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English Teaching Quality Evaluation Model for Higher Education Based on Educational Data Mining Technology



Abstract: - Constructing teaching quality evaluation systems for higher vocational education is beneficial for schools, serving as the cornerstone for developing abilities and enabling precise education management. In this publication, a Dual Relational Graph Attention Network (ETQE-DRGAN)-Based Educational Data Mining Technology English Teaching Quality Evaluation Model for Higher Education is proposed. In three ways, this study assesses and defends the system. An overview of the system's primary components, such as the user and data administration modules, data mining, online assessment, and inquiry modules, is given in the first section. Frequent item sets are divided into two stages and the development of invalid candidate sets is limited to avoid the formation of negative association rules. The Tid-list Vertical Partitioning Query-Apriori Algorithm (TPQ-Apriori algorithm) is improved by these two approaches. The system analysis is covered in section three. In order to assess the success of instruction, this work incorporates a Dual Relational Graph Attention Networks method that takes into account several factors such as age, gender, education, teaching attitude, teaching topic, teaching technique, and teaching effectiveness. The proposed ETQE-DRGAN is implemented in MATLAB, using the School Database for calculation. Numerous performance metrics like response time, precision, accuracy, sensitivity, and F1-score are utilized to calculate the effectiveness of ETQE-DRGAN technique. The obtained outcomes indicate that the ETQE-DRGAN approach achieves the highest precision of 98.5%, Accuracy of 98% and fastest response time of 6.95s when compared to existing methods like ETQE-AA, ETQE-DTA and ETQE-ML.

Keywords: English Teaching, Higher Education, Data Mining, Data management, Teaching attitude, Teaching content, Teaching technique, Teaching effectiveness.

I. INTRODUCTION

The need for a top-notch higher vocational college education to address the challenges of the twenty-first century is becoming more and more obvious as China enters a new phase of supporting socialist modernization progress [1]. In the forefront of this educational landscape, reforming and growing universities and higher vocational schools depend heavily on enhancing the quality of instruction. The direct influence that high-quality instruction has on students' futures and the general trajectory of higher education institutions highlights the importance of good training in these settings [2]. Education stakeholders, who understand the vital importance of high-quality instruction, believe that colleges and universities should set up a robust, impartial system of evaluation for teaching quality [3].

While higher education institutions have long recognized the importance of monitoring and evaluating teaching quality, the existing mechanisms often grapple with limitations in comprehensiveness and objectivity. Traditional evaluation approaches, despite their historical significance, have encountered challenges in providing a nuanced and holistic assessment of instructional effectiveness [5-6]. In response to these shortcomings, recent advancements in big data technology have sparked innovative approaches to teaching quality assessment. In order to address these shortcomings, the suggested English Teaching Quality Evaluation Model for Higher Education Based on Educational Data Mining Technology incorporates the Dual Relational Graph Attention Network (ETQE-DRGAN) [7-10]. This technique improves the overall assessment of instructional quality by overcoming the drawbacks of conventional evaluation systems and by utilizing big data's systematic and quantitative nature [11-13].

With an emphasis on its key elements, the current study offers a comprehensive overview of the English Teaching Quality Evaluation Model for Higher Education [14-16]. Among these are the query module, data management module, data mining module, user administration module, and online assessment module. Acknowledging the limitations of past approaches, the study highlights two novel strategies integrated into the Tid-list Vertical Partitioning Query-Apriori Algorithm (TPQ-Apriori algorithm) to improve its efficacy. These tactics support the robustness and accuracy of the model by reducing the creation of invalid candidate sets and preventing the construction of negative association rules inside frequent item sets. The system analysis demonstrates how instructional efficacy, content, teaching attitude, age, gender, education, and Dual Relational Graph Attention Networks are utilized to assess the quality of instruction [17].

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Using this multimodal approach, the proposed plan aims to usher in a new era of comprehensive, data-driven, and nuanced evaluation of teaching quality in higher vocational education.

II. RECENT RESEARCH WORK: A BRIEF REVIEW

Li [18] developed systems for assessing the caliber of instruction in postsecondary vocational education to achieve precise education management, which serves as the cornerstone for the development of skills. The system's assessment algorithm in this work divided common item groupings using a modified Apriori algorithm based on the association rule algorithm. Data mining technology was used in the development of the assessment system, and system performance and application rules were examined in the created teaching QES to validate the data.

