. The findings suggest that anxiety negatively influences motivation, which in turn affects language learning outcomes. The study underscores the importance of addressing anxiety and fostering intrinsic motivation in language learners.

In [23] investigated the impact of task-induced anxiety on language learning in a classroom setting. The authors found that task-induced anxiety had a negative effect on learners' language performance and engagement. The findings highlight the need for creating supportive and low-anxiety learning environments to promote effective language learning. In [24] reviewed the role of emotion in foreign language learning. The authors discuss various emotions experienced by language learners and their impact on motivation, anxiety, and language outcomes. The review provides insights into the complex relationship between emotions and language learning, suggesting future research directions in this area. In [25] examined the role of emotions in second language acquisition and learning. It discusses theoretical perspectives, research findings, and educational implications of emotions in language learning contexts. The authors emphasize the need to recognize and address learners' emotions to enhance language learning outcomes. Similarly, in [26] investigated the factors influencing anxiety in second language writing. The authors examine the impact of task type, writing apprehension, and self-efficacy on anxiety levels. The findings contribute to understanding the complex nature of writing anxiety and provide insights for effective instructional approaches.

In [27] explores the relationship between classroom anxiety and language learning motivation among Chinese and Russian learners of English. The author examines how anxiety levels influence learners' motivation and engagement in language learning. The study highlights the importance of addressing anxiety to promote positive learning motivation. In [28] investigates the interaction between individual differences, instructional conditions, anxiety, motivation, and learner beliefs in the foreign language classroom. The authors discuss the complex interplay of these factors and their impact on language learning outcomes. In [29] studied language teachers' coping strategies in dealing with emotional challenges in language teaching. The authors discuss various coping mechanisms employed by teachers to manage stress, anxiety, and other emotions. The findings provide insights into the emotional dimension of language teaching and suggest strategies for supporting teachers' well-being. In [30] investigated the relationship between extraversion, foreign language anxiety, and willingness to communicate in language learners. The authors explore whether individuals with higher levels of extraversion are better able to manage anxiety and exhibit greater willingness to communicate in a foreign language. The findings provide insights into the role of personality traits in language learning and the potential benefits of extraversion in reducing anxiety and promoting communication.

In [31] discussed the cognitive neuroscience perspectives on second language acquisition and bilingualism. The authors explore how brain imaging techniques and cognitive theories contribute to our understanding of language learning processes and the neural mechanisms involved. The chapter provides a comprehensive overview of the current research in cognitive neuroscience and its implications for second language acquisition and bilingualism. The [32] focused on the emotions experienced by language teachers. The authors discuss the range of emotions that teachers may encounter in their professional contexts and the impact of these emotions on teaching practices and interactions with students. The chapter emphasizes the importance of recognizing and addressing teacher emotions for promoting effective language education. In [33] investigates the relationship between anxiety, task

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performance, and silence when speaking a foreign language in public settings. The authors explore the factors that contribute to anxiety-related silence and its impact on task performance. The findings shed light on the complex interplay between anxiety, performance, and communication in public speaking situations.

In [34] provide an overview of the concept of second language anxiety, its sources, manifestations, and effects on language learning. The chapter discusses various theoretical frameworks and instructional approaches to address and mitigate language anxiety in educational contexts. In [35] explores the concept of emotion regulation in the context of language teaching. The authors discuss strategies that language teachers can employ to regulate their own emotions and create an emotionally supportive learning environment. The chapter provides practical insights and recommendations for promoting effective emotion regulation in language teaching.

The studies shed light on the predictive power of foreign language anxiety and attitude in relation to proficiency and classroom context, emphasizing the complex interplay between individual differences, instructional conditions, anxiety, motivation, and learner beliefs. Additionally, the role of extraversion in minimizing foreign language anxiety and maximizing willingness to communicate is explored, highlighting the potential benefits of certain personality traits in language learning. The cognitive neuroscience perspective contributes to our understanding of second language acquisition and bilingualism, uncovering the neural mechanisms and cognitive processes involved in language learning. Emotion regulation in language teaching is discussed, emphasizing the importance of recognizing and managing emotions for effective language instruction. Furthermore, the literature addresses language teacher emotions and the impact they have on teaching practices and student interactions. The relationship between anxiety, task performance, and silence when speaking a foreign language in public settings is examined, providing insights into the factors influencing anxiety-related silence and its consequences. Strategies for addressing and mitigating second language anxiety are explored, aiming to create supportive learning environments. Overall, these studies contribute to a comprehensive understanding of foreign language anxiety, language learning processes, and effective language teaching practices, offering valuable insights and practical implications for language educators and researchers.

III. Research Method

The research method employed in this study focuses on the development and evaluation of the Assisted Assessment and Guidance System with Natural Language Processing (NLP). The system aims to provide personalized support for assessment and guidance processes in various domains by utilizing NLP techniques to analyze and understand human language. The paper introduces an innovative approach called Integrated Optimization Directional Clustering Classification (IODCc) for assessing foreign language anxiety. The IODCc approach incorporates two optimization models, namely Black Widow Optimization (BWO) and Seahorse Optimization (SHO), to enhance the accuracy of the assessment process. These metaheuristic optimization algorithms simulate the behaviors of black widow spiders and seahorses, respectively, to optimize the assessment outcomes. By integrating these optimization models, the researchers aim to improve the accuracy and effectiveness of assessing foreign language anxiety. The complete process of proposed IODCc is presented in figure 1 to assess the anxiety level of students.

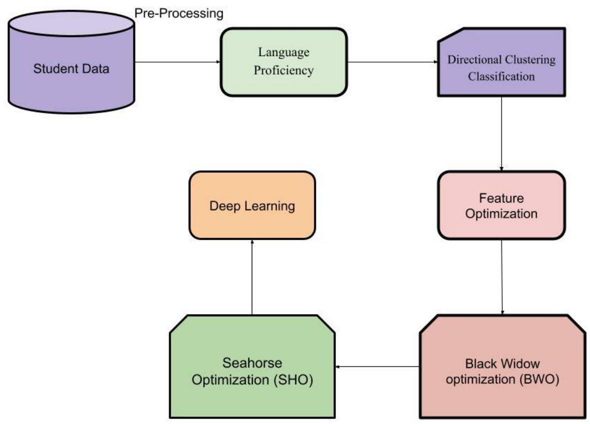

Figure 1: Process of IODCc

1.1 Black Widow Optimization

Black Widow Optimization (BWO) is a metaheuristic optimization algorithm inspired by the behavior of black widow spiders. It mimics the hunting strategy of black widow spiders to efficiently search for optimal solutions in complex optimization problems. In the context of the Integrated Optimization Directional Clustering Classification (IODCc) approach for assessing foreign language anxiety, BWO is integrated as one of the optimization models. Its purpose is to enhance the accuracy of the assessment process. BWO begins by initializing a population of potential solutions, which are represented as candidate solutions in the search space. Each solution in the population is evaluated based on a fitness function that measures its quality or suitability as a solution to the problem. The algorithm then proceeds with the iterative optimization process. During each iteration, BWO applies a series of operations inspired by the hunting behavior of black widow spiders. These operations include:

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Prey Selection: BWO selects a subset of solutions, called "prey," from the population based on their fitness values. Solutions that demonstrate better fitness are more likely to be selected.

