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Assessment Model Construction of International Students' Intercultural Adaptation Based on Dual Attention Graph Convolutional Network

Journal of Electrical Systems

Abstract: - Intercultural adaptability predicated on sojourners' sociocultural adaptation to their new surroundings. Globalization and the development of communication technology have led to a sharp rise in cross-border migration. However, there are significant obstacles to intercultural adaption, including student variations in traditional English cross-cultural instruction, developing students' cross-cultural communication skills, and improving the caliber of instruction. This manuscript proposes a Dual Attention Graph Convolutional Network (DAGCN) optimized with the Cheetah Optimization Algorithm (COA) for assessment model construction of international students' intercultural adaptation. The data are collected from Pakistani students at Huazhong University of Science and Technology, P.R. China. Afterward, the data's are fed to pre-processing. In pre-processing segment; it removes the noise and enhances the input data's utilizing Adaptive Robust Cubature Kalman Filtering (ARCKF). The outcome from the pre-processing data is transferred to the DAGCN. The language proficiency, cultural awareness, communication skill, and emotional resilience are successfully classified by using DAGCN. The COA is used to optimize the weight parameter of DAGCN. The proposed DAGCN-COA is utilized within the MATLAB/Simulink software environment. Performance metrics including accuracy, precision, sensitivity, F1-score, calculation time, and recall were examined in order to determine the proposed strategy. The proposed DAGCN-COA technique yields higher precision (14.89%, 16.89%, and 18.23%), higher sensitivity (16.34%, 12.23%, and 18.54%), shorter computation times (82.37%, 94.47%, and 87.76%), and higher accuracy (16.65%, 18.85%, and 17.89%).The proposed ISIA-DAGCN-COA method is compared with the existing methods such as ISIA-ANN, ISIA-CNN, and ISIA-RBF, respectively.

Keywords: Intercultural Adaptability, Adaptive Robust Cubature Kalman Filtering, Dual Attention Graph Convolutional Network, Cheetah Optimization Algorithm.

I. INTRODUCTION

In social science, the idea of intercultural adaptation is not new [1]. Living in novel and unique social environments presents a number of practical challenges, such as adjusting to the biological aspects of a new environment and more complex network-based problems [2]. It is possible to trace partners' social and cultural fitness back to the measurement of culturally adjustment as a broadly applicable social aptitude test [3]. Sociocultural adjustment was defined as the acquisition of behavior skills necessary for an individual to organize their life in a different social context. It was measured in terms of the degree of self-reported difficulty encountered in interpersonal situations and in carrying out daily tasks [4, 5].Individual mobility causes intercultural adjustment and adaptability to become a socially significant phenomenon. Most students travel abroad in order to further their education and experience life abroad [6, 7]. Every time children travel to another nation for school, they must adapt to the new educational system and the shifting cultural norms [8]. This adaptability, often referred to as intercultural adaptability, refers to initiatives to improve students' well-being for improved academic performance and to increase their enjoyment without feeling stressed [9, 10].

International students lay personal and cultural capital for bilateral coordinated development and further strengthen international collaboration as messengers of cultural exchanges [11]. Millions of students are currently enrolled overseas students are participating in study abroad programs all over the world at an unprecedented rate. Cultural adaptation is also a multifaceted process of "secondary growth," or resocialization [12, 13]. The success of resolving issues related to language, surroundings, eating habits, studies, and other areas where international students must adapt greatly affects their ultimate academic and study quality [14, 15]. Maladjustment will also harm international students' mental health if they are unable to deal with the cultural differences of their new home, which in part indicates that the families of international students and the government's investment in their education have failed [16, 17].

The premise of the current study is that sojourners are encouraged to adapt to the host culture in large part because of the nature and characteristics of informal communities [18]. The person who spent the majority of their time hanging out with other understudies was less interculturally preferred and less mentally pleased than the person who established a more diverse informal community [19].

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Nevertheless, each of them discovered that developing deep relationships with people from different linguistic or socioeconomic backgrounds was incredibly difficult, depending on a variety of factors that influenced the development of their intercultural relationships. Among them, understudy' limited capacity and intercultural competence were found to be important determinants of how adequate intercultural experiences were [20]. Additionally, there are a plethora of other theories and concepts that might be helpful in preparing travelers to make the most of their stay, such as intercultural personality, intercultural friendship, and intercultural informative capability.

Significant contribution to this study, as outlined above;

- Initially, information is obtained through the Huazhong University of Science and Technology, P.R. China, dataset of Pakistani students.
- Using an Adaptive Robust Cubature Kalman Filtering to eliminate the noise of Pakistani students at Huazhong University of Science and Technology, P.R. China dataset in the pre-processing segment.
- The pre-processed data's are fed into the DAGCN, in order to effectively categorize the language proficiency, cultural awareness, communication skill, and emotional resilience of the student data.
- The proposed DAGCN-COA method is implemented, and performance metrics such as calculation time, accuracy, precision, sensitivity, F1-score, and recall are examined.