Hou [19] investigated fresh possibilities and difficulties in the field of English instruction. An analysis was conducted on a decision tree system based on data trees for assessing English language acquisition. The focus was on applying data mining technologies to online English learning platforms in order to assess student learning data, create pertinent models, and investigate the relationships among various elements that are essential for teaching and learning in both classroom settings and for students' English tests. The functions, procedures, and popular machine learning models related to data mining were first presented in the study. After that, student photos were produced and recognized using measurements and data produced by college English tutors. Through these images, insights into student behavior and learning behaviors were gained. The technological training involved the employment of a logistic regression model, the creation of a wooden model, and post-fusion modeling of two models after the design experiment. The analysis of factors influencing students' exam success was carried out based on the prediction results.

Qi et al. [20] discovered that traditional methods of evaluating the quality of English instruction were not very effective, and that compiling assessment statistics was difficult. A machine learning algorithm was used to create a teaching evaluation model that was appropriate for the dominant educational model in order to investigate the integration of AI technology into teacher teaching assessment. The MLGPM was introduced in this study to enhance students' language skills. By representing the circulation features of the samples using a Gaussian mixed model, the model improved the support vector machine. Consequently, an active learning method was suggested. By carefully choosing and annotating samples, this method created a classifier that included the distribution properties of the data. Sparse Bayesian learning and a Gaussian mixed model were then combined.

Zeng [21] conducted a comprehensive analysis to enhance the assessment of teaching quality in college PE curriculum with a focus on accuracy; the study looked at the overall effectiveness of PE instruction in universities with a focus on evaluating instructors' instructional skills and students' learning objectives. The study was conducted in three phases using a hybrid method that included data mining and hidden Markov models. First, a study of the state of the art about the teaching quality assessment approach for the college PE curriculum was conducted. A mathematical model for evaluating the caliber of physical education instruction was developed following an evaluation of the practicality of data mining techniques and hidden Markov models. In the end, a number of experiments based on the mathematical models were carried out, and the outcomes of the trials were carefully examined. The results of the experimental analyses showed that the model created in this work made a substantial contribution to improving the accuracy of college students' assessments of the quality of PE instruction.

Okoye et al. [22] observed that recent trends in educational technology have given rise to approaches like teaching analytics (TA) for comprehending and managing teaching–learning processes. Using significant evidence from educational data to enhance the quality of performance and the teaching–learning process makes performance-based assessment (TA) a new and promising approach in the field of education. To check teacher effectiveness and make recommendations based on information from SET, the study proposed an EPDM+ML model. By combining text mining and machine learning technologies and depending on descriptive decision theory, the educational process and the data mining plus machine learning model were created and put into practice. This theory explores the reasoning behind the judgments made by students using statistical analysis and quantified textual data. The goal of the study was to determine the educational elements that, while taking into consideration the gender of the teachers and the mood and emotions stated in student evaluation of teaching assessments, influenced students' recommendations for their professors. This involved forecasting the teacher

recommendations made by the student automatically using data from the student evaluation of teaching, including the student's gender, average sentiment, and emotional valence.

Xin [23] has emphasized the significant role data play in business and industry, facilitating daily operations. The volume of data continues to increase alongside advancements in IT. Using data mining technologies to assess the caliber of business English training is still crucial in today's environment. Especially in online courses, these approaches have been used in classrooms, especially during the COVID-19 pandemic. This study evaluates the caliber of corporate English training using multimedia and data mining techniques. Data mining employs association rule recommendation algorithms once multimedia data have been first gathered in class. Universities and colleges can create indicators for evaluating the quality of instruction by using collaborative filtering algorithms within association rules. Subsequently, actual teaching data from a university are employed, with a focus on business English instruction.

Chen et al. [24] have highlighted the crucial role of high vocational education as a cornerstone for cultivating quality teaching and technical talents in China. In the current era, the acceleration of modern vocational education development is emphasized further. It is advocated that moral education be upheld and closely integrated with the demands of technological advancements and industrial progress to continually enhance the quality of teaching in high vocational education. The goal is to develop more technically proficient people who possess integrity and the capacity to support modernization initiatives. The application of artificial intelligence technology is considered necessary to address these issues and raise the caliber of instruction in high vocational education against the backdrop of societal informatization. To increase student satisfaction with the caliber of instruction in high vocational education, a data mining technique is used in this study. A survey instrument is designed to measure students' contentment with the level of instruction in foundational courses on entrepreneurship. Mining technology analysis software is used to evaluate the current status of teaching quality in foundational entrepreneurship courses using survey data from vocational education as a case study.