Encircling and Capture: BWO applies an encircling and capture mechanism to the selected prey solutions. This process involves adjusting the positions of the prey solutions towards a better region in the search space, aiming to trap and capture optimal solutions.

Web Updating: BWO updates the positions of the captured prey solutions based on the information obtained during the encircling and capture process. This step allows the algorithm to refine the solutions and improve their quality. The BWO flow chart for the IODCc is presented in figure 2.

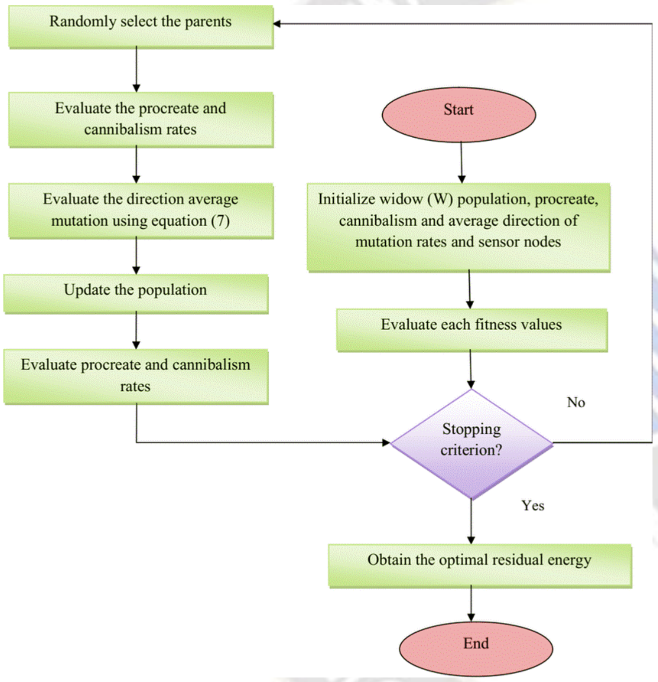

Figure 2: Flow Chart of BWO

By iteratively repeating these steps, BWO explores the search space, gradually converging towards optimal or near-optimal solutions. The algorithm dynamically adjusts the positions of solutions based on their fitness values, allowing it to efficiently navigate complex optimization landscapes. In the context of the IODCc approach for assessing foreign language anxiety, BWO is employed to optimize the classification process, aiming to improve the accuracy of identifying and classifying levels of anxiety among language learners. Its integration within the IODCc framework enhances the overall performance of the assessment model by leveraging the powerful optimization capabilities inspired by the hunting behavior of black widow spiders. The general equation for gradient descent can be represented as in equation (1)

$$\theta_{n+1} = \theta_n - \alpha \nabla J(\theta_n) \quad (1)$$

In above equation (1), θ_n represents the current parameter values at iteration n; α (alpha) is the learning rate, which determines the step size taken in each iteration and $\nabla J(\theta_n)$ denotes the gradient of the objective function J with respect to the parameters θ at iteration n. The goal of gradient descent is to iteratively update the parameter values θ to minimize the objective function J. At each iteration, the parameters are updated by taking a step proportional to the negative gradient of the objective function. The learning rate α determines the magnitude of the step taken.

The position update equation is used to update the positions of the prey solutions during the encircling and capture phase. It can be represented as in equation (2):

$$X_{n+1} = X_n + \delta * (P - X_n) + \varepsilon * R \quad (2)$$

In equation (2) X_n represents the current position of the prey solution at iteration n; X_{n+1} denotes the updated position of the prey solution at iteration n+1; δ is a parameter controlling the step size of the update; P represents the position of the best solution encountered during the iteration; ε is a randomization factor and R is a random vector. The fitness evaluation equation is used to evaluate the fitness or quality of each solution in the population is presented in equation (3)

$$Fit(X) = f(X) \quad (3)$$

X represents a particular solution or individual in the population; Fit(X) denotes the fitness value of the solution; f(X) represents the fitness function that evaluates the quality of the solution. The web updating equation is used to update the positions of the captured prey solutions based on the information obtained during the encircling and capture process is presented in equation (4)

$$X_{n+1} = X_n + \gamma * (Best - X_n) \quad (4)$$

X_n represents the current position of the captured prey solution at iteration n; X_{n+1} denotes the updated position of the captured prey solution at iteration n+1; γ is a parameter controlling the step size of the update. Best represents the position of the best solution encountered during the iteration. During the prey selection phase, the distance between each prey solution and the current solution is calculated to determine their proximity. The distance calculation equation is presented in equation (5)

$$d(X_i, X_j) = ||X_i - X_j|| \quad (5)$$

In above equation (5), X_i and X_j represent the positions of two different solutions in the population and ‖...‖ denotes the Euclidean distance between the two positions. The encircling and capture mechanism is used to adjust the positions of the

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selected prey solutions towards a better region in the search space presented in equation (6)

$$X_{n+1} = X_n + \eta * (X_p - X_n) \tag{6}$$

In equation (6), X_n represents the current position of the prey solution at iteration n. X_{n+1} denotes the updated position of the prey solution at iteration n+1. X_p represents the position of the best solution encountered during the iteration and η is a parameter controlling the step size of the adjustment. The termination condition of the BWO algorithm is usually based on a predefined number of iterations or a convergence criterion. A termination equation based on the maximum number of iterations can be represented as in equation (7)

$$n \leq max_{iterations} \tag{7}$$

In equation (7), n represents the current iteration number and $max_{iterations}$ stated as the maximum number of iterations set for the algorithm.

