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# Teaching Quality Prediction of University English Courses Based on Machine Learning Technology

***Abstract: -*** Students' academic progress and language proficiency are significantly shaped by the quality of instruction in English courses at the university level. English teaching quality prediction is the process of collecting, organizing, and analysing teaching status data in a thorough manner utilizing efficient technical methods in order to assign values and enhance teaching activities. In this manuscript, Teaching Quality Prediction of University English Courses using an Optimized Rotation-Invariant Coordinate Convolutional Neural Network (TQP-UEC-RICCNN-SBOA) is proposed. Initially domestic universities are the source of the input data. The input data is fed to pre-processing using Adaptive-Noise Augmented Kalman Filter (ANAKF) for the removal of incomplete and redundant data from the collected dataset. Then the RICCNN optimized with Secretary Bird Optimization Algorithm (SBOA) for accurate teaching quality prediction of English courses in the university. The proposed TQP-UEC-RICCNN-SBOA approach is implemented in Python and the performance metrics like Accuracy, Precision, Specificity, Recall, F1-Score, and ROC are analysed. The performance of the proposed TQP-UEC-RICCNN-SBOA approach attains18.25%, 22.5% and 30.7% higher accuracy, 17.35%, 24.9% and 31.50% higher Precision and 19.12%, 25.67% and 30.80% higher Recall compared with existing methods such as An Evaluation Approach for English Teaching Quality using DEA Fusion Algorithm(EA-ETQ-DEA-RBF), Online teaching quality evaluation model based on support vector machine and decision tree(OTQ-EM-SVM) and A Teaching Quality Evaluation Model for Preschool Teachers Based on Deep Learning(TQEM-PT-TS-ResNet) models respectively.

***Keywords:*** Adaptive-Noise Augmented Kalman Filter, English Teaching Quality, Rotation-Invariant Coordinate Convolutional Neural Network, Secretary Bird Optimization Algorithm, English Teaching Quality.

## I. INTRODUCTION

English is a language that is widely used worldwide, so it is very important to the process of global integration [1]. In addition to serving as a medium for worldwide communication, it also significantly advances world trade, politics, economics, culture, education, and other sectors [2]. Over time, English has grown in importance in higher education, and proficiency in the language has become a valuable asset for experienced professionals [3]. One of the primary objectives of contemporary higher education is to enhance college students' overall proficiency in English. This has led to a progressive increase in interest in college English instruction [4, 5].Teaching quality is significantly influenced by the credentials and experience of English teachers. Highly skilled and experienced teachers typically give their students superior guidance and support [5, 6]. Effective English instruction requires highly skilled and experienced teachers who have strong language fluency, pedagogical abilities, and current knowledge of language teaching approaches. Maintaining a high standard of instruction can be achieved by providing chances for peer learning, professional development workshops, and training programs that keep English teachers' skills and knowledge up to date [6, 7]. The best way to conduct an efficient and trustworthy assessment and analysis of college English instruction and improving the calibre of English teaching has been a hot subject in higher education research. In today's higher education, comprehensive, excellent training of senior staff is highly regarded [8]. In order to facilitate the exchange and advancement of senior talent, college students in non-English speaking nations are trained in professional knowledge and skills as well as high English proficiency [9]. Enhancing the standard of English instruction in colleges and developing senior talent with exceptional English proficiency are crucial for this [10]. Nevertheless, there are a count of variables that change English instruction in colleges, including English instructors, English teaching management systems and procedures, English teaching concepts, teaching approaches, and teaching methods, in addition to social, human, material, and financial variables. These variables make it more challenging and complex to enhance and assess the level of English teaching in universities [11, 12]. The secret to enhancing the university the goal of teaching English is to raise educational standards, and the most important

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way to do this is through learning evaluation. Since English language instruction has a direct impact on students' academic and professional achievement, it is imperative that universities provide high-quality instruction in the language [13, 14]. It is difficult to predict and evaluate the standard of English teaching, and it calls for a diversified strategy. Since college students are going through a unique time, formative assessment will have a significant effect on them [15, 16].

Formative evaluation, when used with ecological theory as a guide, can address a number of issues, including student aversion to learning and classroom boredom in high school. Additionally, students' self-awareness, enthusiasm in learning, learning strategies, and overall growth can all be enhanced by classroom dynamic evaluation. It can also raise instructor professionalism, increase the general quality of instruction, and improve the atmosphere in which students learn English [17, 18]. Predicting the quality of English instruction is important because it helps to pinpoint areas that need work and put focused interventions in place to improve student outcomes and learning experiences [19]. Colleges and universities may make well-informed judgments and continuously improve their programs to meet the changing needs of the student body and the labour market by evaluating the different components that go into providing effective English training [20].

Decision tree models have the drawback of being prone to over fitting, particularly when the training dataset is limited, which results in subpar generalization performance on fresh, unknown data. This is especially true for teaching quality prediction of university English courses. The disadvantages of SVM include its limited interpretability and forecasts, as well as its reliance on efficient feature engineering for maximum performance. To train the model and capture the intricate spatiotemporal patterns in the quality of English instruction, a sizable and varied dataset may be required for TS-ResNet. The above mentioned disadvantages motivated us to do this work. The purpose of this research is to look into a better technique for Teaching Quality Prediction of University English Courses.

In this research, a novel method for improving TQP-UEC-RICCNN-SBOA is presented. The system seeks to achieve higher accuracy and efficiency by combining SBOA with optimized RICCNN. The suggested approach is put into practice using Python and contrasted to the state-of-the-art methods. It shows notable improvements in a number of measures, like Accuracy, Precision, Specificity, F1-Score, Recall and ROC

The primary contribution of this study is outlined below.