III. SYSTEM ARCHITECTURE

A. User Management Module Design

The English Teaching Quality Evaluation Model for Higher Education Based on Educational DMT includes a user management module, which is essential to the security and integrity of the system. By controlling access to the system through the allocation of different levels of password authorization, this module establishes a hierarchical user management structure. Through user authentication and authorization mechanisms, it verifies the identity of users and assigns appropriate access privileges based on their roles within the institution. This hierarchical approach not only enhances security but also streamlines user access, facilitating efficient management of the system's resources and functionalities.

B. Data Management Module Design

At the core of the system lies the data management module, serving as its control center for handling essential data-related tasks. This module is responsible for selecting data sources, managing basic information such as teacher and student records, and maintaining the integrity of the system's databases. Through robust data source management capabilities, administrators can ensure seamless access to various data repositories while maintaining data accuracy and consistency. Additionally, the module facilitates efficient management of basic data records, enabling administrators to add, delete, and update information as needed to support the system's functionalities and operations effectively.

C. Online Evaluation Module Design

The purpose of the online assessment module is to make it easier for the English Teaching Quality Evaluation Model for Higher Education's evaluation procedures to be carried out smoothly. It empowers educators and administrators to conduct evaluations online, administer surveys, and collect valuable feedback from stakeholders. By providing functionalities for survey administration, feedback collection, and data analysis, this module enables institutions to assess teaching quality effectively and gather insights for continuous improvement. Through streamlined online evaluation processes, institutions can enhance transparency, accountability, and stakeholder engagement in the evaluation and improvement of teaching practices.

D. Data Mining Module Design

The data mining module constitutes a critical component of the evaluation model, leveraging advanced algorithms to extract valuable insights from educational data. Centered around the enhanced Apriori algorithm, this module enables the discovery of meaningful patterns and relationships within the data, supporting decision-making and optimization efforts. Through customizable mining settings and association rule mining results visualization, this module enables educational institutions to find previously unnoticed patterns, pinpoint areas in need of development, and make well-informed decisions to improve the quality of instruction. Through its sophisticated data mining capabilities, this module plays a pivotal role in driving evidence-based practices and fostering continuous improvement in higher education institutions.