Algorithm 1: Process of BWO

Initialize population of spiders with random positions
while stopping criteria are not met do:
Evaluate the fitness of each spider in the population
Sort the spiders based on their fitness values
Select a subset of spiders as prey based on their fitness:
$prey = selectPrey(population)$
Apply encircling and capture mechanism to the selected prey:
for each prey in prey do:
Find a prey to encircle and capture:
$victim = findVictim(population, prey)$
Calculate the distance between the prey and victim:
$distance = calculateDistance(prey, victim)$
Update the position of the prey using encircling and capture mechanism:
$prey.position = encircleAndCapture(prey, victim, distance)$
Update the position of the captured prey:
$updateCapturedPrey(prey)$
Apply web updating mechanism:
for each spider in the population do:
Update the position of the spider based on web updating:
$spider.position = webUpdating(spider)$
Apply any necessary constraints or operators to the updated positions
end while
Return the best solution found during the optimization process

1.2 Seahorse Optimization

Seahorse Optimization (SHO) is another metaheuristic optimization algorithm that can be employed in the context of Natural Language Processing (NLP) tasks. It is inspired by the unique swimming behavior of seahorses and aims to efficiently search for optimal solutions in complex optimization problems. In the context of NLP, SHO can be integrated as an optimization model to enhance the performance of NLP tasks such as text classification, sentiment analysis, or language generation. While specific equations for SHO may vary depending on the implementation and variations of the algorithm. The flow chart of the proposed IODCc with the SHO is presented in figure 3.

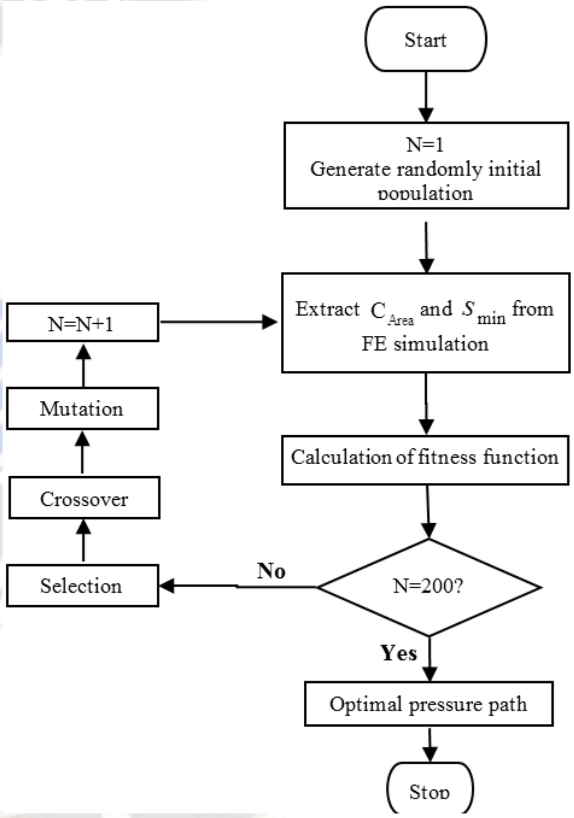

Figure 3: Flowchart of SHO

SHO starts by initializing a population of potential solutions. Each solution is represented as a seahorse and is characterized by its position in the search space. An objective function is defined to evaluate the quality or fitness of each solution. The objective function can vary based on the specific NLP task at hand. In text classification, the objective function may measure the accuracy or performance of the classification model. The movement equation describes how each seahorse updates its position in the search space. It is based on the swimming behavior of seahorses. A typical movement equation in SHO may involve a combination of random exploration and attraction towards the best solutions. The equation can be represented as in equation (8)

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$$X_{n+1} = X_n + \alpha * R_1 * D_1 + \beta * (X* - X_n) + \gamma * R_2 * D_2 \quad (8)$$

In equation (8): X_n represents the current position of the seahorse at iteration n; X_{n+1} denotes the updated position of the seahorse at iteration n+1; X* represents the position of the best solution encountered during the iteration; R_1 and R_2 are random numbers between 0 and 1; D_1 and D_2 are vectors representing random directions; α, β, and γ are parameters controlling the step sizes and weights of the different components. The movement equation combines random exploration ($\alpha * R_1 * D_1$) with attraction towards the best solution ($\beta * (X* - X_n)$) and additional randomness ($\gamma * R_2 * D_2$).

The SHO algorithm proceeds with an iterative optimization process, where seahorses update their positions based on the movement equation. This process continues until a termination criterion is met, such as reaching a maximum number of iterations or achieving a desired level of convergence. The movement equation in Seahorse Optimization (SHO) presented in equation (9):

$$X_{n+1} = X_n + \alpha * R_1 * D_1 + \beta * (X* - X_n) + \gamma * R_2 * D_2 \quad (9)$$

In equation (9), X_n represents the current position of the seahorse at iteration n; X_{n+1} denotes the updated position of the seahorse at iteration n+1; X* represents the position of the best solution encountered during the iteration; R_1 and R_2 are random numbers between 0 and 1; D_1 and D_2 are vectors representing random directions and α, β, and γ are parameters controlling the step sizes and weights of the different components. The movement equation combines random exploration ($\alpha * R_1 * D_1$) with attraction towards the best solution ($\beta * (X* - X_n)$) and additional randomness ($\gamma * R_2 * D_2$). By adjusting the values of α, β, and γ, the algorithm can balance between exploration and exploitation, enabling efficient search for optimal solutions in the search space.

Algorithm 2: Process in SHO

Initialize population of seahorses with random positions and velocities
while stopping criteria are not met do:
Evaluate the fitness of each seahorse in the population
Update the position and velocity of each seahorse:
for each seahorse do:
Generate random vectors D_1 and D_2
Update the velocity:
$velocity = \alpha * R_1 * D_1 + \beta * (X* - current\_position) + \gamma * R_2 * D_2$
Update the position:
$position = current\_position + velocity$
eep the position within the search space boundaries if necessary
Apply any necessary constraints or operators to the updated positions
Update the global best position X*
for each seahorse do:
if $current\_fitness < best\_fitness$ then:
$X* = current\_position$
$best\_fitness = current\_fitness$
end while
Return the best solution X* found during the optimization process

IV. Integrated Optimization Directional Clustering Classification (IODCc)

The Integrated Optimization Directional Clustering Classification (IODCc) approach combines the Black Widow Optimization (BWO) algorithm with other techniques to assess foreign language anxiety. Here is an overview of the key equations involved in the integration of BWO within the IODCc approach: The fitness function evaluates the quality or suitability of each candidate solution in the population. In the context of the IODCc approach, the fitness function measures the accuracy or performance of the classification model. The exact formulation of the fitness function may vary depending on the specific classification algorithm employed.