The following is the arrangement of the remaining sections of this manuscript: Sector 2 looks at a survey of the literature, while Sector 3 describes the proposed plan of action. Sector 4 provides a discussion and results; and sector 5 completes.

II. LITERATURE REVIEW

Many studies were proposed in the literature concerning the international students intercultural adaptation; this review covers a few current works,

Jiang and Hou [21] have suggested that creation and implementation of a neural network-based vast system of open online courses for English-language intercultural communication courses. to investigate the enlargement and implementation of the MOOCs platform in the English neural network course-based cross-cultural communication. Initially, the general function modules of the MOOC system are explained, with particular focus on the system database design, Administrator, student, and instructor function modules regarding the intercultural communication classes in English. Secondly, the MOOC system's teaching methodology relied on a genetic algorithm, and its teaching quality indicator was chosen using principal component analysis in an inter-cultural communication training in English.

Dai and Zhao [22] have introduced that convolution neural networks are the basis of an intelligent analysis technique for practical failure in intercultural dialogue. Practical breakdown in intercultural communication, the study aims to make the conversation methodical, academic, and scientific. The convolutional network's complexity will be significantly decreased with this feature. Both speech noise reduction and the original voice's clarity may be improved by the convolution process in the convolution layer. Theoretically and practically, convolutional neural networks have been used to investigate the astute analytical techniques of practical failure in intercultural dialogue. The study object utilized in the presentation of the optimal end-to-end model was a deep convolution neural network. The construction of this model was based on the intelligent analytic method to pragmatic failure in cross-cultural communication.

Wang and Gao [23] have suggested that Neural network-based student satisfaction evaluation methodology for overseas students studying abroad. The five primary factors that determine the quality of education services were modeled and analyzed using a neural network. This study examines the issues surrounding the standard of instruction offered to foreign students in China by dissecting each of the model's five constituent parts.

Yassin et al. [24] have suggested that Sustainable learning for international students in Malaysian universities is impacted by intercultural learning obstacles. Through the use of a new assessment technique, investigating intercultural learning challenges that affect international students' ability to continue their education was the aim of this project. The data were examined using variance-based structural equation modeling, which were gathered via a survey from 273 foreign students enrolled in higher education institutions in Malaysia.

Senyshyn [25] have developed that a seminar course for first-year students that encourages the growth of intercultural communication competence while assisting overseas students in their transition to higher education. This study looks at a specialized first-year seminar course that lets foreign students engage with classmates from their home country outside of the classroom. The course, along with the interaction component, was created to meet the International students' demands for academic and social transitions. This study specifically looked at a three-year analysis of cohorts of foreign students enrolled for their first semester (N = 58), analyzing the first-year seminar's efficacy in the context of intercultural communication.

Novikov [26] have presented that influence of COVID-19 emergency switch to online instruction on views of Russian University's educational process among foreign students. Given that during Russia's statewide pandemic lockdown in the spring of 2020, students had to transition from in-person instruction to multiple online platforms, The aim of this research is to examine techniques for enhancing the adaptability of first-year international college students. After a seamless one-day transition to remote learning, the study aimed to investigate the different technological, sociological, and other obstacles that foreign students and how these challenges impacted their academic performance, motivation, attendance history, and other quantitative and qualitative data. The noteworthy increase in the adoption of online learning, which was already growing exponentially before the events of 2020, further cemented the research topic's significance. The study methodologies combine a review of potential threats, opportunities, weaknesses, and strengths with a theoretical look at present trends in online learning and how they have evolved. Statistical data was gathered and handled through the digital ecosystem of the university.

Gong et al. [27] have suggested that Study abroad students from New Zealand in China discuss issues and techniques related to cultural adaptation. This investigation looked at the obstacles a group of students from New Zealand faced and the tactical measures they used to adjust to Chinese culture. Fifteen participants were invited to create reflective notebooks as part of the inquiry, and group interviews were held to delve deeper into their experiences. The study exposed the range of difficulties encountered by the participants, encompassing linguistic, life style, academic, sociological, and psychological difficulties.

A. Motivation

The biggest problem is that overseas students are generally recognized to come from diverse cultural and educational backgrounds and to have unique experiences. The growing trend of globalization and internationalization in education may make international students' learning sustainability a persistent issue that keeps coming up, rather than just a one-time problem. In addition, a number of challenges for international students including acclimating to their host countries' new educational and cultural systems as well as normal living adaptability and academic difficulties. Cultural adaptation is a serious problem that needs more consideration. In actuality, international students participating in study abroad programs encounter and must adjust to challenges, demands, or difficulties resulting from cultural differences. Potential stressors that are directly linked to international students' cultural adjustment in Western colleges fall into five primary categories: discriminatory, linguistic, intellectual, sociological, practical, and lifestyle acculturative pressures. International students had two main challenges when adjusting to new countries and institutions in terms of socio-cultural adjustment. One is acclimating to new academic knowledge and skills in a foreign tongue, while the other is assimilating into a strange and novel host culture. Very few approach-based works have been provided in the literature to address this issue; these shortcomings and issues have inspired this study effort.