IV. PROPOSED METHODOLOGY

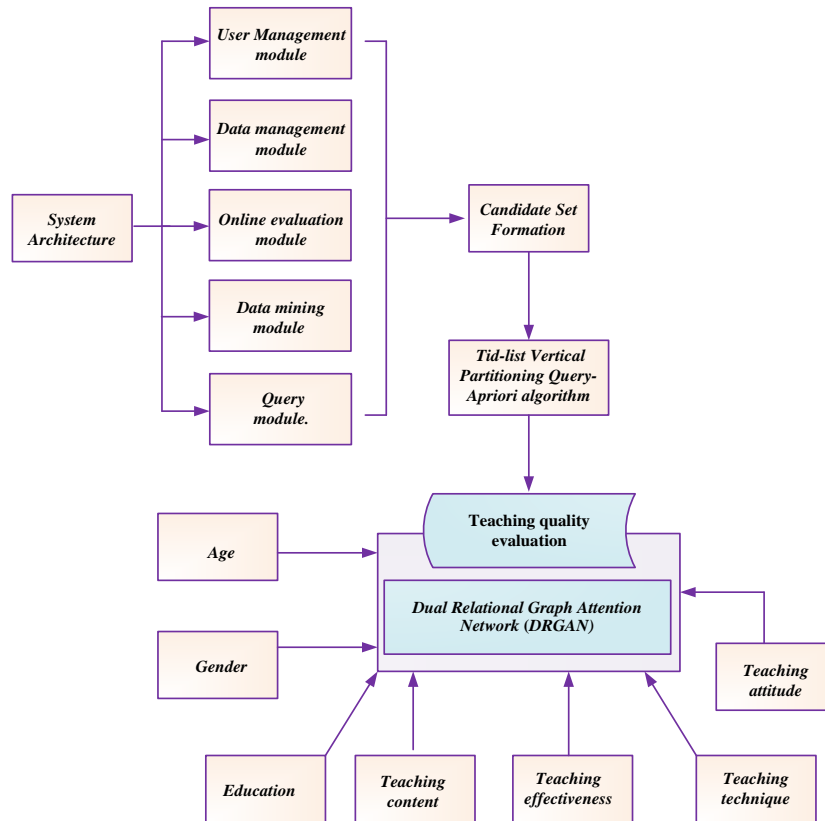


Fig 1: Block schematic of the proposed system

Fig 1 illustrates the proposed methodology for evaluating teacher performance, consisting of interconnected modules designed to collect, analyze, and assess various aspects of teaching effectiveness. The system begins with the User Management Module, responsible for creating and managing user accounts. Subsequently, the Data Management Module collects and stores data on teacher performance from multiple sources, including online evaluations and classroom observations. The System Architecture Module defines the overall structure of the system and guides interactions between different modules. Teachers engage with the Online Evaluation Module to provide feedback on their teaching abilities, while the Candidate Set Formation Module selects specific teachers for evaluation based on predetermined criteria. The Data Mining Module utilizes advanced techniques to analyze patterns and trends in teacher performance data. Users can then query the system through the Query Module to obtain information on teacher performance. Finally, the Teaching Quality Evaluation Module integrates data from various sources to generate comprehensive evaluations, supplemented by tailored feedback for improvement. Additionally, the Dual Relational Graph Attention Network (DRGAN) is introduced as a powerful machine learning model to analyze complex relationships between factors influencing teaching quality, depicted in the diagram. This methodology offers a systematic approach to assess and enhance teacher performance within educational contexts.

A. Data acquisition

The University of Wisconsin-Madison's Statistics Department collected the data, which include evaluations of teaching effectiveness from 151 TA assignments finished over the course of two summer semesters and three regular semesters [25]. The scores were split into three roughly equal-sized groups ("low," "medium," and "high") to form the class variable.

B. Pre-processing using Data-Adaptive Gaussian Average Filtering (DAGAF)

Pre-processing data using DAGAF involves several steps to clean and enhance the quality of the data [26]. Here's a stepwise process:

Identify missing values in the dataset, denoted as $x_i = NaN$ for the i th data point.

Impute missing values using techniques such as mean imputation:

$$\hat{x}_i = \frac{1}{n} \sum_{j=1}^n x_j \quad (1)$$

Alternatively, more advanced imputation methods like regression imputation can be used.

Detect inconsistencies or outliers in the dataset, denoted as x_i deviating significantly from the rest of the data.

Compute the Z-score each piece of data:

$$Z_i = \frac{x_i - \mu}{\sigma} \quad (2)$$

where the dataset's mean is μ and its standard deviation is σ .

Identify outliers based on a predefined threshold for the Z-score, such as $Z_i > \text{threshold}$.

Apply Data-Adaptive Gaussian Average Filtering (DAGAF) to smooth the data:

$$\hat{x}_i = \frac{1}{\sum_{j=1}^N w_j} \sum_{j=1}^N w_j x_j \quad (3)$$

Here w_j represents the weight assigned to each data point, calculated using a Gaussian kernel:

$$w_i = \frac{1}{\sqrt{2\pi\sigma_j}} e^{-\frac{(x_j - x_i)^2}{2\sigma_j^2}} \quad (4)$$

Here, σ_j represents the standard deviation of the Gaussian kernel, which is adaptively adjusted based on the local data density.

The value of σ_j can be determined using techniques such as nearest neighbor density estimation or mean-shift clustering.

Apply DAGAF filtering to the dataset by modifying parameters like the Gaussian kernel's standard deviation σ_j using libraries or bespoke implementations.

Assess the quality of the filtered data visually and by comparing it with the original dataset.

Repeat the preprocessing steps iteratively, adjusting parameters and refining the filtering process as needed.

By following these steps, the dataset can be effectively preprocessed using Data-Adaptive Gaussian Average Filtering (DAGAF), reducing noise and improving the quality of the data for subsequent mining processes.

