

¹Yinchun Tang*

Quality Evaluation of College Students' Sports Work Based on Intellectual or Intuitive Fuzzy Information in Language



Abstract: - Numerous factors influence college students' athletic behaviour and psychological qualities such as sports learning interest, autonomy support in sports play important roles in forming their participation in sports activities. The study used acceptable research methodologies to analyse effect of sports learning interest, autonomy support in sports on college students' sports behaviour, specifically their physical activity levels. In this research work, Quality Evaluation of College Students' Sports Work Based on Intellectual or Intuitive Fuzzy Information in Language (QECSSW-IGNN-QCTO) is proposed. The input data are collected from College student data from Sichuan University. Then, the input data are pre-processed using Adaptive-Noise Augmented Kalman Filter (ANAKF) for finding missing data and cleaning the duplicate data. Then the pre-processed data are given to Iso-Geometric Neural Network (IGNN) for evaluating the quality of college students sports work (sports exercise grade). In general, IGNN doesn't express some adoption of optimization approaches for determining optimal parameters to evaluating the quality of college students' sports work. Hence QCTO is proposed to optimize IGNN classifier which precisely evaluates the quality of college student's sports work. The proposed QECSSW-IGNN-QCTO method is implemented in Python, and it assessed with several performance metrics like, Accuracy, Cross validation scores, Recall, F1 score, and ROC. The results show QECSSW-IGNN-QCTO attains 23.4%, 28.3%, and 22.6% higher Accuracy, 25.9%, 17.6%, and 29.4% lower Cross validation scores, 24.6%, 27.5%, and 18.7% higher Recall are analysed with existing methods such as, prediction method of college students' sports behaviour depend on machine learning method (PMC-SSB-MLM), Designing and implementing an innovative sports training system for college students' mental health education (DII-STSC-SMHE), The effect of sports science students' online learning attitudes on their readiness to learn online in emerging coronavirus pandemic (ESS-SOLA-ECP) methods respectively.

Keywords: Adaptive-Noise Augmented Kalman Filter, College students' data, Iso-Geometric Neural Networks, Quantum Class Topper Optimization.

I. INTRODUCTION

Simultaneously, society and educational institutions tend to prioritize students' intellectual growth while minimizing the importance of physical education. Students are burdened with an overwhelming academic workload, leaving little time for leisure, exercise. There is urgent need to increase social attention to physical education. The physical education class is the major platform for pupils to understand, participate physical activities in schools [1, 2]. Teachers in these workshops not only impart physical skills to their students, but also promote healthy lifestyle. The assessment of physical education outcomes has a direct impact on students' attitudes, views of physical education classes, learning. Though, existing methods of measuring physical education presentation have numerous flaws, frequently resulting in unpleasant emotions among students, greatly reducing effectiveness of physical education programs [3, 4]. The use of new methods is critical in helping kids appreciate the value of physical education, increase their passion, and create a genuine understanding and love of sports. This method is critical for addressing the present reduction in students' physical health [5, 6]. Unfortunately, there has been a lack of innovative development and improvement in how students' physical education performance is assessed in instructor evaluations. The majority of physical education classes continue to focus on sports methods; with competency or physical fitness strength serving as the primary evaluation criterion [7, 8]. This evaluation approach plainly falls short of the criteria of contemporary physical education teaching changes. It struggles to comprise, reflect on students' physical health state, affecting whole advancement of physical education curriculum, teaching change [9, 10]. Data mining has several facets, with association rule mining being a critical component. Exploring group features and behaviours is a complicated and important aspect of suggestion rule mining. An obvious example is relationship among students' individual natural information, employment behavior in student employment scheme [11, 12]. Traditional performance prediction research frequently uses previous performance or single kind of behavioural data forecast objective presentation, ignoring the varied degrees of influence that multiple behavioural features may have on grades [13, 14]. The data show important positive association among sports success, academic achievement, implying kids who excel in athletics also perform well academically. Furthermore, self-efficacy among college students is significantly positively correlated with the network structure of both athletic and academic success [15, 16].