III. PROPOSED METHODOLOGY

In this section, international student intercultural adaptability using Dual Attention Graph Convolutional Network model along with Cheetah Optimization Algorithm (DAGCN-COA) is discussed. Block diagram illustrating the proposed strategy is displayed in Fig 1. It is separated into three phases: classification, pre-processing, and data gathering. Consequently, a thorough explanation of each step is provided below.

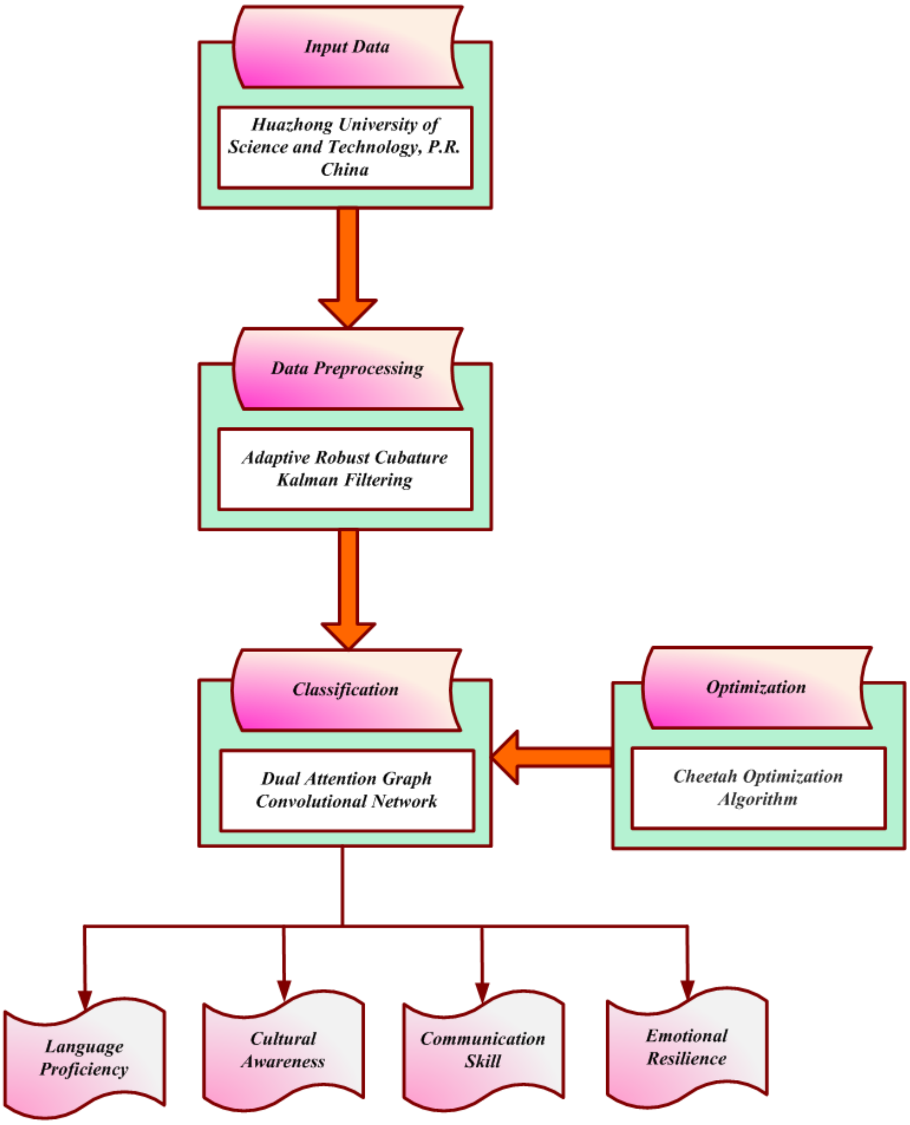

Fig 1: Block diagram illustrating the proposed strategy

A. Data Collection

Information gathered from Pakistani students are gathered by data analysis of a survey that 15 of them completed at Huazhong University of Science and Technology in the People's Republic of China [28], about language, psychological adaptation, and socio-cultural adaptation. Examining Pakistani students' life and academic experiences from their viewpoints and to comprehend the difficulties they encountered in their cross-cultural communication on Chinese campuses, psychological measures of cultural adjustment were employed as an analytical lens.