C. Candidate set formation:

1) Limiting Formation of Invalid Candidate Sets:

Candidate sets are subsets of items from the dataset that are considered potentially frequent and are candidates for becoming frequent item sets.

In the TPQ-Apriori algorithm, the formation of invalid candidate sets is limited [27]. This means that during the candidate generation phase, only those candidate sets that have the potential to become frequent item sets are generated.

By limiting the formation of invalid candidate sets, unnecessary computational overhead is reduced, leading to more efficient execution of the algorithm.

2) *Dividing Frequent Item Sets:*

Frequent item sets are sets of items that occur together frequently in the dataset.

In the TPQ-Apriori algorithm, to avoid the formation of negative association rules, frequent item sets are split up. Negative association rules represent itemsets that have a negative correlation, meaning that the occurrence of one item negatively influences the occurrence of another.

By dividing frequent itemsets, the algorithm ensures that negative association rules are not generated, leading to more meaningful and accurate results.

3) *Improving TPQ-Apriori Algorithm:*

These two strategies collectively contribute to improving the performance and effectiveness of the TPQ-Apriori algorithm.

By splitting up frequent item sets and reducing the creation of invalid candidate sets, the algorithm becomes more efficient in identifying truly frequent itemsets and generating association rules that accurately represent the underlying patterns in the dataset.

In summary, these strategies are implemented to enhance the TPQ-Apriori algorithm's efficiency and accuracy in mining frequent itemsets and association rules from large datasets.

D. *Analyzing Teaching Quality with Dual Relational Graph Attention Networks*

In this section, the system analyzes the quality of teaching evaluation using Dual Relational Graph Attention Networks (DRGAN) [28] based on specific attributes. Here's a breakdown:

This analysis focuses on evaluating teaching quality through the examination of specific instructor attributes. These characteristics include teaching effectiveness, teaching content, teaching style, age, gender, and education level. They also include teaching attitude. Dual Relational Graph Attention Networks (DRGAN) are utilized to model the interrelationships among these attributes within a graph structure. Each attribute serves as a node in the graph, with edges representing the connections between attributes. DRGAN's attention mechanism calculates attention scores for individual attributes based on their relationships with neighboring attributes. The collective information from all nodes in the graph is then utilized to predict teaching quality evaluations. To gauge the effectiveness of DRGAN, evaluation metrics like mean squared error (MSE) and cross-entropy loss are computed between predicted teaching quality evaluations and actual evaluations from ground truth data. This meticulous analysis offers valuable insights into teaching quality based on diverse instructor attributes, facilitating informed decision-making in education management.

E. *Dual Relational Graph Attention Networks (DRGAN):*

DRGAN is utilized to analyze relationships between attributes. Let's denote the input attributes as X and the output (teaching quality evaluation) as Y .

The graph attention mechanism in DRGAN can be represented as:

$$Attention(X) = \text{soft max}(Leakey ReLU(XW)) \quad (5)$$

where W is a learnable weight matrix, soft max and $Leakey ReLU$ are activation functions.

The output of the attention mechanism can be combined with the input attributes to generate the output:

$$Y = ReLU(X \cdot Attention(X) + b) \quad (6)$$

where b is a bias term and $ReLU$ is the rectified linear unit activation function.

F. *System Analysis:*

The system assesses teaching quality using the output Y obtained from DRGAN.

Let $Y_{predicted}$ represent the predicted teaching quality evaluation, and Y_{actual} represent the actual evaluation from ground truth data.

The system analyzes the performance of DRGAN by comparing $Y_{predicted}$ with Y_{actual} using evaluation metrics such as mean squared error (MSE).

V. RESULT AND DISCUSSION

The experimental outcomes of the suggested method are covered in this section. Next, MATLAB is used to simulate the proposed technique using the specified performance criteria. The proposed ETQE-DRGAN

approach is implemented in MATLAB using Tennis Action dataset. The proposed ETQE-DRGAN approach's result is examined in comparison to current systems, such as ETQE-AA, ETQE-DTA, and ETQE-ML, in that order.

A. Performance Measures

1) Accuracy

It is computed as the number of forecasts produced overall for a dataset divided by the number of forecasts that are accurate. It is quantified using equation (7).

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{7}$$

True positive (*TP*) true negative (*TN*) false positive (*FP*) and false negative (*FN*) are the respective representations in this case.