¹Associate Professor, PE Division, Sichuan University Jinjiang College, Meishan, Sichuan, 620860, China

*Email: phdyinchuntang@gmail.com

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The current approach of evaluating pupils' athletic performance based purely movement method; physical quality assessment impedes growth of cognition, confidence, and interest. Study argues for a change in assessment of college students' sports presentation to correspond with the objectives of the "new curriculum reform" and stresses reflecting student's dominant location [17, 18]. Investigators point out, whereas physical education courses and teaching methods have altered greatly, physical assessment methodologies have stayed constant. The use of degree of mastery assessment criteria for student evaluation may reduce students' passion for studying physical education and, in the long term, hamper reform of physical education instruction [19, 20].

A. Problem statement and motivation

The problematic of predicting student grades inattentive into time series classification difficult by taking into account the varying effects of students' behavioural characteristics on academic achievement over time. This method predicts weighted average grade of students at conclusion of term using their behavior data. Traditional grade prediction algorithms frequently neglect the unique effects of many behavioural factors on grades. This restriction is addressed by abstracting grade prediction issue into time series classification issue, which recognizes that behavioural data collected over different time periods has various effects on student grades.

This manuscript a bridges applicable factors affect college students' sports behaviour. Investigation assesses level of forecast method through building of forecast method of DL process, assessment technique to define optimal forecast method. The IGNN method executes better in combination of sports learning interest, motor autonomy support, owing to combination of linear classification features, higher flexibility and computational efficacy to outlier processing.

Major contributions to this work are brief below:

- Developing a comprehensive framework for analyzing and comprehend different facets of sports behavior exhibited by college students.
- Deploying inventive techniques to collect pertinent data, guaranteeing a thorough and precise portrayal of the sports behavior displayed by students.
- Considering a variety of factors, such as sports learning interest, autonomy, and other important features, in the assessment process to provide a complete view.
- Developing prediction models that use IGNN to predict and measure sports behavior among college students.

II. LITERATURE REVIEW

Numerous research works presented in literatures were depend on College students' sports work; few of them were reviewed here,

Liu et al [21] have presented to build PMC-SSB depend on ML technique. Here, combines relevant aspects impacting college students' sports behavior, specifically their levels of physical activity, while taking into account sports autonomy and learning interest. Analysis was supplemented with a demographic, sociological survey of college students. Investigation assesses forecast method's efficacy using machine learning algorithms and comparison approaches. This strategy seeks to create and find the best prediction model. It provides high Accuracy, and it provides high Cross validation score.

Wang and Park [22] have presented DII sports training system for college SMHE. Here, considers user information such as age, BMI, and physical health state. Based on this analysis, it suggests student-specific sports programs, resulting in the implementation of an intelligent sports program recommendation function. This suggestion function was done by examining the entities and relationships within the intelligent sports system. It provides low Cross validation score, and it provides low Recall.

Hergüner et al. [23] have presented effect of online learning attitudes of sports sciences students on learning readiness to learn online in era of ECP. Here, artificial intelligence suggestion algorithm considers user information such as age, BMI, and physical health state. Based on this analysis, it suggests student-specific sports programs, resulting in the implementation of an intelligent sports program recommendation function. This suggestion function was done by examining the entities and relationships within the intelligent sports system. It provides high Recall, and it provides low F1 score.

Lotfi [24] have presented a sport outcomes forecast using ML algorithms. Here, current analysis techniques employed in literature, examining forecast progressions utilized in modeling data gathering, exploration. The

objective was to identify the characteristics of the variables influencing performance. Ultimately, the paper will propose a consistent instrument for data mining analysis techniques employing ML. It provides high F1 score, and it provides low ROC.

ZhaoriGetu [25] have presented forecast of sports performance combined by DL technique with analysis of influencing factors. Here, investigated the prediction method and model for sporting achievements. The influencing elements on sports successes will be examined through experiments, followed by the application of the deep learning gradient compression model approach to improve sports performance. The impacting factors were analysed across four dimensions. It provides high ROC, and it provides low Accuracy.

Jiang [26] have presented a Construction of Correlation Analysis Model of College Students' Sports Performance depend on CNN. Here, creations of employment analysis scheme depend on suggestion conditions. To address the limitation of traditional grade forecast techniques, which ignore varying impacts of distinct behavioural features on grades, to recognize behavioural data from altered periods exert diverse effects on student grades, grade forecast issue was reframed as time series classification issue. It provides high ROC, and it provides low Recall.

Xu [27] have presented forecast with planning of sports competition depend on DNN. Here, investigates the use of autoregressive summation method forecast to create a predictive model for sports tournaments. It evaluates the model's performance and universality to determine whether it was suitable for predicting sports results. It has most successful to improve the performance prediction, resulting in a reduction in systematic errors in forecasts. It provides high F1 score, and it provides high Cross validation score.