B. Data Pre-processing with Adaptive Robust Cubature Kalman Filtering

This section proposes the use of adaptive robust cubature kalman filtering as a preprocessing method [29]. In pre-processing segment, it confiscates the reduction of the dynamics error using in the adaptive robust cubature kalman filtering before discussing the ARCKF algorithm. Eliminating measurement and system noise, ARCKF can reduce the negative impacts of observation and innovation outliers. The state estimation error covariance matrix should be modified to various scenarios, an adaptive technique is devised.
The cubature point generation is given with the appropriate state estimate error covariance matrix; the statistical features can be represented by cubature points that can be created. Formally, get

$$Y_{i,k-1} = \hat{y}_{k-1} + \xi_i \sqrt{\hat{Q}_{k-1}}, \qquad i = 1,\ldots\ldots.2n \qquad (1)$$

Here, $Y_{i,k-1}$ is denoted as the i^{th} cubature point of $\hat{y}_{k-1}$, n is denoted as the dimension of state variables, $\sqrt{(.)}$ is denoted as the process of cholesky decomposition, ξ_i is denoted as the basic data point set's ith column.
The state transition function is utilized to instantiate the cubature points. After that, the corresponding state error covariance can be computed as

$$Y^*_{i,k} = f\left(Y_{i,k-1,}\, u_{k-1}\right),\ i = 1, \ldots\ldots, 2n \tag{2}$$

$$\tilde{Q}_k = \frac{1}{2n}\sum_{i=1}^{2n} Y^*_{i,k}\left(Y^*_{i,k}\right)^T - \tilde{y}_k \tilde{y}_k^T + P_{k-1} \tag{3}$$

Where, $Y^*_{i,k}$ is denoted as the modified points of cubature, $\tilde{Q}_k$ is denoted as the associated covariance of errors, the superscript T is denoted as the transposition of a matrix.
Finally, the filtering method is updating the better covariance matrix and this cubature filters are used to estimate the errors. The data are sent to DAGCN for classification following noise reduction.

C. Classification Based on Dual Attention Graph Convolutional Network

DAGCN are covered in this [30]. The fully connected classifier, the layer of self-attention pooling, and the attention graph convolution module are the three main parts of the DAGCN. This section addresses the issue with typical GCNs first, and then recommends our self-attention pooling layer and attention graph convolution module. One can compute the system dynamics using Eqn (4).

$$W^{j+1} = \phi(\tilde{V}\tilde{D}^{-1}W^{j}U) \qquad W^{0} = Y, \tag{4}$$

Where, $\tilde{V}\tilde{D}^{-1}$ is the graph structure that has been normalized, $\tilde{D}$ is denoted as the diagonal node degree matrix, $\tilde{V} = V + I_m$ is each node's adjacency matrix with self-connection, and U is the training parameter for the model. When this procedure is performed j times, W^j is transformed into a node attributes vector with j-hop local structure data.
With the exception of W^j, the outcome of each step in the recurrence of Eqn (4) is limited to using it to generate the convolution result that follows. Our attention graph convolution layer's primary objective is to enhance the model so that it may take useful information from each hop in addition to relying just on the k-hop convolution result. The key data derived from multiple hop convolution procedures will be included in a hierarchical representation that is the convolution output as a consequence. Display the attention behavior and apply it to Eqn (5) to create the following hierarchical node representation γ_{s_m} as below:

$$\gamma_{s_m} = \sum_{k=1}^{j} \alpha_{ki} W^{j}_{s_m} \tag{5}$$

To simplify, evaluate each hop's aggregation result's relevance using vanilla attention, where $W^{j}_{s_m}$ stands for node s_m local structure in j-hops and α is the attention weight. The information about the hierarchical structure is contained in the final node representation.

$$\gamma^{n+1}_{s_m} = \sum_{k=1}^{j} \alpha_k W^{j}_{s_m} \qquad W^{0}_{s_m} = \gamma^{n}_{s_m} + Y \tag{6}$$

To maximize the benefits of deep learning and uncover more profound hidden features, build an attention graph convolutional module and stack m attention convolution layers using the Residual Learning technique to produce an improved final node representation γ_{s_m}. Each AGC layer takes as input the total of its predecessor's output and the original Y.

$$\gamma_{s_m} = Dense\ (\{\gamma^{0}_{s_m}, \gamma^{1}_{s_m}, \ldots, \gamma^{n}_{s_m}\}, \theta) \tag{7}$$

Where each attention graph convolution layer's output is combined in a dense layer called $Dense\,()$. At this point, the node representation for every vertex in $s \in Q$ is γ. To keep things simple, we can describe the network as an m-by-c matrix Q, where each row represents a node.

$$Q = \left(\gamma_{s_1}, \gamma_{s_2}, \ldots, \gamma_{s_m}\right) \tag{8}$$

Utilize the attention mechanism to produce the weights vector α by feeding in the convolution module's learnt graph node representation.

$$\beta = soft\max(\,h_2 \tan w(h_1 Q^T)) \tag{9}$$

The weight matrices h_1 and h_2 have the c-by-c and c-by-r shapes, correspondingly, and r is denoted as a hyper-parameter that controls the quantity of subspaces required to transfer the node illustration to the graph representation. α is no longer a vector but a weight matrix when $r \geq 1$.