2) Precision (P)

The count of favourable events that are accurately predicted is a metric known as accuracy. We use Equation (8) to scale this.

$$Precision = \frac{TP}{(TP + FP)} \tag{8}$$

3) F1 Score

The weighted mean of accuracy and precision is known as the F1-Score. Equation (9) can be utilized to express it.

$$F1Score = \frac{TP_{\alpha}}{\left(TP_{\alpha} + \frac{1}{2} [FP_{\lambda} + FN_{\gamma}] \right)} \tag{9}$$

4) Recall

4) Recall

This is defined with the help of eqn (10),

$$Recall = \frac{\delta}{\delta + \lambda} \tag{10}$$

5) Mean Squared Error (MSE):

$$MSE = \frac{1}{N} \sum_{i=1}^N (Y^i_{predicted} - Y^i_{actual})^2 \tag{11}$$

B. Performance Analysis

The proposed ETQE-DRGAN approach's simulation results are shown in Figure 2 to 8. Then, the proposed ETQE-DRGAN technique is compared with existing technique such as, ETQE-AA, ETQE-DTA and ETQE-ML respectively.

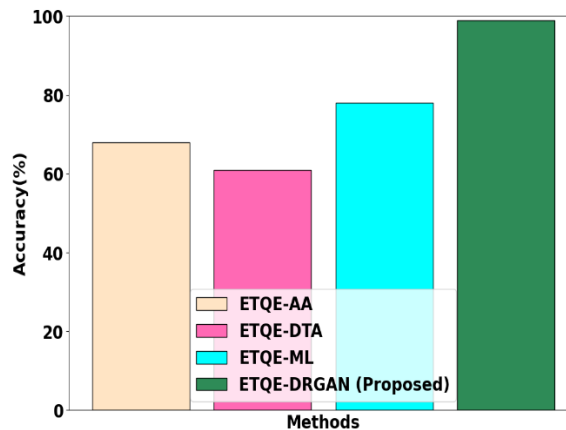


Fig 2: Accuracy comparison between proposed and existing techniques

Fig 2 displays the Accuracy comparison between proposed and existing techniques. The accuracy for ETQE-AA technique is 70%. The accuracy for ETQE-DTA method is 60%. For ETQE-ML method the

accuracy is 79%. For the proposed ETQE-DRGAN method the accuracy is 99% which is the highest while compared to other existing technique.

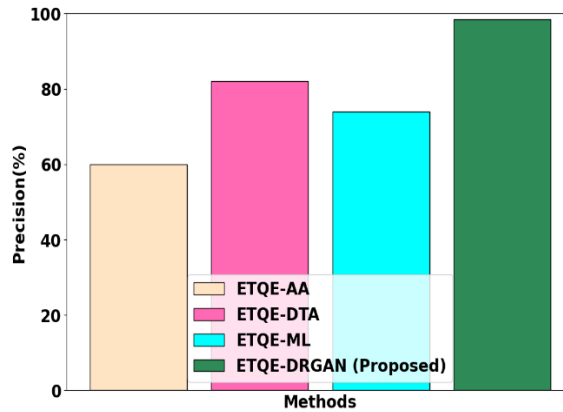


Fig 3: A comparison of the precision of the proposed and existing methods

The comparison of the precision of the proposed and existing methods are displays in fig 3. In ETQE-AA method the precision is 60%. In ETQE-DTA method the precision is 81%. In ETQE-ML method the precision is 68%. For the proposed ETQE-DRGAN method the precision is 99% which is very high comparing other existing technique.

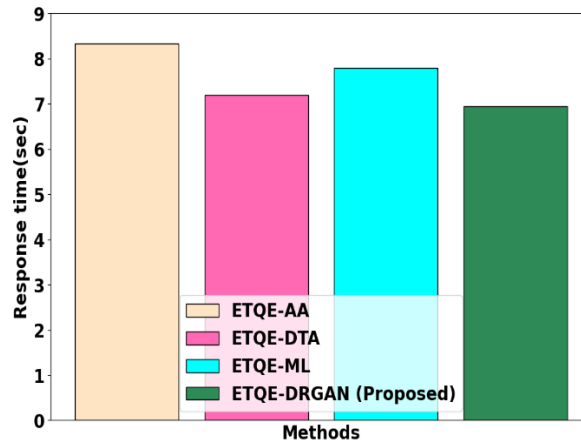


Fig 4: Comparison of response times using proposed and current techniques

Fig 4 depicts the Comparison of response times using proposed and current techniques. For the ETQE-AA method the response time is 8.4sec. For ETQE-DTA method the response time is 7.1sec. For ETQE-ML method the response time is 7.8sec. For the proposed ETQE-DRGAN method the response time is 7sec which lower compared to other existing technique.