III. PROPOSED METHOD

In this section, QECSSW-IGNN-QCTO is discussed. The block diagram of proposed QECSSW-IGNN-QCTO shown in figure 1, dataset, pre-processing, evaluation, and optimization are processes make up this procedure. Thus, full description of all stage is given below,

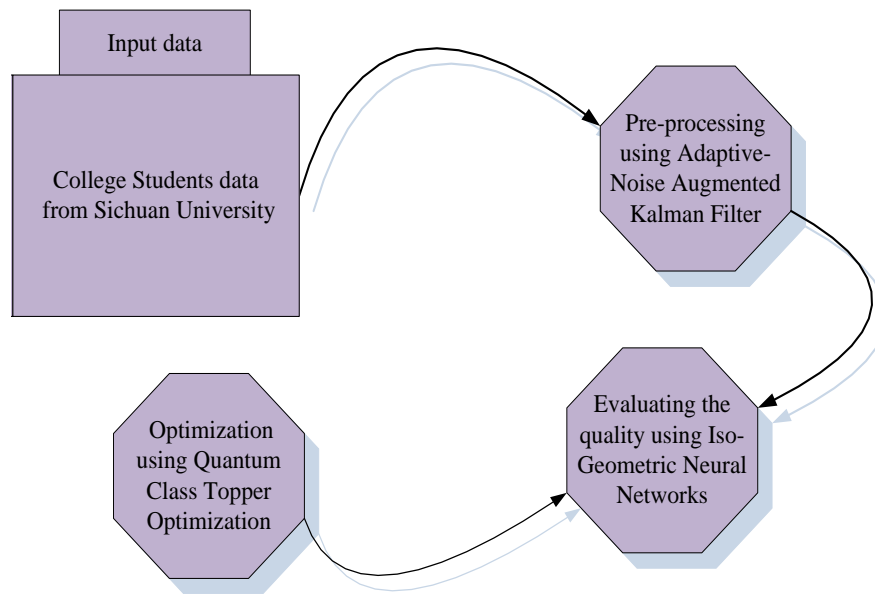


Figure 1: Block Diagram of QECSSW-IGNN-QCTO for Evaluating the Quality of College Students Sports Work

A. Data acquisition

The input data is gathered from College Students data at Sichuan University, ranging from 45,000 to 49,999 students. This includes demographic information such as age, gender, and academic majors, as well as facts on the types of athletic activities individuals participate in, the frequency with which they participate, and their motives for participating. Furthermore, the data collecting method collects information about students' physical fitness levels, any injuries sustained during sports activities, and their attitudes toward the role of sports in their general well-being.

B. Pre-processing Using Adaptive-Noise Augmented Kalman Filter

The pre-processing using ANAKF [28] is discussed. ANAKF is used to find the missing data and cleaning the duplicate data. ANAKF has the capacity to dynamically adapt its filtering process in real time, allowing for quick responses to unexpected changes or abnormalities in the data. This competence is required to successfully manage dynamic datasets. ANAKF's adaptive feature helps to reduce sensitivity to outliers or abnormalities in the data. This feature is especially useful in pre-processing activities when outliers have the ability to alter the integrity of the entire dataset. Consequently, the prediction error for the measured data is expressed in equation (1).

$$E^o = \frac{1}{n_o} \sqrt{\sum_{l=1}^{n_o} \left(\arg \min_{\theta} \|\theta y_l^o - (y_l^o - \hat{y}_l^o)\|_2 \right)^2} \tag{1}$$

Where, $y_l^o = [y_{l_1}^o \dots y_{l_j}^o \dots y_{l_N}^o]$ denotes response acquired at $(i - th)$ scaled AKF, Similarly, $\hat{y}_l^o = [\hat{y}_{l_1}^o \dots \hat{y}_{l_j}^o \dots \hat{y}_{l_N}^o]$ signifies response re-assessed by AKF, (θy_l^o) denotes linear equation, vector (y_l^o) utilized to normalize deviation to get dimensionless estimation, AKF user from necessity of choosing ad-hoc bounds for variables to tuned prediction error for unmeasured quantities is given in equation (2),

$$E^p = \frac{1}{n_e} \sqrt{\sum \left(\arg \min_{\beta} \|\beta y_l^e - (y_l^e - \hat{y}_l^e)\|_2 \right)^2} \tag{2}$$