Graph representation matrix: the total matrix yields a complete representation of the graph, and each row represents a graph in a single sub-space. Finally, G is used as the input for a completely linked layer and a $soft\max$ layer to complete the graph categorization.

$$X = soft\max(ZG + C) \tag{10}$$

Where, the second input dimension is used to conduct the $soft\max$ function.

Finally, the DAGCN processing, which divides the data into categories based on linguistic ability, cultural awareness, communication skill, and emotional resilience. Typically, DAGCN doesn't offer the optimization technique needed to determine the best variables to confirm a precise detection. Therefore, in order for the optimization algorithm to optimize, the DAGCN weight parameter γ_{s_m} is crucial.

D. Optimization Technique Using Cheetah Optimization Algorithm

Optimization of Cheetahs Based on the population technique, the search algorithm is known as a meta-heuristic algorithm [31]. Prey can be found when a cheetah is roaming or monitoring its surroundings. When it spots its prey, a cheetah may choose to remain quietly and wait for the animal to approach before attacking. There are phases for rushing and capturing in the attack mode. The cheetah may abandon up hunting for a variety of reasons, including running out of energy or feasting its prey quickly. They might then return home to recover and begin hunting again.

Step 1: Initialization

Set the input factors to their initial values. The DAGCN weight parameter is represented by the $\left(\gamma_{s_m}\right)$notation

Step 2: Random Generation

Following initialization, a random vector is used to produce the input parameters at random.

$$Y = \begin{bmatrix} y_{1,1} & y_{1,2} & y_{1,3} \\ y_{2,1} & y_{2,2} & y_{2,3} \\ y_{3,1} & y_{3,2} & y_{3,3} \end{bmatrix}$$

(11)

Where, Y is the random generation.

Step 3: Fitness Function

The fitness is chosen based on the objective function.

$$F = Optimizing\left(\gamma_{s_m}\right) \tag{12}$$

Step 4: Searching the Prey

In order to locate their prey, cheetahs scan or actively search their search area as well as the areas nearby. Throughout the hunting season, cheetahs may choose to use a combination of these two search strategies, contingent upon the state of their prey, the extent of their territory, and their own health. Let $y_{i,j}^{t}$ is denoted as the cheetah's present location $\mathrm{i}\,(\mathrm{i} = 1,2,3,\ldots,\mathrm{n})$ in relation to j $\mathrm{j}\,(\mathrm{j} = 1,2,3,\ldots,\mathrm{D})$, here n is denoted as the number of the cheetah's population, D is denoted as the optimization problem's dimension. A random search equation is provided for every arrangement in order to update the cheetah's new position based on its current location. A random action is

$$y_{i,j}^{t+1} = y_{i,j}^{t} + r_{i,j}^{-1} \cdot \alpha_{i,j}^{t} \tag{13}$$

Where, $y_{i,j}^{t+1}$ and $y_{i,j}^{t}$ is denoted as the cheetah i's now and in future locations in arrangement j, correspondingly. Index t is denoted as the current hunting time. $r_{i,j}^{-1}$ and $\alpha_{i,j}^{t}$ is denoted as the randomization parameter and step length for cheetah i in arrangement j, respectively.

Step 5: Sit-and-Wait

A cheetah's field of vision may be exposed to the prey while it is in the searching mode. In this case, the cheetah's every move could make the prey aware of its presence and allow the animal to escape. To get near enough to the prey to escape this concern, the cheetah may decide to ambush. During this phase, the cheetah stays in place and waits for the prey to arrive.

$$y_{i,j}^{t+1} = y_{i,j}^{t} \tag{14}$$

Where, $y_{i,j}^{t+1}$ and $y_{i,j}^{t}$ is denoted as the cheetah i's revised and current locations in arrangement j, correspondingly.

Step 6: Attack Strategy

Two essential components that cheetahs use in their attacks on prey are speed and adaptation. A cheetah decides to attack, it moves swiftly in the direction of its victim. When the prey senses that the cheetah is attacking, it starts to run. The cheetah quickly follows the prey in the path of interception with its sharp vision. By tracking the prey's position, the cheetah modifies its trajectory to occasionally obstruct its route. The prey's last location and the cheetah's next position are close together; the cheetah's fastest speed over this short distance has been reached. To survive, the victim must run and shift positions quickly. It is likely that the lone cheetah does not engage in a hunting process that is entirely consistent with cheetah norms. The cheetah uses its quick reflexes and dexterity to grab its prey at this stage. When using a cooperative hunting strategy, individual cheetahs may adjust their position in response to escaping prey as well as the leader's or other cheetahs' location. To put it simply, all of the cheetahs' assault techniques are covered by the following mathematical definitions:

$$y_{i,j}^{t+1} = y_{\beta,j}^{t} + r_{ij} \cdot \beta_{i,j}^{t} \tag{15}$$

Where, $y_{\beta,j}^{t}$ is denoted as the prey's present location in arrangement j. r_{ij} and $\beta_{i,j}^{t}$ is denoted as the cheetah i's tuning factor and interaction factor in arrangement j. $y_{\beta,j}^{t}$ is When employed in their offensive mode, cheetahs' maximum speed rushing approach enables them to quickly approach the prey's location as closely as possible. The tuning factor $\beta_{i,j}^{t}$ is depicts how a cheetah and its leader interact when the cheetah is in the capture mode.