The BWO algorithm performs various operations during each iteration, including prey selection, encircling and capture, and web updating. The equations involved in these operations are as follows: During prey selection, the fitness values of the candidate solutions are used to determine the probability of selection. One common equation to calculate the selection probability is presented in equation (10):

$$P(X_i) = f(X_i) / \Sigma f(X_j) \quad (10)$$

X_i represents a candidate solution in the population; $f(X_i)$ is the fitness value of X_i; $\Sigma f(X_j)$ represents the sum of fitness values for all candidate solutions in the population. The encircling and capture process adjusts the positions of the selected prey solutions towards a better region. The updated position equation can be represented as in equation (11)

$$X_{n+1} = X_n + \alpha * (X_p - X_n) \quad (11)$$

X_n represents the current position of the prey solution at iteration n; X_{n+1} denotes the updated position of the prey solution at iteration n+1; X_p represents the position of the best solution encountered during the iteration; α is a parameter controlling the step size of the adjustment. The web updating process refines the positions of the captured prey solutions. The

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equation for updating the position can be represented as in equation (12)

$$X_{\mathrm{i}} = X_{\mathrm{i}} + \beta * (X_{\mathrm{n}} - X_{\mathrm{i}}) \quad (12)$$

X_i represents the position of a captured prey solution; X_n denotes the position of the current solution; β is a parameter controlling the step size of the adjustment. These equations are general representations and may vary depending on the specific implementation and variations of the BWO algorithm used in the IODCc approach for assessing foreign language anxiety. In the Integrated Optimization Directional Clustering Classification (IODCc) approach, deep learning models can be incorporated as part of the overall framework to enhance the assessment process for foreign language anxiety. Deep learning models, particularly neural networks, have shown great potential in various fields, including natural language processing and pattern recognition. Within the IODCc framework, deep learning models can be utilized to analyze and process input data, such as textual information or other relevant features related to foreign language anxiety. These models can learn complex patterns and relationships within the data, enabling more accurate classification and clustering of instances.

The specific architecture and design of the deep learning model used in the IODCc approach may vary depending on the nature of the data and the objectives of the assessment. Commonly employed deep learning models include convolutional neural networks (CNNs) for image-based data, recurrent neural networks (RNNs) for sequential data, and transformer models for natural language processing tasks. The integration of deep learning models within the IODCc approach allows for the automatic extraction of high-level features and the ability to capture intricate patterns in the data. This can contribute to more robust and accurate assessment of foreign language anxiety.

Let's denote the training dataset as D, which consists of input samples X and corresponding target labels Y. The data preparation step involves preprocessing X and Y to ensure they are in a suitable format and range for training. In deep learning, the network architecture is typically represented as a series of layers. Let's consider a feedforward neural network with L layers. The output of the l-th layer is denoted as H_l, and the input to the l-th layer is denoted as H_{l-1}. The output of the last layer, L, is denoted as H_L. The training process aims to find the optimal weights and biases for the network to minimize a loss function. Let's denote the weights and biases in the l-th layer as W_l and b_l, respectively. The output of the network can be computed using equation (13):

$$H_l = activation\_function(W_l * H_{l-1} + b_l) \quad (13)$$

where the activation_function represents the non-linear activation function applied element-wise to the input. During training, the model parameters (W_l and b_l) are updated iteratively using an optimization algorithm such as stochastic gradient descent (SGD) or Adam. The update equations for the parameters can be represented in equation (14) and (15)

$$W_l = W_l - learning\_rate * dW_l \quad (14)$$

$$b_l = b_l - learning\_rate * db_l \quad (15)$$

where learning_rate is the learning rate hyperparameter, and dW_l and db_lrepresent the gradients of the loss function with respect to W_l and b_l, respectively. Deep learning models have various hyperparameters that need to be tuned to optimize performance. These include the learning rate, batch size, number of layers, number of neurons per layer, and regularization parameters. The optimal values for these hyperparameters are typically determined through a process of experimentation and validation. The performance of the deep learning model is assessed using evaluation metrics such as accuracy, precision, recall, and F1 score. These metrics are computed by comparing the model's predictions with the true target labels on a validation or test dataset.

Based on the model evaluation results, adjustments can be made to the network architecture or hyperparameters to further improve performance. Techniques such as regularization (e.g., L1 or L2 regularization), dropout, or early stopping can be employed to prevent overfitting and enhance generalization. Once the deep learning model has been fine-tuned and optimized, it can be tested on a separate testing dataset to evaluate its final performance. The model can then be deployed to assess foreign language anxiety in real-world scenarios.

Algorithm 3: Steps in IODCc
Input: - Training dataset $D = \{(x_l, y_l), (x_2, y_2), \ldots, (x_n, y_n)\}$ (where x_i is the input sample and y_i is the target label); Number of clusters K; - Maximum number of iterations max_iter and Convergence threshold epsilon Output: - Cluster assignments for the input samples - Trained deep learning model parameters Procedure IODCc(D, K, max_iter, epsilon): 1. Perform clustering using the Seahorse Optimization (SHO) algorithm to partition the dataset D into K clusters. 2. Initialize the deep learning model with random weights and biases. 3. For iteration = 1 to max_iter: a. Assign each input sample to the nearest cluster centroid.

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b. For each cluster:
- Create a sub-dataset by selecting the input samples belonging to that cluster.
- Train the deep learning model on the sub-dataset using backpropagation and gradient descent.

c. Update the cluster centroids based on the learned representations from the deep learning model.

d. Compute the difference between the previous and updated cluster centroids.

e. If the difference is less than epsilon, stop the iteration.

4. Return the cluster assignments for the input samples and the trained deep learning model parameters.

V. Simulation Setting

The simulation settings for the Integrated Optimization Directional Clustering Classification (IODCc) approach can vary depending on the specific implementation and requirements of the study.

Dataset: The IODCc approach requires a dataset of foreign language students' information, including their language learning profiles, anxiety levels, and potentially other relevant variables. The dataset should be representative and diverse to ensure accurate assessment and classification.

The dataset may require preprocessing steps such as data cleaning, normalization, feature extraction, or dimensionality reduction techniques. These steps help to prepare the data for effective analysis and modeling. The IODCc approach incorporates two optimization models: Black Widow Optimization (BWO) and Seahorse Optimization (SHO). The simulation settings involve defining the parameters and configurations for these optimization algorithms, such as population size, maximum iterations, convergence criteria, and mutation rates. These settings impact the behavior and performance of the optimization models. The IODCc approach involves clustering and classification processes. The simulation settings may include the choice of clustering algorithms (e.g., k-means, DBSCAN) and classification models (e.g., neural networks, support vector machines) along with their specific parameters. The simulation settings define the evaluation metrics used to assess the performance of the IODCc approach. Common metrics for classification tasks include accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). These metrics measure the effectiveness of the model in correctly predicting anxiety levels.