Where $\hat{y}_l^e = [\hat{y}_{l_1}^e \dots \hat{y}_{l_j}^e \dots \hat{y}_{l_N}^e]$ denotes response is estimates AKF through current window, diagonal elements of matrix signify variance of all unknown input estimation error. ANAKF has find missing data and cleaned the duplicate data and it is shown in equation (3),

$$E^u = \sqrt{\frac{1}{N} \sum_{j=k}^{k+N} \frac{P_j^{uu}}{\hat{u}_j^2}} \tag{3}$$

Where, squared amplitude of corresponding assessed input at each jth time-step within window (\hat{u}_j^2) utilized for normalization, zero diagonal entries for (P^{uu}) . ANAKF is more challenging for datasets based on time series. Finally, ANAKF is finded the missing and cleaned the duplicate data and then the pre-processed data is given to IGNN for evaluating the quality of college students sports work.

C. Evaluating the quality using Iso-Geometric Neural Networks (IGNN)

In this section evaluating the quality using IGNN [29] is discussed, IGNN classifier which precisely evaluating the quality of college students sports work. Iso-geometric neural networks provide a multidimensional representation of sports-related data, making it possible to conduct thorough examination of the elements that influence the quality of college students' sports work. This incorporation of geometric continuity into the evaluation process helps to provide a greater understanding of students' athletic activities. Also, the networks' ability to generalize effectively across varied sports contexts increases their relevance and reliability for evaluating the overall quality of college students' athletic performance. This performance shows a relationship between geometry and solution in similar parametric area. The area defines linear combination of control points, whereas solution represents linear combination of IGNN-forecast coefficients that is given in equation (4),

$$\hat{u}_{IGN}(X(\xi, n, Z)) = \sum_{i=0}^n \sum_{j=0}^m R_{i,p}(\xi) R_{j,q}(\eta) \hat{u}_{IGN,ij} \tag{4}$$

Where, $(\hat{u}_{IGN,ij})$ denotes coefficients outputted by IGN, (ξ, n) parametric coordinate directions. IGN to parameterized PDE denotes, $(\hat{u}_{IGN,ij}(\theta; Z))$, $(\hat{u}_{IGN,ij}(\theta, N; Z))$ refers outputs of IGN. outcome is combined over area. It is given in equation (5),

$$a(\tilde{u}, u) = l(\tilde{u}) \tag{5}$$

Where, (a) is the weak formulation, (\tilde{u}) is a test function, (l) test function space. It statement is recast into finite-dimensional form selecting to denotes test, trial functions as linear combination; this is given in equation (6),

$$\hat{u}^h(X(\xi, n,)) = \sum_{i=0}^n \sum_{i=0}^m R_{i,p}(\xi) R_{j,q}(\eta) \hat{u}_{i,ij} \tag{6}$$

Where, $(\hat{u}_{IGN,ij})$ denotes coefficients outputted by IGN, (ξ, n) parametric coordinate directions. IGN to parameterized PDE signifies, $(\hat{u}_{IGN,ij}(\theta; Z))$, $(\hat{u}_{IGN,ij}(\theta, N; Z))$ refers number of outputs of the IGN. The integrals over the domain can be restated as the sum of integrals spanning knot intervals, similar to elements in the finite element approach, under the Isogeometric Analysis discretization. At elemental, left-hand side of equation (7) is evaluated.

$$K_{el} = \int_{\hat{\Omega}} \nabla_X R^T \nabla_X R |J| d\hat{\Omega} \tag{7}$$

Where, $(\nabla_X R)$ is an array, $(\hat{\Omega})$ parametric domain, parametric space $(|J|)$. The elemental stiffness matrices collected into global stiffness matrix this is shown in equation (8),

$$K_{ij}(Z) \hat{u}_j(Z) = F_i(Z) \tag{8}$$

Where, (K_{ij}) is a global stiffness matrix, global forcing vector denotes as (F_i) , (\hat{u}_j) vector of coefficients and (Z) is the local forcing vector. IGNN has evaluated the quality of college students sports work in the given equation (9),

$$\min_0 \zeta = \frac{1}{N_k} \sum_{k=1}^{N_k} \|F_i(Z_k) - K_{ij}(Z_k) \hat{u}_{IGN,j}(Z_k)\|_2 \tag{9}$$

Where, average of residuals is minimized through training. Each stiffness matrices, forcing vectors are collected once at outset of training for exact choices of (Z) . Finally IGNN evaluated quality of college students sports work (sports exercise grade). Due to its convenience, pertinence, AI-depend optimization approach is taken into account in IGNN classifier. The QCTO is employed to enhance IGNN optimum parameters (\hat{u}, a) . The QCTO is employed for turning weight, bias parameter of IGNN.