- In this research, Teaching Quality Prediction of University English Coursesusing an Optimized Rotation-Invariant Coordinate Convolutional Neural Network (TQP-UEC-RICCNN-SBOA) is proposed.
- Develop Adaptive-Noise Augmented Kalman Filter (ANAKF) based preprocessing method for the removal of incomplete and redundant data from the collected dataset.
- Propose a RICCNN optimized with SBOA for accurate prediction of English teaching quality in university.

Remaining manuscripts arranged as below: Sector 2 Literature Survey; Sector 3 Proposed method, Sector 4 outcomes with discussions, Sector 5 conclusion.

## II. LITERATURE SURVEY

Numerous investigations based on deep learning works were suggested in literature related to TQP-UEC; few current works are reviewed here.

Tan,et al. [21] has presented EA-ETQ-DEA-RBF. This research Study the issue of evaluating the standard of English language education offered at colleges and creates a model that uses the DEA fusion algorithm to do this. A model has been established to assess the quality of English education offered by universities and other facilities. This model considers both qualitative and quantitative research findings. It attains higher Precision and it provides lower Recall

Hou, et al. [22] has presented OTQ-EM-SVM. As a predictor for supervised prediction, we now offer a support vector regression. This work maps complicated non-linear interactions onto high-dimensional space to generate linear connections that are similar to those in low-dimensional space. Additionally, the model in this work was fed both small- and large-scale data sets in order to do tests on teaching quality evaluation. It attains higher Specificity and it provides lower Recall.

Ge, et al. [23] has presented TQEM-PT-TS-ResNet. This study offered a deep learning-based approach for assessing preschool teachers' teaching quality. First, a progressive hierarchical structure was developed for the relevant assessment indices. Next, using the fuzzy relationship synthesis approach, a fuzzy comprehensive assessment of each index layer and evaluation criterion was created. It attains higher Recall and it provides lower Specificity.

Liu, et al. [24] have suggested Evaluation of College English Teaching Quality Based on Grey Clustering Analysis. The evaluation of college English instruction was presented, along with the elements that influence college English instruction quality. As a result, an improved and conceptually unique assessment method for judging the level of college English teaching was established. Grey clustering analysis and the entropy weight approach were then combined to create a powerful model for assessing the quality of English instruction at the collegiate level. It attains greater Accuracy and it provides lower Recall.

Fang et al. [25] have presented an intelligent online learning environment built on a complicated network and the SVM algorithm. Both the pre-processing of assessment indicators and the development of the support vector machine teaching quality evaluation model have been thoroughly studied. The creation of an evaluation model for teaching quality based on machine learning theory was the primary goal. Additionally, this study reduced the dimensionality of the assessment index by enhanced principal component analysis, avoiding the prediction effect being impacted by the excessively complicated network model. It attains higher specificity and it provides lower accuracy.

Li, et al. [26] have suggested A Fuzzy Evaluation Model of College English TQ Based on AHP. This study developed a fuzzy evaluation model based on the analytic hierarchy technique and thoroughly examines the fuzzy assessment of college ELT quality. First, an enhanced multi-angle EIS for college English teaching quality was created using theoretical analysis and model computation. A model for evaluating the quality of college English instruction was developed using both quantitative and qualitative evaluations, and it can handle fuzzy indices. It attains higher F1-Score and it provides lower Specificity

Han, [27] have presented an Evaluation of English online teaching based on remote supervision algorithms and deep learning. This study simulates and studies the use of supervision algorithms in the teaching process, and it develops a system structure for the assessment process of online English education, and integrates deep learning algorithms with remote supervision in order to satisfy the needs of English online instruction. In addition, the teacher's method of instruction was rated, and the student's and teacher's viewpoints were taken into consideration while evaluating the student's activities and learning process. It delivers less accuracy and achieves a better specificity.

## III. PROPOSED METHODOLOGY

This section, teaching quality prediction of university English courses using Rotation-Invariant Coordinate Convolutional Neural Network (TQP-UEC-RICCNN-SBOA) is proposed. This process consists of three steps: data acquisition, Pre-processing, and optimization. Data’s are collected from the domestic university. Dataset are pre-processed in the proposed quality prediction system so they are ready for quality prediction. It covers such stages as Adaptive-Noise Augmented Kalman Filter (ANAKF), Rotation-Invariant Coordinate Convolutional Neural Network (RICCNN), and Secretary Bird Optimization Algorithm (SBOA). Block diagram of proposed TQP-UEC-RICCNN-SBOA method is in Figure 1. Thus, detailed explanation about every step given below,