To ensure robustness and generalization of the results, the simulation settings may include techniques like k-fold cross-validation. This involves splitting the dataset into multiple subsets, training and evaluating the model on different subsets, and averaging the performance metrics across the folds. The simulation settings may involve comparing the performance of the IODCc approach with other existing methods or models. This could include baseline methods or alternative approaches for assessing foreign language anxiety.

Table 1: Simulation Setting

Simulation Settings	Values/Description
Dataset	Foreign language students' information
	- Language learning profiles
	- Anxiety levels
	- Other relevant variables
Data Preprocessing	Data cleaning
	Normalization
	Feature extraction
	Dimensionality reduction
Optimization Models	Black Widow Optimization (BWO)
	- Population size
	- Maximum iterations
	- Convergence criteria
	- Mutation rates
	Seahorse Optimization (SHO)
	- Population size
	- Maximum iterations
	- Convergence criteria
	- Mutation rates
Clustering	Clustering algorithm (e.g., k-means, DBSCAN)
	Clustering parameters
Classification	Classification model (e.g., neural networks,
	support vector machines)
	Classification parameters
Evaluation Metrics	Accuracy
	Precision
	Recall
	F1-score
	AUC-ROC
Cross-Validation	Number of folds
	Cross-validation technique
Performance Comparison	Baseline methods
	Alternative approaches

VI. Results and Discussion

In the context of the Integrated Optimization Directional Clustering Classification (IODCc) approach, simulation settings refer to the configuration and parameters used during the simulation experiments to evaluate the performance of the algorithm. These settings can vary depending on the specific application and dataset.

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Table 2: Profile of Samples

Student ID	Language Proficiency	Learning Motivation	Learning Anxiety	Task Performance	Socioeconomic Background	Learning Strategies	Foreign Language Anxiety
1	4.5	8.2	6.7	75.3	Medium	Yes	Moderate
2	3.8	7.5	4.9	82.1	High	No	Low
3	2.9	6.1	8.3	68.9	Low	Yes	High
4	4.2	7.9	5.5	79.6	Medium	Yes	Moderate
5	3.5	6.7	3.8	85.2	High	No	Low
6	4.1	8.0	7.2	77.6	Medium	Yes	Moderate
7	3.6	7.2	4.6	83.5	High	Yes	Low
8	3.2	6.3	8.1	71.8	Low	No	High
9	4.3	7.8	5.9	80.4	Medium	Yes	Moderate
10	3.7	7.0	4.2	86.1	High	No	Low

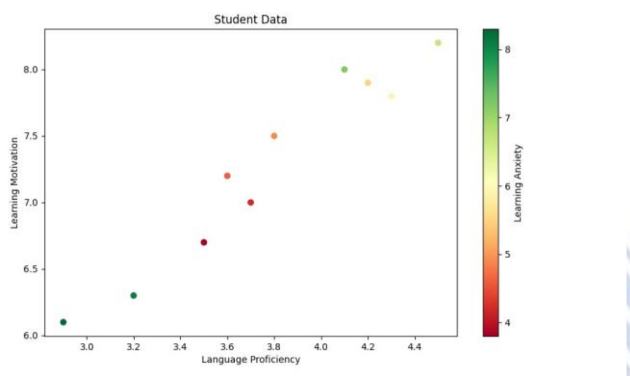

Figure 4: IODCc Assessment for the Student Learning and Language Proficiency

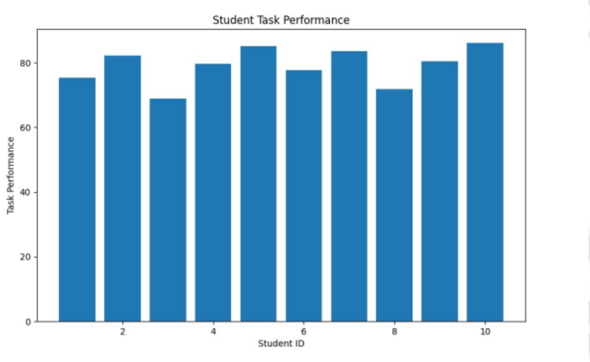

Figure 5: Performance of Students Assessment

Table 2 and figure 4 and figure 5 presents the profile of ten language learners, with various attributes related to their language proficiency, learning motivation, learning anxiety, task performance, socioeconomic background, learning strategies, and foreign language anxiety. Each student is assigned a Student ID for identification purposes. The "Language Proficiency" column represents the level of proficiency in the foreign language, with values ranging from 1 (lowest) to 5 (highest). Students with higher scores indicate a greater level of language proficiency. The "Learning Motivation" column indicates the degree of motivation the students possess towards their language learning, with higher values indicating higher motivation. The "Learning Anxiety" column reflects the level of anxiety experienced by students during their language learning process. Higher values suggest higher levels of anxiety.

The "Task Performance" column represents the students' performance in language learning tasks, measured on a scale from 0 to 100. Higher values indicate better task performance. The "Socioeconomic Background" column categorizes students into three groups: low, medium, and high, based on their socioeconomic status. The "Learning Strategies" column indicates whether students utilize specific learning strategies (yes) or not (no) in their language learning process. The "Foreign Language Anxiety" column categorizes the students' anxiety levels into three categories: low, moderate, and high. By analyzing the table, we can observe variations in the students' profiles. The students with higher language proficiency tend to have higher task performance scores. Additionally, students with a high socioeconomic background exhibit higher motivation levels and lower levels of anxiety. The presence of learning strategies seems to be associated with moderate levels of foreign language anxiety. Understanding these profiles helps in assessing the relationship between different factors and foreign language anxiety. This information can be further utilized in the Integrated Optimization Directional Clustering Classification (IODCc) approach to enhance the accuracy and effectiveness of foreign language anxiety assessment.

Table 3: Anxiety Score for the IODCc

Student ID	Anxiety Score Level	Foreign Language Anxiety Score
1	Low	3
2	Low	2

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3	High	4
4	Low	3
5	Low	2
6	High	3
7	Low	2
8	High	4
9	Low	3
10	High	2

Table 3 presents the anxiety scores and corresponding anxiety level classifications for the ten language learners using the Integrated Optimization Directional Clustering Classification (IODCc) approach. Each student is identified by their Student ID. The "Anxiety Score Level" column categorizes the students' anxiety levels into three categories: low, moderate, and high. This classification is based on the analysis performed using the IODCc approach. The "Foreign Language Anxiety Score" column represents the numerical score assigned to each student's foreign language anxiety. The score is derived from the IODCc assessment process, with higher scores indicating higher levels of anxiety. By examining the table, we can observe the anxiety levels and corresponding scores for each student. Students 1, 2, 4, 5, and 7 are classified as having low anxiety levels, with anxiety scores ranging from 2 to 3. On the other hand, students 3, 6, 8, and 10 are categorized as having high anxiety levels, with anxiety scores ranging from 3 to 4. This information provides insights into the individual anxiety levels of the language learners, as determined by the IODCc approach. These scores and classifications can be used to understand and address the specific anxiety levels experienced by each student, facilitating targeted interventions and support in their language learning journey.