D. Optimization using Quantum Class Topper Optimization (QCTO)

The weight parameters (\hat{u}, a) of proposed IGNN are optimized using the proposed Quantum Class Topper Optimization (QCTO) [30] is discussed. QCTO is a hybrid iteration of the Class Topper Optimization method. The original CTO algorithm was designed to mimic the learning behavior of a student striving for the top spot in a class. Typically, a class divided into sections, each by certain pupils studying a particular set of topics. Examinations are used to evaluate student performance. Especially; the absence of a transfer parameter during the transition from exploration phase to the exploitation phase directly influences process's performance. Initiation of involves the initialization step.

1) Stepwise process of QCTO

Here, stepwise process defines to get ideal value of IGNN based on QCTO. Initially, QCTO makes the equally distributing populace to optimize parameter IGNN. Ideal solution promoted using QCTO algorithm, linked flowchart given Figure 2.

Step 1: Initialization

Students' knowledge levels are represented as Q-bits in Q-CTO. Within a section, pupils learn from their assigned section leader. The mathematical paradigm for transforming a student's knowledge level into quantum states is as follows. The increase of a student's knowledge is described as follows in equation (10),

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \dots \\ X_i \\ \dots \\ X_N \end{bmatrix} = \begin{bmatrix} x_1^1 & x_1^2 & \dots & x_1^j & \dots & x_1^d \\ x_2^1 & x_2^2 & \dots & x_2^j & \dots & x_2^d \\ \dots & \dots & \dots & \dots & \dots & \dots \\ x_i^1 & x_i^2 & \dots & x_i^j & \dots & x_i^d \\ \dots & \dots & \dots & \dots & \dots & \dots \\ x_N^1 & x_N^2 & \dots & x_N^j & \dots & x_N^d \end{bmatrix} \tag{10}$$

Here, (X) denotes number of Students, (N) denotes total students in Class room (x_i^j) signifies initial position of solution candidates.

Step 2: Random generation

Input parameters made at randomly. Best fitness value selection is depending upon obvious hyper parameter condition.

Step 3: Fitness function

The result comes from initialized evaluation and random response. Then fitness calculated by equation (11)

$$FitnessFunction = Optimizing (\hat{u}, a) \tag{11}$$

Step 4: Exploration Phase for Student level Update

Updating the phase angle is critical for modifying the student level, as it serves as a measure of the students' knowledge level. The representation of student learning is expressed in the following equation (12),

$$\theta_{t+1}^S = \theta_t^S + \Delta\theta_{t+1}^S \tag{12}$$

Where, (θ_{t+1}^S) is the updated phase, (θ_t^S) is the present phase, $(\Delta(\theta_{t+1}^S))$ denotes change in phase. The learning of section topper represented as follows in equation (),

Step 5: Exploitation Phase for optimizing (\hat{u}, a)

Following the enhancement of student's knowledge level, updated phase is corrected utilizing quantum rotation gate. It is a method for reversing the phase to quantum states. This is given in equation (13),

$$\theta_{a+1}^{\hat{u}} = \theta_a^{\hat{u}} + \Delta\theta_{t+1}^{\hat{u}} \tag{13}$$

Where, $(\theta_{a+1}^{\hat{u}})$ denotes updated phase which represents knowledge of section topper, $(\theta_a^{\hat{u}})$ present phase which represents knowledge of section topper, $(\Delta(\theta_a^{\hat{u}}))$ denotes change in phase.

Step 6: Termination

The weight parameter values (\hat{u}, a) of generator from Iso-Geometric Neural Network is enhanced by support of QCTO, iteratively repeat the step 3 until fulfil halting conditions $X = X + 1$ is met. Then IGNN predicts the citation and academic trends with greater accuracy by lessening computational time with error.