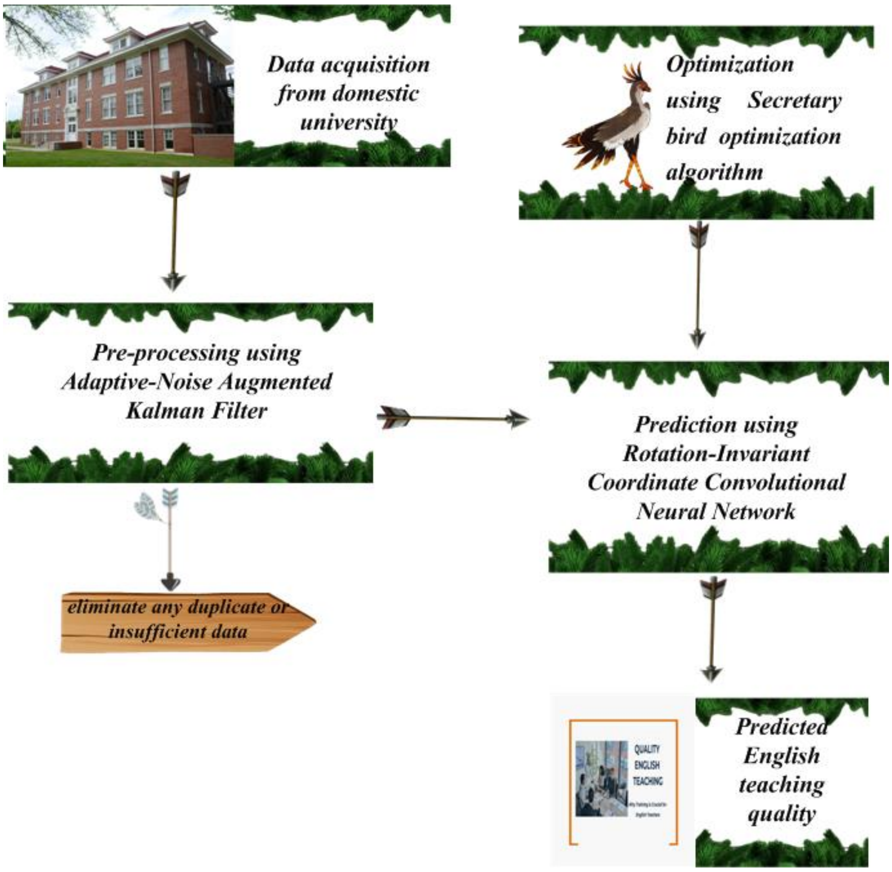


Figure1: Block Diagram for Proposed TQP-UEC-RICCNN-SBOA Method

*A. Data Acquisition*

At first, the domestic university provides the input data.. The input dataset contains the English instructions such as English teaching management systems and procedures, English teaching concepts, teaching approaches, and teaching methods. A quarter of the data is used as the test set and the remaining seventy-five percent is used as the training set in the TQP-UEC-RICCNN-SBOA model.

*B. Pre-processing using ANAKF*

In this section, ANAKF [28] technique is utilized which is used for the removal of incomplete and redundant data from the collected dataset. Enhancing data quality and model resilience are two benefits of using the adaptive-noise augmented Kalman filter to forecast the standard of English teaching. The main objectives of pre-processing using Adaptive-Noise Augmented Kalman Filter are to provide a robust and reliable framework for predicting the standard of English language teaching in universities and colleges. In relation to the observed quantities, the forecast's error can be easily measured by the following equation (1)

$$D^0 = \frac{1}{m_0}\sqrt{\sum_{i=1}^{m_0}\left(\arg\min_\theta \left\|\theta x_i^0 - \left(x_i^0 - \hat{x}_i^0\right)\right\|_2\right)^2} \tag{1}$$

Where, $x_i^0$ indicates the current position of the input variable data with index $i$; $\arg\min_\theta$ indicates the input to be returned for which the output is at its lowest or highest value; $D^0$ denotes the measurement error of the predicted quantities. The error quantification equation considers unmeasured responses, providing a global understanding of the accuracy of the AKF response prediction during the examined time frame. To quantify the prediction error, the formulation in Eq. (1) can be recast as provided in equation (2) for the unmeasured response values.

$$D^h = \frac{1}{m_p}\sqrt{\sum_{i=1}^{m_p}\left(\arg\min_\beta \left\|\beta x_i^p - \left(x_i^p - \hat{x}_i^p\right)\right\|_2\right)^2} \tag{2}$$

Where, $D^h$ denotes the uncertainty in the forecast for the unmeasured variables; $\hat{x}_i^p$ denotes the response that the filter calculated for the current window; $x_i^p$ denotes actual input data. Without changing the generality of the data, ANKAKF can eliminate certain redundant data and data that conflicts with other data. It is given in equation (3)

$$k_m^0 = \Psi^0 g_m \tag{3}$$

Where, $k_m^0$ denotes the output data; $g_m$ denotes the input dataset; $\Psi^0$ denotes the reduction basis of the filter. Normalization is one of the pre-processing steps that make sure the input data are consistent and similar between scales. This is required for the adaptive-noise augmented Kalman filter to correctly depict the dynamics of English teaching quality across time. It is given in equation (4)

$$g_k = \Psi^0 k_m^0 \tag{4}$$

Where, $g_k$ denotes the input data set; $k_m^0$ denotes the filtered dataset. The inaccuracy in the input estimate is inherent in the error covariance matrix when the ANKAKF is used for input-state estimation. It is given in equation (5)

$$B = \begin{bmatrix} B^{nn} & B^{nu} \\ B^{un} & B^{uu} \end{bmatrix} \tag{5}$$

Where, $B$ denotes the input dataset's error covariance matrix; $B^{un}$ denotes covariance of the unidentified input mistake. By processing ANKAKF method have successfully eliminate any incomplete and redundant data from the collected dataset. Then the pre-processed data are fed to English teaching quality prediction.

*C. Prediction using Rotation-Invariant Coordinate Convolutional Neural Network*

In this part, prediction using RICCNN [29] is discussed. The proposed RICCNN is used to predict the TQ of English courses in university with high accuracy. RICCNN can minimize computational complexity compared to regular CNNs by avoiding the need to process numerous rotated copies of the same data separately. Because of their efficiency, they are well-suited to assessing enormous volumes of educational materials, which are widespread in universities. RIC-CNNs' rotation-invariant nature allows them to generalize efficiently across various teaching styles and approaches. This means that the network may learn from a wide variety of teaching examples and use that knowledge to predict teaching quality across contexts and instructors. The benefits of utilizing RICCNN to predict English teaching quality at colleges include more accurate and robust evaluations by successfully analysing visual teaching materials while addressing the diversity of educational content. RICCNN effectiveness is determined by the ratio of linear weighted input indicators to output indicators which is given in equation (6)

$$Z = \left( s.\cos\left(\phi + \frac{l.2\pi}{8s}\right), s.\sin\left(\phi + \frac{l.2\pi}{8s}\right)\right) \tag{6}$$