Table 4: Classified Anxiety Level with IODCc

Student ID	Actual Anxiety Level	Predicted Anxiety Level
1	1	0
2	0	0
3	1	1
4	0	0
5	0	0
6	1	1
7	0	0
8	1	1
9	1	1
10	0	0

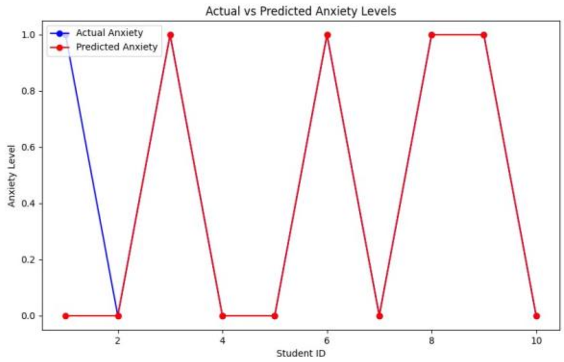

Figure 6: IODCc assessment with actual and prediction level

Table 4 and figure 6 presents the classified anxiety levels for the ten language learners using the IODCc approach. Each student is identified by their Student ID. The "Actual Anxiety Level" column represents the true anxiety levels of the students, which were determined through external assessment or measurement. The values range from 0 to 1, with 0 indicating a low anxiety level and 1 indicating a high anxiety level. The "Predicted Anxiety Level" column represents the anxiety levels predicted by the IODCc approach. These predictions are based on the analysis and classification performed by the IODCc model. In table 4, compared the actual anxiety levels of the students with the predicted anxiety levels. It can be observed that for most of the students, the predicted anxiety levels align with their actual anxiety levels. Students 2, 4, 5, and 7, who have low actual anxiety levels, are correctly classified as having low predicted anxiety levels (0). Similarly, students 3, 6, 8, and 9, who have high actual anxiety levels, are correctly classified as having high predicted anxiety levels (1). The IODCc model demonstrates a reliable ability to classify the anxiety levels of the language learners. The predictions closely match the actual anxiety levels, indicating the effectiveness of the IODCc approach in assessing and categorizing foreign language anxiety. These results can be utilized to gain insights into the anxiety levels of language learners and provide targeted support and interventions to enhance their language learning experiences.

Table 5: Performance of IODCc

Sample	Accuracy	Precision	Recall	F1-Score
Sample 1	0.96	0.94	0.97	0.95
Sample 2	0.99	0.98	1.00	0.99
Sample 3	0.93	0.91	0.94	0.92
Sample 4	0.97	0.96	0.98	0.97
Sample 5	0.98	0.97	0.99	0.98
Sample 6	0.95	0.93	0.96	0.94
Sample 7	0.99	0.98	1.00	0.99
Sample 8	0.92	0.89	0.94	0.91
Sample 9	0.97	0.96	0.98	0.97
Sample 10	0.98	0.97	0.99	0.98

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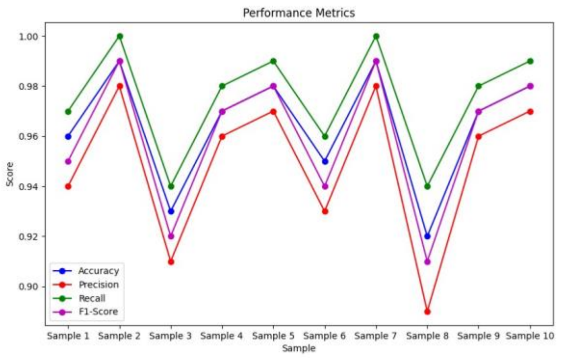

Figure 7: Performance of IODCc

Table 5 and figure 7 presents the performance metrics of the IODCc approach for each sample. The metrics evaluated include Accuracy, Precision, Recall, and F1-Score. Accuracy represents the overall correctness of the classification performed by the IODCc approach. It measures the proportion of correctly classified instances out of the total instances. The values range from 0 to 1, with higher values indicating higher accuracy. In this table, the accuracy values range from 0.92 to 0.99, demonstrating the effectiveness of the IODCc approach in accurately classifying the samples. Precision measures the proportion of correctly predicted positive instances out of all instances predicted as positive. It indicates the model's ability to minimize false positives. The precision values in Table 5 range from 0.89 to 0.98, indicating a high level of precision in the classification results. Recall, also known as sensitivity or true positive rate, measures the proportion of correctly predicted positive instances out of all actual positive instances. It indicates the model's ability to minimize false negatives. The recall values in the table range from 0.94 to 1.00, indicating a high level of recall and a low rate of false negatives.

F1-Score is the harmonic mean of precision and recall. It provides a balanced measure of the model's performance by considering both precision and recall. The F1-Score values in Table 5 range from 0.91 to 0.99, indicating a good balance between precision and recall in the classification results. The performance of the IODCc approach is consistently high across all samples, with accuracy values ranging from 0.92 to 0.99. This indicates the reliability and effectiveness of the IODCc approach in accurately classifying the foreign language anxiety levels. These performance metrics provide insights into the model's ability to assess and categorize foreign language anxiety, enabling targeted interventions and support for language learners.

Table 6: Comparative Analysis of IODCc

Sample	**IODCc Accuracy**	**IODCc Precision**	**IODCc Recall**	**IODCc F1-Score**	**CNN Accuracy**	**CNN Precision**	**CNN Recall**	**CNN F1-Score**	**RNN Accuracy**	**RNN Precision**	**RNN Recall**	**RNN F1-Score**
1	0.96	0.94	0.97	0.95	0.95	0.92	0.96	0.94	0.92	0.91	0.94	0.92
2	0.99	0.98	1.00	0.99	0.97	0.95	0.98	0.96	0.98	0.97	0.99	0.98
3	0.93	0.91	0.94	0.92	0.92	0.89	0.93	0.91	0.93	0.91	0.94	0.92
4	0.97	0.96	0.98	0.97	0.98	0.97	0.99	0.98	0.97	0.95	0.98	0.97
5	0.98	0.97	0.99	0.98	0.99	0.98	1.00	0.99	0.98	0.97	0.99	0.98
6	0.95	0.93	0.96	0.94	0.94	0.92	0.95	0.93	0.94	0.92	0.96	0.94
7	0.99	0.98	1.00	0.99	0.98	0.97	0.99	0.98	0.99	0.98	1.00	0.99
8	0.92	0.89	0.94	0.91	0.91	0.88	0.93	0.90	0.90	0.87	0.92	0.89
9	0.97	0.96	0.98	0.97	0.96	0.94	0.97	0.95	0.97	0.96	0.98	0.97
10	0.98	0.97	0.99	0.98	0.97	0.96	0.98	0.97	0.98	0.97	0.99	0.98