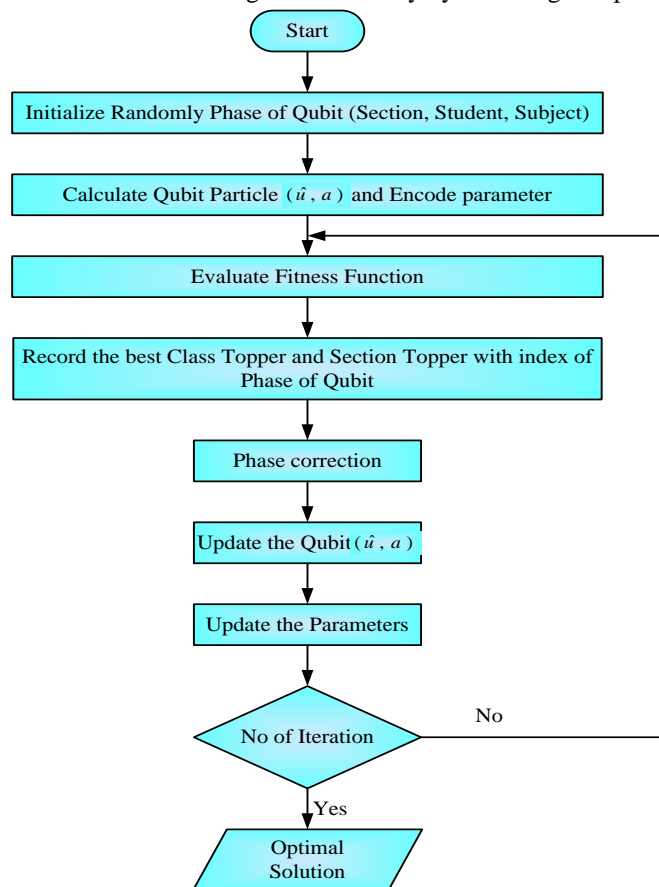


Figure 2: Flowchart of QCTO for enhancing IGNN parameter

IV. RESULT WITH DISCUSSION

Experimental results of QECSSW-IGNN-QCTO technique have evaluating the quality of college students' sports work. In execution work was carried out Intel(R) core(TM) i7 CPU M60 @ 2.80 GHz in Python and evaluated by using several performance analyzing metrics like Accuracy, Cross validation scores, Recall, F1 score, and ROC are analysed. The results of QECSSW-IGNN-QCTO technique are analysed with existing methods likes PMC-SSB-MLM, DII-STSC-SMHE and ESS-SOLA-ECP.

A. Performance metrics

This is analysed to scale effectiveness of proposed technique. To achieve this, following confusion matrix is crucial.

1) Accuracy

The value of accuracy is intended as ratio of number of samples exactly considered by system with total samples. It is computed using equation (14),

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \quad (14)$$

Where, (TP) denotes true positive, (TN) refers true negative, (FP) represents false positive, (FN) denotes false negative.

2) Cross validation scores

Cross-validation is a mechanism for evaluating a model's performance on previously unseen data. The procedure comprises dividing dataset into multiple subset, utilizing one of such folds as validation set, train method on residual folds, which has shown in equation (15),

$$Crossvalidation\ score = \frac{1}{k} \sum_{i=1}^k Metric_i \quad (15)$$

3) Recall

It is a metrics computes forecasts made by correct number of positive predictions made by total positive forecasts. It is given in equation (16),

$$Recall = \frac{TP}{TP+FN} \quad (16)$$

4) F1-score

It is a measure utilized to assess efficiency of a deep learning method. Precision and recall are combined into a single score (F1 score). Thus it's give this equation (17),

$$F1\ score = \frac{Precision * Recall * 2}{(Precision + Recall)} \quad (17)$$

5) ROC

ROC expressed as ratio among changes in one variable comparative to equivalent change in another, graphically; rate of change represents slope of line. It is given in equation (18)

$$ROC = 0.5 \times \left(\frac{TP}{TP+FN} + \frac{TN}{TN+TP} \right) \quad (18)$$

B. Performance analysis

The simulation results of QECSSW-IGNN-QCTO method are showed in figure 3 to 7. The QECSSW-IGNN-QCTO approach is analysed with existing PMC-SSB-MLM, DII-STSC-SMHE and ESS-SOLA-ECP models.