Here, Z represents an acronym for the RICCNN's efficiency assessment index; $s.\cos$ denotes the input indicator weight vector; $s.\sin$ denotes the output indicator weight vector. The RICCNN is made up of rotation-invariant modules. These modules are intended to detect in a manner that is insensitive to rotation. This can be accomplished by implementing systems like rotational pooling. It is given in equation (7)

$$\phi_{RIC-C}(H_0, K(H)) = \sum_{Z \in R_{H_0}} D(V).\ K(H_0 + Z) \tag{7}$$

Where, $\phi_{RIC-C}$ denotes invariant to any rotation around the input data; $D(V)$ denotes the rotated version; $\sum_{Z \in R_{H_0}}$ denotes the rotational pooling. Instead of analysing input data values directly, the RIC-CNN first encodes input data with coordinate information. This encoding assists the network in understanding the spatial links between various portions of the dataset. Equation (8) contains it.

$$Z_\alpha^{'} = T_\theta Z_\alpha \tag{8}$$

Where, $T_\theta$ and $Z_\alpha$ denotes the weight parameter of network; $Z_\alpha^{'}$ denotes the input data with coordinate information. Pooling layers are commonly used in networks to reduce the dimensionality of input data while retaining crucial information. Pooling processes may be rotation-invariant to retain the network's overall ability to accommodate rotated input data. It is given in equation (9)

$$\phi_{RIC-C}(H_0, K(H)) = \sum_{N \in M} D(V).\ K(H_0 + N + \Delta N) \tag{9}$$

Here, $K(H)$ denotes the input data; $\Delta N$ denotes the learnable parameter generated by using RICCNN network; $N \in M$ denotes the order of the input data. The network ends with one or more layers for predicting English teaching quality. These layers take the input dataset and transform it into the desired output. This may be found in equation (10)

$$\phi_{RIC-C}(H_0, K(H)) = \sum_{N \in M} D(V).\ K(H_0 + N + (Z - N)) \tag{10}$$

Where, $Z - N$ denotes the filtered dataset; $\sum_{N \in M}$ denotes the pooling layer of the network that takes the input data and transform it into the desired output. Finally, RICCNN predicts the university English teaching quality. The RICCNN prediction incorporates optimisation approach because of its relevance and ease of usage. In this case, the RICCNN is optimised using SBOA. In this case, the weight and bias parameters of the RICCNN are adjusted using SBOA.

*D. Optimization using SBOA*

The proposed SBOA [30] is utilized to enhance weights parameters $T_\theta$ and $Z_\alpha$ of proposed RICCNN. The Secretary Bird is a remarkable African raptor with unusual look and mannerisms. It is widespread in open riverine environments, savannas, and grasslands in Africa south of the Sahara Desert. Wide tropical grasslands, treeless savannas, and open areas with tall grass are ideal habitats for secretary birds. They can also be found in woodland areas with clearings and semi-desert locations. Secretary birds have white chests, a deep black belly, and grey-brown feathers on their wings and backs. One of Secretary Birds' most remarkable abilities is that they can fight snakes, which makes them a formidable foe to these animals. The Secretary Bird is a very smart bird when it comes to snake hunting. The aim function establishes the fitness of the system. To determine the function of fitness, With years of expertise handling snakes, the Secretary Bird can easily predict the snake's next move while keeping control of the situation. The survival strategies of secretary birds in their natural habitat served as a major source of inspiration for the proposed SBOA approach. Here, step by step procedure for obtaining appropriate RICCNN values using SBOA is described here. To creates a uniformly distributed population for optimizing the ideal RICCNN parameters. The step process in its entirety is then displayed below.

***Step1:*** initialization

In the SBOA's initial implementation, Eq. (11) is used to randomly initialize the locations of Secretary Birds in the search area.

$$A_{l,k} = jd_k + i \times (vb_k - jd_k), l = 1,2,...., Dim \tag{11}$$

Here, $vb_k$ and v represent the lower and upper boundaries; $i$ represents a random number between 0 and 1; and $A_l$ represents the location of the $l^{th}$ secretary bird.

***Step2:*** Random generation

The input weight parameter $T_\theta$ and $Z_\alpha$ developed randomness via SBOA method.

***Step 3:*** Fitness Function

The system's fitness is determined by the target function. In order to ascertain the fitness function,

$$Fitness Function = optimizing\ [T_\theta \text{ and } Z_\alpha] \tag{12}$$

Where, $T_\theta$ is used for increasing the Accuracy and $Z_\alpha$ is used for increasing the Recall.

***Step 4:*** Hunting strategy of secretary bird ***(***$T_\theta$***)***

When hunting snakes, SB typically hunt in three stages: locating prey, devouring prey, and attacking prey.

***Stage 1:*** searching for prey

Secretary birds begin their hunting process by searching for prey, particularly snakes. Secretary birds have keen vision and can detect snakes in the long grass of the savannah. They scan the ground gently with their lengthy legs, keeping an eye on their surroundings for snakes. Diversity can help prevent being caught in local optima by implementing differential mutation procedures. The possibility of discovering the global optimum is increased by the ability for individuals to investigate various areas of the solution space. Therefore, equation (13) may be used to quantitatively simulate updating the SB's location during the Searching for Prey step.

$$While\, f < \frac{1}{3}F, a_{l,k}^{new,p1} = a_{l,k} + (a_{randam\_1} - a_{randam\_2}) \times S_1 \times T_\theta \tag{13}$$

In the first stage iteration, $a_{randam\_1}$ and $a_{randam\_2}$ are the arbitrary contestant solutions, while $f$ denotes the current iteration number and $F$ the maximum iteration number.