Step 7: Termination

This method takes into account two scenarios.

(1) The cheetah should relocate or return to its territory if it is unable to capture its prey.

(2) If it hasn't found any successful prey in a while, it can move to where the last prey was found and search the area around it.

Verify the stopping criteria; if the best solution is found, the procedure is over; if not, move on to step 3. Lastly DAGCN classifies the student data likes language proficiency, cultural awareness, communication skill, and emotional resilience by lower computational time.

IV. RESULT AND DISCUSSION

This sector discusses the experimental results of the DAGCN-COA method evaluation model construction of international students' intercultural adaption methodology. The MATLAB/Simulink working platform is used for the simulations. MATLAB is used to simulate the proposed method under various performance criteria. DAGCN result examined using existing methodologies including ANN, CNN, and RBF.

A. Performance measures

In order to choose the optimal classifier, this is an important task. Performance indicators like recall, sensitivity, F1-score, accuracy, and precision are analyzed to assess performance. The confusion matrix will be used to scale the performance measures, it is decided. False Negative (FN), False Positive (FP), True Negative (TN), and True Positive (TP) values are needed to scale the confusion matrix.

1) Accuracy

It is the ratio of the entire quantity of predictions made for a dataset separated by the count of exact forecasts. It is measured through Eqn (16),

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{16}$$

2) F1-Score

F-score is a metric used to analyze the performance of proposed ISIA-DAGCN-COA technique. It is computed in Eqn (17),

$$F\ score = F1score = \frac{TP}{TP + \frac{1}{2}[FP + FN]} \tag{17}$$

3) Precision (P)

Precision is a metric which quantifies the count of correct positive prediction made. This is computed via following Eqn (18)

$$P = \frac{TP}{TP + FP} \tag{18}$$

4) Recall(R)

Recall is a measure that determines how accurate a forecast is based on the total number of accurate forecasts made. To measure it, use Equation (19),

$$R = \frac{TP}{TP + FN} \tag{19}$$

B. Performance Analysis

Fig 2 to 7 shows the simulation outcomes of ISIA-DAGCN- COA. Then the outcomes are analyzed with existing ISIA-ANN, ISIA-CNN, and ISIA-RBF methods.

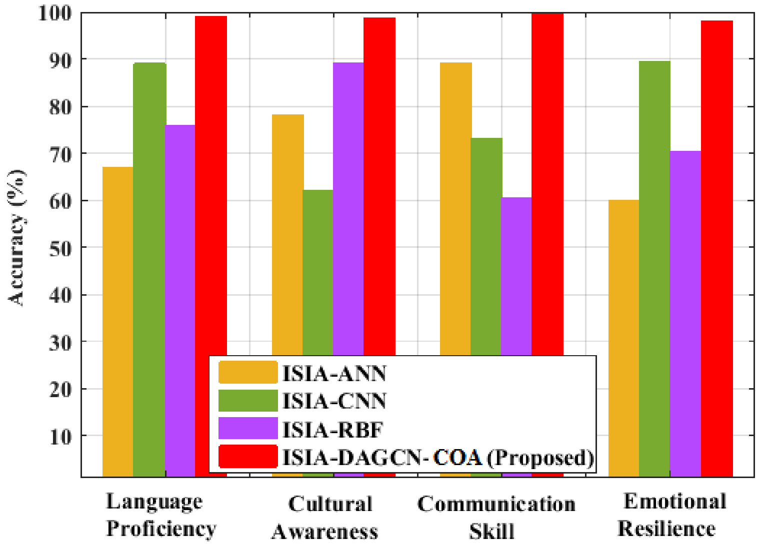

Fig 2: Accuracy value comparison between the proposed and existing methods.

Accuracy value comparison between the proposed and existing methods is displayed in Fig 2. The performance of the proposed ISIA-DAGCN-COA technique results in accuracy that are 50.56%, 20.76%, 35.97% higher for the classification of language proficiency, 20.46%, 35.58%, 23.54% higher for the classification of cultural awareness and 21.45%, 30.76%, 18.43% higher for the classification of communication skill, 21.44%, 30.86%, 15.43% higher for the classification of emotional resilience upon comparison with the existing ISIA-ANN, ISIA-CNN, and ISIA-RBF models correspondingly.