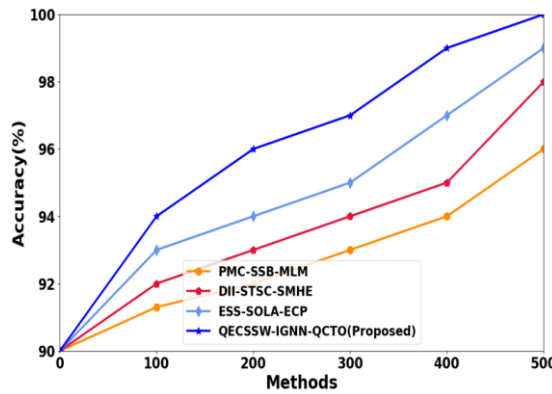


Figure 3: Accuracy analysis

Figure 3 shows accuracy analysis. In Accuracy analysis, rate of method predictions is utilized as a metric to assess classification model performance. It is basically defines ratio of exactly anticipated occurrences to total instances. This comparison evaluates the prediction accuracy of models built with various machine learning methods. In this context, the proposed QECSSW-IGNN-QCTO method attains 23.4%, 28.3%, and 22.6% higher Accuracy; as analysed with existing methods like PMC-SSB-MLM, DII-STSC-SMHE and ESS-SOLA-ECP respectively.

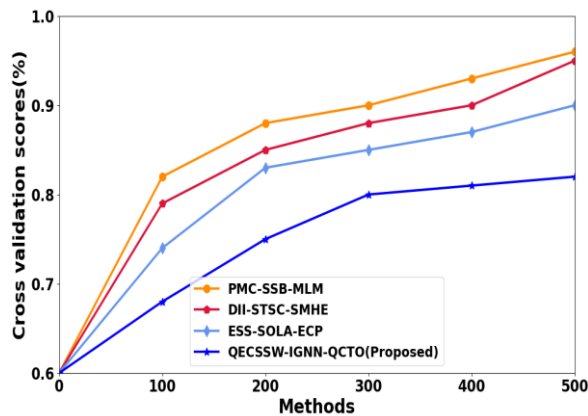


Figure 4: Cross validation score analysis

Figure 4 shows cross validation score analysis. In cross validation score analysis, ML method incorporated optimal subset of features to forecast college students' sports behavior, considering factors such as interest in sports learning and autonomy. The QECSSW-IGNN-QCTO method attains 25.9%, 17.6%, and 29.4% lower Cross validation score; as analysed with existing methods like PMC-SSB-MLM, DII-STSC-SMHE and ESS-SOLA-ECP respectively.

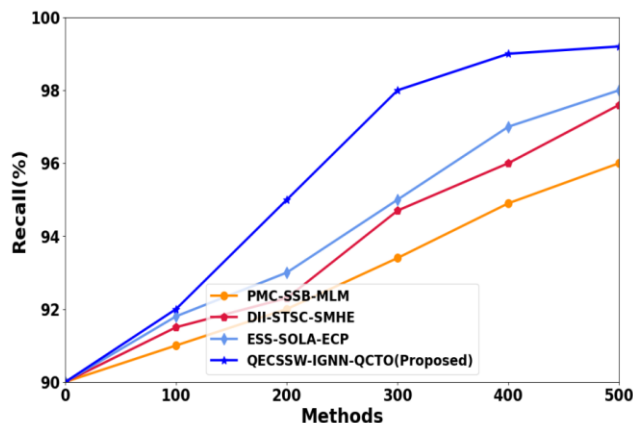


Figure 5: Recall analysis

Figure 5 shows recall analysis; it utilized as basis for judging overall result of different ML methods. It rate is probability of sample forecast the actual sample and original sample. It denotes to probability of forecasting college students' sports work (physical exercise level) giving to show status, forecast outcome consistent by

unique data outcome. The QECSSW-IGNN-QCTO method attains 24.6%, 27.5%, and 18.7% higher Recall; as analysed with existing techniques likes PMC-SSB-MLM, DII-STSC-SMHE and ESS-SOLA-ECP respectively.