***Stage 2:*** Consuming Prey

A SB's uses a unique hunting technique when it spots a snake. The secretary bird uses its deft footwork to avoid the snake, in contrast to other raptors that charge headlong into battle. The secretary bird maintains its position, watching the snake closely from above. It progressively wears out its opponent's stamina by hovering, jumping, and provocating the snake with its astute observation of its movements. A mathematical model can be created to update the position of the secretary bird during the Consuming Prey stage. It is given in equation (14)

$$While \frac{1}{3}F < f < \frac{2}{3}F,\; a_{l,k}^{new,p1} = a_{best} + \exp((f/F) \wedge 4) \times (SG - 0.5) \times (a_{best} - a_{l,k}) \tag{14}$$

Where, $a_{best}$ represents the current best value; $a_{l,k}^{new,p1}$ represents the new state of the $l^{th}$ secretary bird.

***Stage 3:*** Attacking Prey

When the snake is worn out, the SB recognizes when it is the best time to strike and uses its strong leg muscles to do so. During this phase, the secretary bird usually uses its leg-kicking technique, which entails quickly raising its leg and precisely kicking with its keen talons, frequently going after the snake's head. These kicks are intended to swiftly immobilize or kill the snake so that you won't get bitten in return. Individuals can get at the optimal position more rapidly by using large steps to aid the algorithm in exploring the global range of the search area, while small steps enhance the accuracy of the optimization. Therefore, equation (15) may be used to quantitatively simulate updating the SB location during the Attacking Prey stage.

$$While\, f > \frac{2}{3}GF,\; a_{l,k}^{new,p1} = a_{best} + \left(\left(1 - \frac{f}{F}\right) \wedge \left(2 \times \frac{f}{F}\right)\right) \times a_{l,k} \times RL \tag{15}$$

Where, $RL$ represents the weighted Levy battle to improve the algorithm's optimisation accuracy.

***Step 5:*** Escape strategy of secretary bird ***(*** $Z_\alpha$ ***)***

Large predators like eagles, hawks, foxes, and jackals are the secretary birds' natural adversaries because they can attack them or take their food. Secretary birds usually use a variety of evasion techniques to defend themselves or their food when faced with these hazards. These tactics can be divided roughly into two primary groups. The initial tactic is either fighting or sprinting quickly. The second tactic is concealment. In the first method, secretary birds first look for an appropriate camouflage environment when they sense the presence of a predator. If they can't find a safe and appropriate hiding place nearby, they'll fight or run quickly to get away. In conclusion, it is possible to represent both of the evasive techniques used by secretary birds mathematically. It is given in equation (16)

$$a_{l,k}^{new,p1} = \begin{cases} C_1 : a_{best} + (2 \times RL - 1) \times \left(1 - \frac{1}{F}\right)^2 \times a_{l,k}, & if\ i\ and < i_r \\ C_2 : a_{l,k} + R_2 \times \left(a_{randam} - E \times a_{l,k}\right) \times Z_\alpha, & else \end{cases} \tag{16}$$

Here, $i = 0.5$ and $R_2$ indicates the array dimension's arbitrary creation; $a_{randam}$ represents the current iteration's potential solution and $E$ indicates the arbitrary selection of integer 1or 2.

***Step 6:*** Termination Criteria

The weight parameter value of generator $T_\theta$ and $Z_\alpha$ from Rotation-Invariant Coordinate Convolutional Neural Network (RICCNN) is optimized by SBOA. The iterative refinement guided by halting criteria $A = A + 1$, ensures optimal weight convergence, maximizing RICCNN generator performance. Then flowchart of SBOA for optimizing the weight parameters of RICCNN for prediction of English teaching quality in university is dispayed in figure 2.

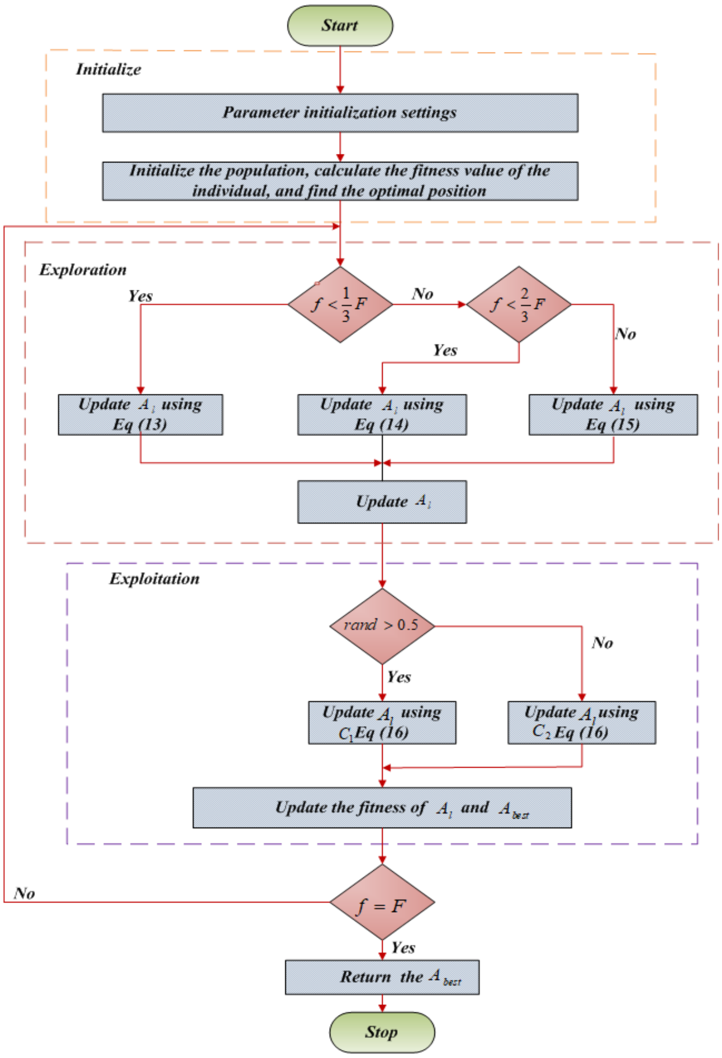

Figure 2: Flow Chart of SBOA for Optimizing RICCNN

## IV. RESULT AND DISCUSSION

This section discusses the proposed method's experimental results. Next, using the previously indicated performance indicators, the recommended technique is simulated in Python.. The proposed TQP-UEC-RICCNN-SBOA approach is implemented in Python. The obtained outcome of the proposed TQP-UEC-RICCNN-SBOA approach is analyzed with existing systems like EA-ETQ-DEA-RBF [21], OTQ-EM-SVM [22] and TQEM-PT-TS-ResNet [23] respectively.