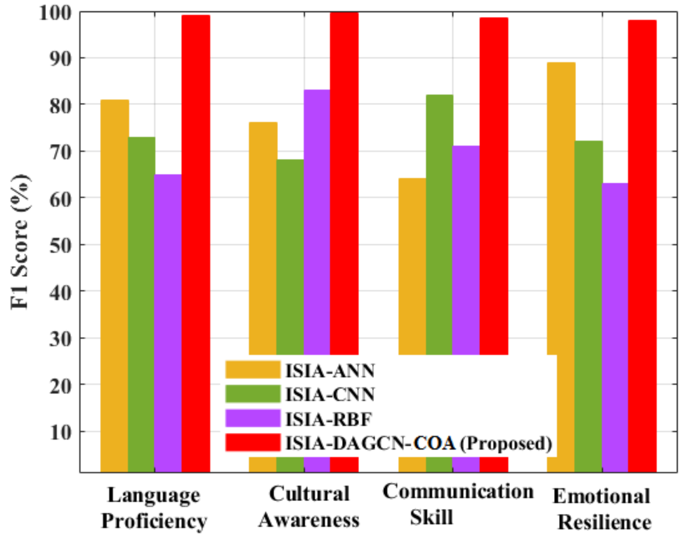

Fig 3: Analyze the proposed and existing methods perform in terms of F1-score value.

Analyze the proposed and existing methods perform in terms of F1-score value is displayed in Fig 3. The performance of the proposed ISIA-DAGCN-COA technique results in F1-score that are 22.56%, 21.76%, 33.97%, higher for the classification of language proficiency, 21.46%, 33.58%, 23.54% higher for the classification of cultural awareness and 21.45%, 30.76%, 18.43% higher for the classification of communication skill, 20.44%, 30.86%, 15.43% higher for the classification of emotional resilience when estimated to the existing ISIA-ANN, ISIA-CNN, and ISIA-RBF models correspondingly.

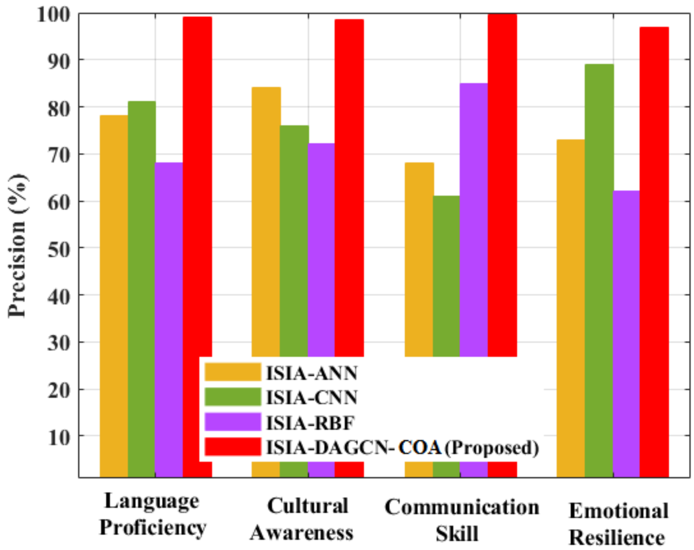

Fig 4: Precision value comparison between the proposed and existing methods.

Precision value comparison between the proposed and existing methods is displayed in Fig 4. Here, a direct comparison with proposed approaches is offered to show how the suggested method's precision is higher. The proposed method provides for a more extensive analysis of a proposed and has higher precision than existing methods due to its wider consideration of factors. The performance of the proposed ISIA-DAGCN-COA technique results in precision that are 30.56%, 21.76%, 35.97%, higher for the classification of language proficiency, 21.46%, 33.58%, 23.54% higher for the classification of cultural awareness and 21.45%, 30.76%, 18.43% higher for the classification of communication skill, 20.44%, 30.86%, 15.43% higher for the classification of emotional resilience when evaluated to the existing ISIA-ANN, ISIA-CNN, and ISIA-RBF models correspondingly.

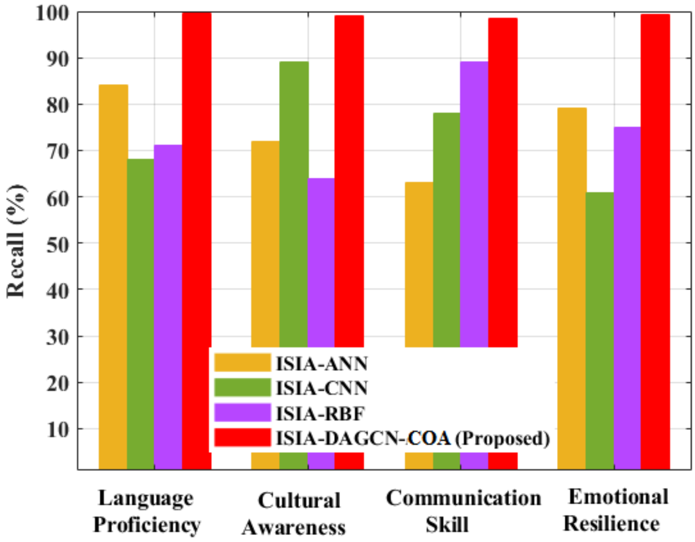

Fig 5: The recall value comparison between the proposed and existing systems.