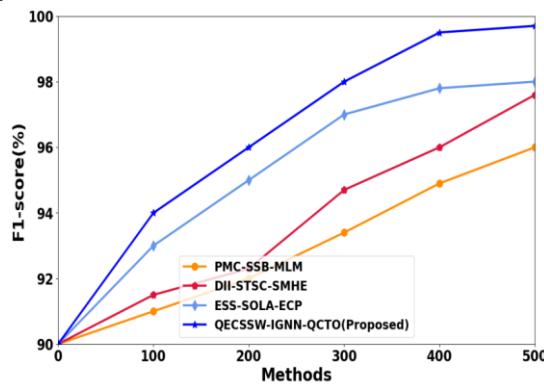


Figure 6: F1-score analysis

Figure 6 shows FI-score analysis. Examine F1-scores to define general effectiveness of different forecast methods. It is significant metric for assessing model quality, providing a full evaluation conclusion depend on both accuracy, recall rates. The QECSSW-IGNN-QCTO method attains 16.8%, 25.9%, and 28.2% higher F1 score; as analysed with existing methods like PMC-SSB-MLM, DII-STSC-SMHE and ESS-SOLA-ECP respectively.

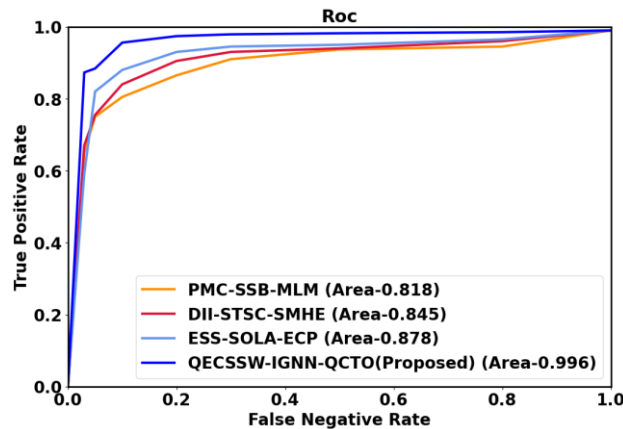


Figure 7: ROC analysis

Figure 7 shows ROC analysis. In ROC analysis, it is created with testing different thresholds, it suggests more model proficiency. It measures model's quality. In this context, the proposed QECSSW-IGNN-QCTO method attains 19.1%, 22.2%, and 20.8% higher ROC; as analysed with existing methods like PMC-SSB-MLM, DII-STSC-SMHE and ESS-SOLA-ECP respectively.

C. Discussion

Incorporating deep learning and teaching requires significant research and data mining efforts. This growing discipline demonstrates traits such as multidisciplinary, multi-level considerations, multi-accurateness, and situational, semantic difficulties. It symbolizes integrated improvement trend of exactness education by combining education, computer science, and statistics. The fields of teaching management, psychology, data mining provides students, teachers, and education administrators with a variety of benefits. Real-time understanding of learning inadequacies and prompt adjustment of learning tactics enables pupils to improve their future performance. Predictive and feedback information helps teachers detect students' learning barriers, alter teaching approaches, and effectively treat learning disabilities. Managers use research findings to well support teachers, students. Looking ahead, ML is positioned to make a substantial contribution to the larger field of education, promoting general service and educational progress. Evaluating the prediction accuracy rates of several models reveals that logistic regression method has higher accurateness. It can be linked to the selected distinctive features of sports learning interest, autonomy, both of which have pedagogical potential. The logistic regression algorithm performs well because of its fit for data characteristics, adaptability to high-dimensional features, capacity to handle small samples and category imbalances, and simplicity and speed. Despite the complexity of forecasting college students' sports behavior using joint components, the logistic

regression model is noteworthy, as evidenced by its F1 score and ROC curve analysis. While gathering additional training features improves the model's effectiveness, the study uses a 9:1 ratio in the training and test sets, taking into account the frequency of lower-level sports behaviours among college students. Future prediction models should take into account additional potential factors and expand the link between dominant and potential elements to ensure more robust modeling.

V. CONCLUSION

In this section, Quality Evaluation of College Students' Sports Work Based on Intellectual or Intuitive Fuzzy Information in Language(QECSSW-IGNN-QCTO) was effectively executed. The QECSSW-IGNN-QCTO is executed in Python. The QECSSW-IGNN-QCTO is used to evaluate the quality of college student sports work (sports exercise grade). Evaluating the performance of approach, the results highlight distinct improvements and achieving 16.8%, 25.9%, and 28.2% higher F1 score, 19.1%, 22.2%, and 20.8% higher ROC: are analysed with existing methods like PMC-SSB-MLM, DII-STSC-SMHE and ESS-SOLA-ECP respectively.

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