### *A. Performance Measures*

Selecting the best classifier requires taking this critical step. Performance metrics like as F1-score, ROC, recall, accuracy, precision, and specificity are evaluated in order to evaluate performance. The performance metric is deemed in order to scale the metrics. The True Negative, True Positive, False Negative, and False Positive samples are required in order to scale the performance metric.

- True Negative $(TN)$ : Indicates the count of instance which is accurately predicted as negative.
- True Positive $(TP)$ : Indicates the count of instance which is accurately predicted the positive.
- False Positive $(FP)$ : Indicates the count of instance which is inaccurately predicted as positive.

- False Negative $(FN)$ : Indicates the count of instance which is inaccurately predicted as negative.

*1) Accuracy*

Equation (17) provides the accuracy, which quantifies the percentage of samples both positive and negative in addition to the entire amount of samples.

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{17}$$

*2) Precision*

Precision, or how accurately a machine learning model predicts the future, is one indicator of the algorithm's efficacy. The calculation of precision involves dividing the entire amount of positive predictions by the amount of true positives, as indicated in equation (18).

$$\Pr ecision = \frac{TP}{(TP + FP)} \tag{18}$$

*3) Recall*

The proportion of data samples that a machine learning model correctly recognises as belonging to a class of interest is called recall, sometimes referred to as the TPR. It is measured by following equation (19)

$$\mathrm{R}ecall = \frac{TN}{(FP + TN)} \tag{19}$$

*4) Specificity*

Specificity is the metric used to evaluate a model's ability to predict true negatives for each given category. You may use these metrics with any category model. It is given in equation (20)

$$Specificity = \frac{TP}{FN + TP} \tag{20}$$

*5) F1-score*

One statistic used to assess a machine learning model's performance is the F-score. Equation (21) shows how accuracy and recall are combined into a single score.

$$F1 - Score = 2 \times \frac{recall \times precision}{recall + precision} \tag{21}$$

*6) ROC*

It is graphical depiction of prediction method at numerous threshold settings. It is made by plotting TPR against FPR for different threshold values. Here, ROC is predicted in to TPR, FPR**.** Thus given in equation (22)

$$ROC = 0.5 \times \left( \frac{TP}{TP + FN} + \frac{TN}{TN + TP} \right) \tag{22}$$

*B. Performance Analysis*

The simulation outcomes of the proposed TQP-UEC-RICCNN-SBOA method are shown in Fig. 3 to 8. Then, the proposed TQP-UEC-RICCNN-SBOA method is likened with existing EA-ETQ-DEA-RBF [21], OTQ-EM-SVM [22] and TQEM-PT-TS-ResNet [23] methods respectively.

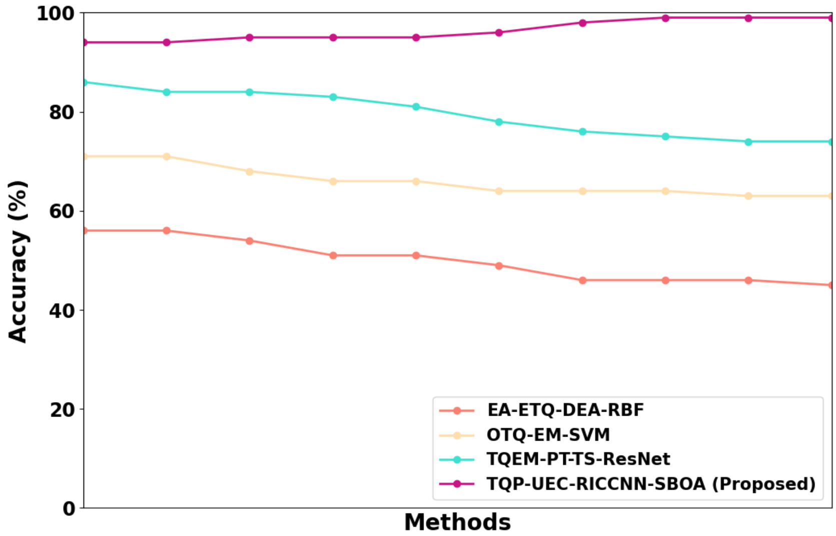


Figure 3: Performance Analysis of Accuracy

Figure 3 displays Accuracy analyses. An accuracy graph is used to illustrate how well a model performs in properly predicting the quality of ELT in university. The proposed TQP-UEC-RICCNN-SBOA method accuracy is shown compared with the existing methods on the graph. The main objective is to get stable accuracy, which will demonstrate the model's efficacy in predicting quality of English teaching in university. The proposed TQP-UEC-RICCNN-SBOAmethod attains 18.25%, 22.5% and 30.7% higher accuracy for predicting quality of ELT in university estimated to the existing, EA-ETQ-DEA-RBF, OTQ-EM-SVM and TQEM-PT-TS-ResNet models respectively.