The recall value comparison between the proposed and existing systems is displayed in Fig 5. The performance of the proposed ISIA-DAGCN-COA technique results in recall that are 23.56%, 22.76%, 31.97% higher for the classification of language proficiency, 22.46%, 31.58%, 22.54% higher for the classification of cultural awareness and 22.45%, 29.76%, 17.43% higher for the classification of communication skill, 19.44%, 29.86%, 14.43% higher for the classification of emotional resilience when evaluated to the existing ISIA-ANN, ISIA-CNN, and ISIA-RBF models correspondingly.

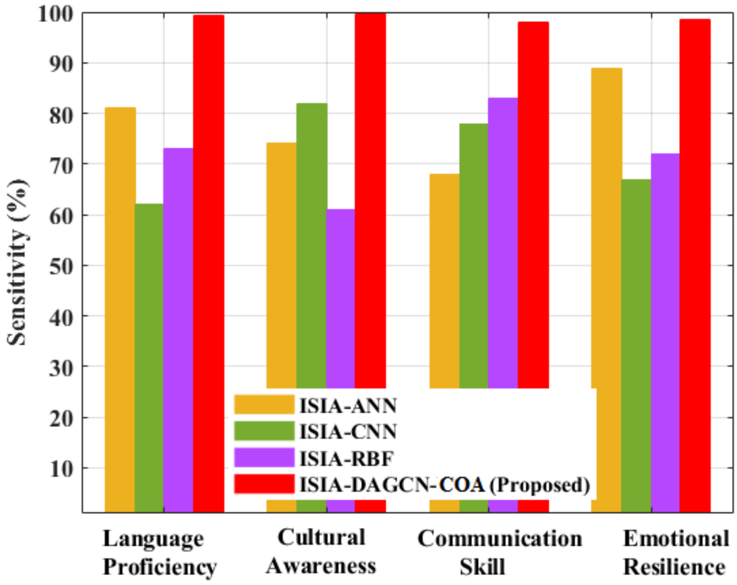

Fig 6: The sensitivity value comparison between the proposed and existing systems.

The sensitivity value comparison between the proposed and existing systems is displayed in Fig 6. The performance of the proposed ISIA-DAGCN-COA technique results in sensitivity that are 30.56%, 21.76%, 35.97%, higher for the classification of language proficiency, 21.46%, 33.58%, 23.54% higher for the classification of cultural awareness and 21.45%, 30.76%, 18.43% higher for the classification of communication skill, 20.46%, 35.58%, 23.54% higher for the classification of emotional resilience when evaluated to the existing ISIA-ANN, ISIA-CNN, and ISIA-RBF models correspondingly.

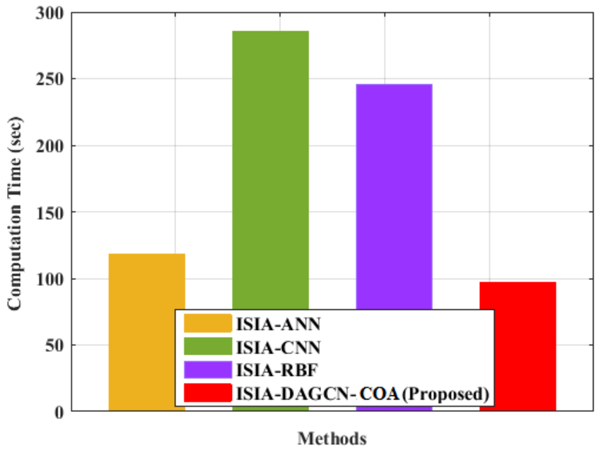

Fig 7: Computation time analysis utilizing both proposed and existing techniques.

Computation time analysis utilizing both proposed and existing techniques is displayed in Fig 7. When compared to existing approaches such as ISIA-RNN, ISIA-CNN, and ISIA-RBF, the proposed ISIA-DAGCN-COA method yields 5.34%, 10.11%, and 10.26% lower computing time, correspondingly.

V. CONCLUSION

In conclusion, this research harnesses the power of DAGCN to significantly model construction of international student's intercultural adaptation. Utilizing Huazhong University of Science and Technology in the People's Republic of China, is a crucial initial step. The student data is pre-processed using the Adaptive Robust Cubature Kalman Filtering. The DAGCN receives the pre-processed result and uses it to effectively classify language proficiency, cultural awareness, communication skill, and emotional resilience of student. The MATLAB/Simulink working environment is used to evaluate the proposed strategy and compare it with other existing techniques. A variety of scenarios, including precision, accuracy, sensitivity, F1-score, calculation time, and recall, are examined in relation to the proposed methodology. The DAGCN classifier, utilized at the end of the system, has increased its accuracy to 98% thanks to its accurate identification of the recommended optimum region expansion technique. This shows that the system is capable of effectively recognizing language proficiency, cultural awareness, communication skill, and emotional resilience of student.

Acknowledgements

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