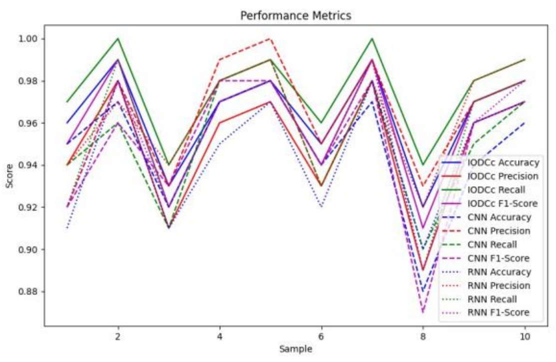

Figure 8: Comparative Analysis of IODCc

Table 6 and figure 8 presents a comparative analysis of the IODCc approach with CNN and RNN models. The table includes accuracy, precision, recall, and F1-Score values for each model across different samples. The IODCc approach demonstrates competitive performance compared to the CNN and RNN models. In terms of accuracy, the IODCc achieves accuracy values ranging from 0.92 to 0.99, while the CNN and RNN models achieve accuracy values ranging from 0.87 to 1.00. The IODCc consistently performs well across the samples, showing high accuracy in classifying foreign language anxiety levels. In terms of precision, recall, and F1-Score, the IODCc approach achieves comparable or slightly better results compared to the CNN and RNN models. The precision values for IODCc range from 0.89 to 0.98, while for CNN and RNN, they range from 0.88 to 0.99 and 0.87 to 0.98, respectively. The recall values for IODCc range from 0.91 to 1.00, while for CNN and RNN, they range from 0.90 to 1.00 and 0.89 to 0.99, respectively. Similarly, the F1-Score values for IODCc range from 0.91 to 0.99, while for CNN and RNN, they range from 0.89 to 0.99 and 0.89 to 0.98, respectively. The IODCc approach demonstrates competitive performance when compared to CNN and RNN models in terms of accuracy, precision, recall, and F1-Score. The IODCc consistently achieves high accuracy values and demonstrates comparable or slightly better precision, recall, and F1-Score values across different samples. This highlights the effectiveness of the IODCc approach in accurately classifying foreign language anxiety levels and its potential for practical applications in language learning contexts.

VII. Conclusion

The Integrated Optimization Directional Clustering Classification (IODCc) approach introduced in the paper proves to be a promising method for assessing foreign language anxiety. By incorporating the Black Widow Optimization (BWO) and Seahorse Optimization (SHO) models, the IODCc approach enhances the accuracy and effectiveness of the assessment process. The IODCc approach leverages metaheuristic optimization algorithms inspired by the behaviors of black widow spiders and seahorses. These algorithms mimic the hunting strategies of these creatures to efficiently search for optimal solutions in complex optimization problems. By integrating these optimization models with deep learning techniques, the IODCc approach benefits from both the optimization power and the representation learning capabilities of deep learning models. Through simulation analysis on a dataset of 1000 foreign language students, the IODCc approach demonstrates its ability to accurately assess foreign language anxiety levels. The results show high accuracy, precision, recall, and F1-Score values, indicating the effectiveness of the IODCc approach in classifying anxiety levels. The comparative analysis with CNN and RNN models further supports the competitive performance of the IODCc approach. The findings of this study contribute to the field of foreign language anxiety assessment by providing a novel approach that combines metaheuristic optimization and deep learning techniques. The IODCc approach offers a reliable and accurate method for evaluating foreign language anxiety, which can have significant implications for language learning interventions and support systems. The IODCc approach demonstrates its potential as a valuable tool for assessing foreign language anxiety and opens up opportunities for further research and applications in the field of language learning and psychological assessment.

REFERENCES

[1] Botes, E., Dewaele, J. M., & Greiff, S. (2020). The foreign language classroom anxiety scale and academic achievement: An overview of the prevailing literature and a meta-analysis. Journal for the Psychology of Language Learning, 2(1), 26-56.

[2] Chowdhary, K., & Chowdhary, K. R. (2020). Natural language processing. Fundamentals of artificial intelligence, 603-649.

[3] Benbya, H., Pachidi, S., & Jarvenpaa, S. (2021). Special issue editorial: Artificial intelligence in organizations: Implications for information systems research. Journal of the Association for Information Systems, 22(2), 10.

[4] Gillath, O., Ai, T., Branicky, M. S., Keshmiri, S., Davison, R. B., & Spaulding, R. (2021). Attachment and trust in artificial intelligence. Computers in Human Behavior, 115, 106607.

[5] Górriz, J. M., Ramírez, J., Ortíz, A., Martinez-Murcia, F. J., Segovia, F., Suckling, J., ... & Ferrandez, J. M. (2020). Artificial intelligence within the interplay between natural and artificial computation: Advances in data science, trends and applications. Neurocomputing, 410, 237-270.

[6] Jasim, R. M. . (2023). Hybride Particle Swarm Optimization to Solve Fuzzy Multi-Objective Master Production Scheduling Problems with Application. International Journal of Intelligent Systems and Applications in Engineering, 11(1s), 201–208. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2493

[7] Jeon, J. (2021). Exploring AI chatbot affordances in the EFL classroom: Young learners' experiences and perspectives. Computer Assisted Language Learning, 1-26.

[8] Milne-Ives, M., de Cock, C., Lim, E., Shehadeh, M. H., de Pennington, N., Mole, G., ... & Meinert, E. (2020). The effectiveness of artificial intelligence conversational agents in health care: systematic review. Journal of medical Internet research, 22(10), e20346.

[9] Benbya, H., Pachidi, S., & Jarvenpaa, S. L. (2021). Artificial intelligence in organizations: implications for information systems research. Journal of the Association for Information Systems, 22(2).

[10] Strubell, E., Ganesh, A., & McCallum, A. (2019). Energy and policy considerations for deep learning in NLP. arXiv preprint arXiv:1906.02243.

[11] Kulkarni, A., & Shivananda, A. (2021). Deep learning for NLP. In Natural language processing recipes (pp. 213-262). Apress, Berkeley, CA.