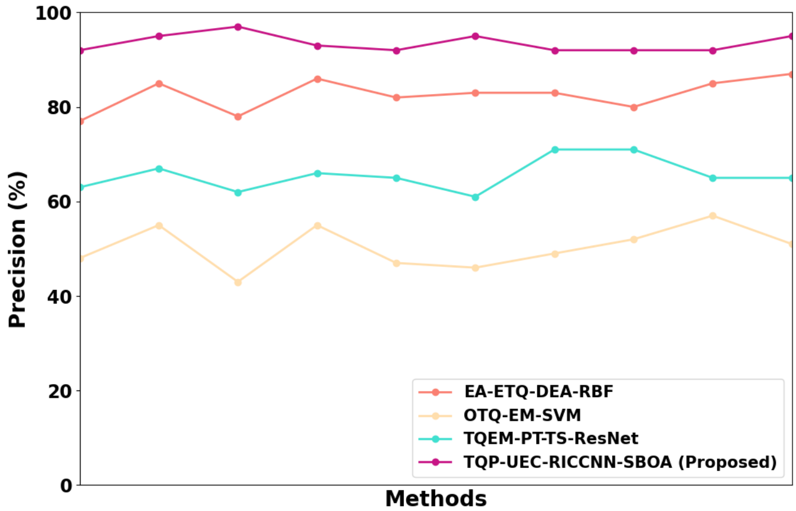


Figure 4: Performance Analyses of Precision

Figure 4 displays Precision Analyses. The precision graph illustrates how the proposed TQP-UEC-RICCNN-SBOA model reduces false positives and negatives to provide accurate prediction of the quality of ELT in university. TQP-UEC-RICCNN-SBOA model preforms significantly better than the current methods (EA-ETQ-DEA-RBF, OTQ-EM-SVM and TQEM-PT-TS-ResNet). The proposed TQP-UEC-RICCNN-SBOAmethod attains 17.35%, 24.9% and 31.50% higher Precision for predicting the quality of ELT in university estimated to the existing EA-ETQ-DEA-RBF, OTQ-EM-SVM and TQEM-PT-TS-ResNet models respectively

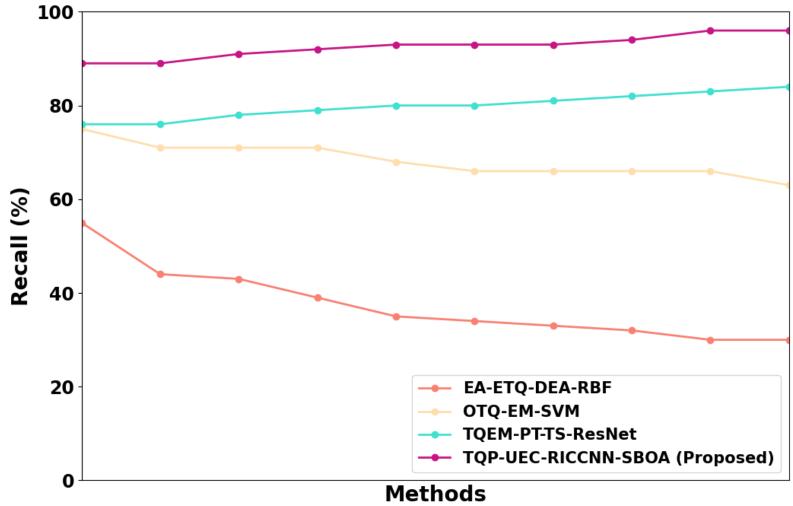


Figure 5: Performance Analysis of Recall

Figure 5 displays Recall analysis. When using TQP-UEC-RICCNN-SBOA method to predict the quality of ELT in university, recall graphs show how effectively the proposed method predicts the quality of ELT in university. A high recall indicates that the model minimizes false negatives. The proposed TQP-UEC-RICCNN-SBOA method attains19.12%, 25.67%, 30.80% higher recall for predicting the daily rainfall intensity estimated to the existing EA-ETQ-DEA-RBF, OTQ-EM-SVM and TQEM-PT-TS-ResNet models respectively

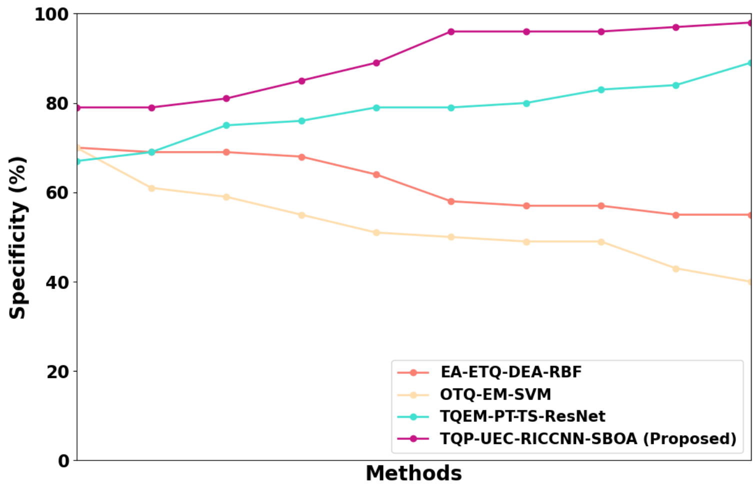


Figure 6: Performance Analysis of Specificity

Figure 6 displays Specificity analysis. Specificity graphs highlight another facet of the proposed model performance: its ability to prevent predicting negative outcome. A high, steady value on the x-axis (specificity value) would be ideal for the specificity graph. This suggests that the model successfully predicting the quality of ELT in university. The proposed TQP-UEC-RICCNN-SBOA method attains 18.4%, 24.36% and 31.08% higher Specificity for predicting the quality of ELT in university estimated to the existing EA-ETQ-DEA-RBF, OTQ-EM-SVM and TQEM-PT-TS-ResNet models correspondingly.