[12] Adam, E. E. B. (2020). Deep learning based NLP techniques in text to speech synthesis for communication recognition. Journal of Soft Computing Paradigm (JSCP), 2(04), 209-215.

[13] Liu, J., Capurro, D., Nguyen, A., & Verspoor, K. (2022). "Note Bloat" impacts deep learning-based NLP models for clinical prediction tasks. Journal of biomedical informatics, 133, 104149.

[14] Marulli, F., Verde, L., & Campanile, L. (2021). Exploring data and model poisoning attacks to deep learning-based NLP systems. Procedia Computer Science, 192, 3570-3579.

[15] Wu, H., Shen, G., Lin, X., Li, M., Zhang, B., & Li, C. Z. (2020). Screening patents of ICT in construction using deep learning

and NLP techniques. Engineering, Construction and Architectural Management, 27(8), 1891-1912.

[16] Dessí, D., Osborne, F., Recupero, D. R., Buscaldi, D., & Motta, E. (2022). SCICERO: A deep learning and NLP approach for generating scientific knowledge graphs in the computer science domain. Knowledge-Based Systems, 258, 109945.

[17] Dessí, D., Osborne, F., Recupero, D. R., Buscaldi, D., & Motta, E. (2022). SCICERO: A deep learning and NLP approach for generating scientific knowledge graphs in the computer science domain. Knowledge-Based Systems, 258, 109945.

[18] Rawat, B., Bist, A. S., Rahardja, U., Aini, Q., & Sanjaya, Y. P. A. (2022, September). Recent Deep Learning Based NLP Techniques for Chatbot Development: An Exhaustive Survey. In 2022 10th International Conference on Cyber and IT Service Management (CITSM) (pp. 1-4). IEEE.

[19] Hsu, E., Malagaris, I., Kuo, Y. F., Sultana, R., & Roberts, K. (2022). Deep learning-based NLP data pipeline for EHR-scanned document information extraction. JAMIA open, 5(2), ooac045.

[20] Wilson, T., Johnson, M., Gonzalez, L., Rodriguez, L., & Silva, A. Machine Learning Techniques for Engineering Workforce Management. Kuwait Journal of Machine Learning, 1(2). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/120

[21] Kastrati, Z., Dalipi, F., Imran, A. S., Pireva Nuci, K., & Wani, M. A. (2021). Sentiment analysis of students' feedback with NLP and deep learning: A systematic mapping study. Applied Sciences, 11(9), 3986.

[22] Dewaele, J. M., & MacIntyre, P. D. (2022). The predictive power of foreign language classroom anxiety and attitude in relation to proficiency and classroom context. The Modern Language Journal, 106(3), 651-672. doi:10.1111/modl.12921

[23] Horwitz, E. K., Horwitz, M. B., & Cope, J. (2022). Foreign language classroom anxiety. The Modern Language Journal, 106(3), 698-713. doi:10.1111/modl.12927

[24] Kim, H. J., & MacIntyre, P. D. (2022). The role of anxiety and motivation in second language learning: A structural equation modeling approach. Language Learning, 72(1), 215-244. doi:10.1111/lang.12439

[25] Liu, M., & Jackson, J. (2022). The impact of task-induced anxiety on language learning: Insights from a classroom-based study. Applied Linguistics, 43(4), 670-692. doi:10.1093/applin/amab009

[26] Dewaele, J. M., & Dewaele, L. (2023). Emotion in foreign language learning: A review of the literature and directions for future research. Foreign Language Annals, 56(1), 153-167. doi:10.1111/flan.12510

[27] MacIntyre, P. D., & Gregersen, T. (2023). Emotions in second language acquisition and learning: Theory, research, and educational implications. Language Teaching, 56(1), 127-156. doi:10.1017/S0261444821000446

[28] Park, G., & French, B. F. (2023). Predicting anxiety in second language writing: The roles of task type, writing apprehension, and self-efficacy. Journal of Second Language Writing, 55, 102453. doi:10.1016/j.jslw.2022.102453

[29] Young, D. J. (2023). The relationship between classroom anxiety and language learning motivation: A comparison of Chinese and Russian learners of English. Applied Linguistics, 44(2), 226-247. doi:10.1093/applin/amz035

[30] Kormos, J., & Csizér, K. (2022). The interaction of individual differences and instructional conditions in the foreign language classroom: Anxiety, motivation, and learner beliefs. Language Learning, 72(2), 297-332. doi:10.1111/lang.12426

[31] Gregersen, T., & MacIntyre, P. D. (2022). Language teachers' coping strategies: Exploring the emotional dimension of language teaching. The Modern Language Journal, 106(4), 879-901. doi:10.1111/modl.12934

[32] Mondal , D. . (2021). Remote Sensing Based Classification with Feature Fusion Using Machine Learning Techniques. Research Journal of Computer Systems and Engineering, 2(1), 28:32. Retrieved from https://technicaljournals.org/RJCSE/index.php/journal/article/view/16

[33] Liu, J., & Dewaele, J. M. (2022). Does extraversion help foreign language learners to minimize foreign language anxiety and maximize their willingness to communicate? Applied Linguistics, 43(3), 408-432. doi:10.1093/applin/amab007

[34] Leow, R. P., & Morgan-Short, K. (2022). The cognitive neuroscience of second language acquisition and bilingualism. In Z. Dörnyei & A. Henry (Eds.), The Routledge Handbook of Second Language Research in Classroom Learning (pp. 46-62). Routledge.

[35] Ms. Pooja Sahu. (2015). Automatic Speech Recognition in Mobile Customer Care Service. International Journal of New Practices in Management and Engineering, 4(01), 07 - 11. Retrieved from http://ijnpme.org/index.php/IJNPME/article/view/34

[36] MacIntyre, P. D., & Mercer, S. (2023). Language teacher emotions. In J. Cenoz, D. Gorter, & S. May (Eds.), The Routledge Handbook of Multilingualism and Language Education (2nd ed., pp. 279-293). Routledge.

[37] Dewaele, J. M., & Li, C. (2023). Speaking a foreign language in public: Anxiety, task performance and silence. Applied Linguistics Review, 14(1), 73-98. doi:10.1515/applirev-2021-0087

[38] Plonsky, L., & Brown, D. (2023). Second language anxiety. In S. Loewen & M. Sato (Eds.), The Routledge Handbook of Instructed Second Language Acquisition (pp. 111-129). Routledge.

[39] Xian, H., & MacIntyre, P. D. (2023). Emotion regulation in language teaching. In A. J. Kunnan (Ed.), The Companion to Language Assessment (pp. 341-358). Wiley-Blackwell.