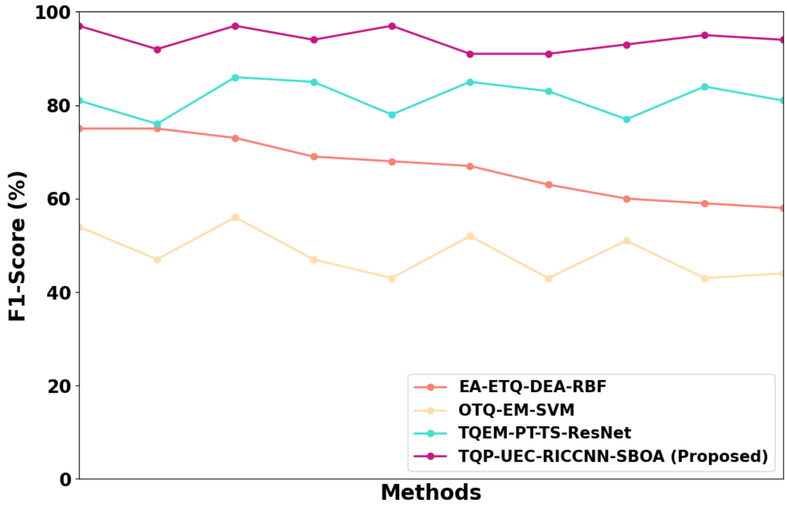


Figure 7: Performance Analyses of F1-Score

Figure 7 displays F1-Score analysis. Precision and Recall results are combined in F1 across training epochs is shown in F1-Score graphs for proposed TQP-UEC-RICCNN-SBOAmethod-based prediction of the quality of ELT in university. The value should ideally increase and stay high to demonstrate that the model appropriately predicts the intensity of the quality of ELT in university.The proposed TQP-UEC-RICCNN-SBOA method attains18.9%, 19.6% and 21.4% higher F1-score higher F1-Score for predicting the quality of ELT in university estimated to the existing EA-ETQ-DEA-RBF, OTQ-EM-SVM and TQEM-PT-TS-ResNet models respectively.

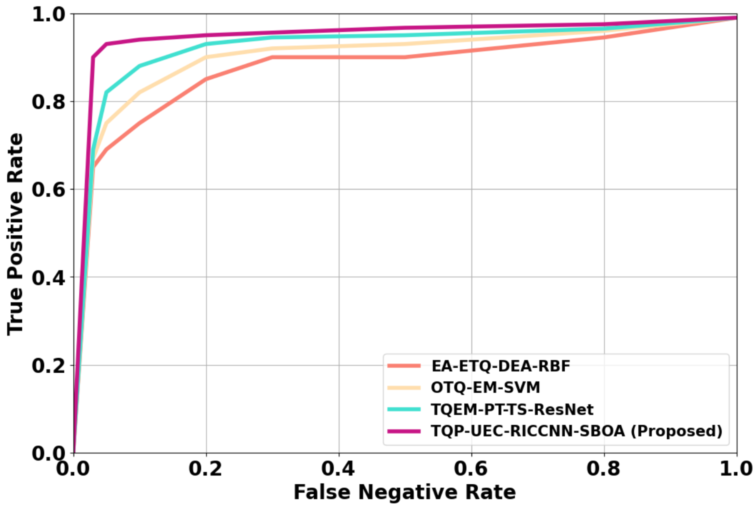


Figure 8: Performance Analyses of ROC

Figure 8 displays ROC Analyses. Plotting the likelihood of a TP against the likelihood of a FP is known as the ROC curve. Here in the figure true positives might be the cases in which the model accurately predicts the quality of ELT, while a false negative might be the cases in which the model inaccurately predicts the quality of ELT. The proposed model is successful in predicting the quality of ELT in university. The TPR should be high and stable. The proposed TQP-UEC-RICCNN-SBOAmethod attains0.97%, 0.98% 0.99% greater ROC for predicting the quality of ELT in university estimated to the existing EA-ETQ-DEA-RBF, OTQ-EM-SVM and TQEM-PT-TS-ResNet models respectively

*C. Discussion*

Teaching Quality Prediction of University English Coursesusing an Optimized RICCNN is developed in this paper**.** In the realm of automated research, predicting the quality of ELT in university is a crucial subject that needs the greatest focus. In this work, an input dataset from domestic university for the prediction of the quality of ELT was generated. Our primary focus in this study has been to predict the quality of ELT. The pre-processing technique an ANAKF is used for the removal of incomplete and redundant data from the collected dataset. The highly effective RICCNN optimized with SBOA for accurate prediction of English teaching quality in university. For all of the performance metrics looked at, this model performs better than the others at predicting the English teaching quality in university. The TQP-UEC-RICCNN-SBOA model outperforms the EA-ETQ-DEA-RBF, OTQ-EM-SVM, and TQEM-PT-TS-ResNet models in terms of accuracy, precision, recall, specificity, and F1-score, respectively.

## V. CONCLUSION

In this manuscript teaching quality prediction of university English courses using Rotation-Invariant Coordinate Convolutional Neural Network (TQP-UEC-RICCNN-SBOA) was successfully implemented. The proposed TQP-UEC-RICCNN-SBOA approach is implemented in Python with dataset collected from domestic university. According to the experimental results, TQP-UEC-RICCNN-SBOA performed better when used with the Co-training technique than when used separately regards FI-Score and ROC.The performance of the proposed TQP-UEC-RICCNN-SBOA approach contains 18.9%, 19.6% and 21.4% higher F1-score and 0.97%, 0.98% 0.99% greater ROC Score when analyzed with the existing methods like EA-ETQ-DEA-RBF, OTQ-EM-SVMand TQEM-PT-TS-ResNet methods respectively.To improve the accuracy of predicting the quality and computation time of English instruction, future research may concentrate on developing algorithms with greater complexity and combining big data and deep learning. Likewise, the machine learning approach's training model can be accelerated and system response times increased by big data technologies like cloud and edge computing.

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