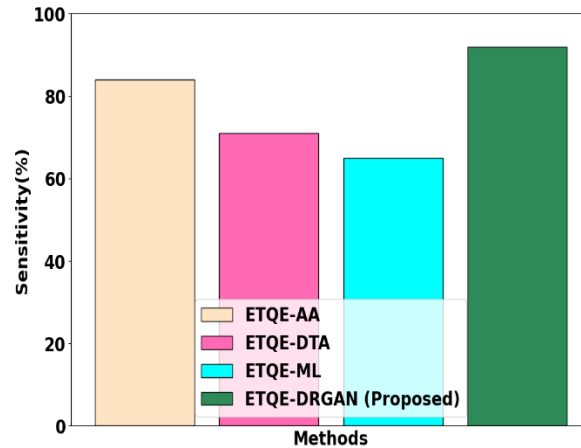


Fig 5: Comparison the sensitivity of proposed and current approaches

The Comparison the sensitivity of proposed and current approaches is displays in fig 5. In ETQE-AA method the sensitivity is 85%. In ETQE-DTA method the sensitivity is 70%. In ETQE-ML method the sensitivity is 65%. For the proposed ETQE-DRGAN method the sensitivity is 90%. The proposed approach provides the maximum sensitivity when compared to other current techniques.

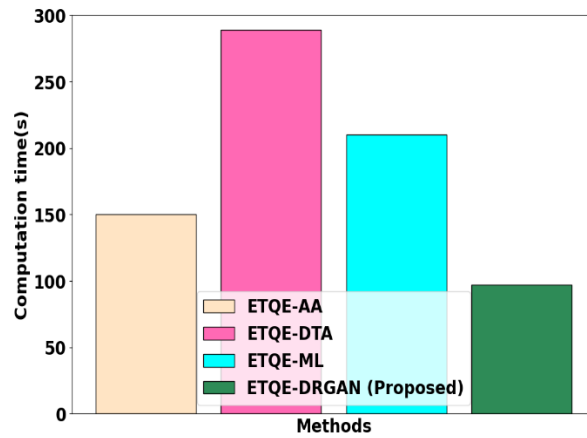


Fig 6: Comparison of the current and proposed methodologies' calculation times

Fig 6 displays the Comparison of the current and proposed methodologies' calculation times For ETQE-AA method the computational time is 150s. For ETQE-DTA method the computational time is 290s. For ETQE-ML method the computational time is 220s. For proposed ETQE-DRGAN method the computational time is 90s. which is very lower compared to other existing technique.

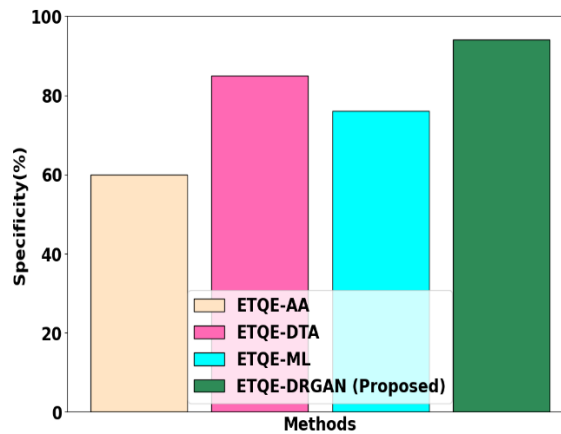


Fig 7: Comparison the specificity of proposed and current approaches

The Comparison the specificity of proposed and current approaches is displays in fig 7. In ETQE-AA method the specificity is 60%. In ETQE-DTA method the specificity is 85%. In ETQE-ML method the specificity is 75%. In the proposed ETQE-DRGAN method the specificity is 97% which higher than the other existing technique.

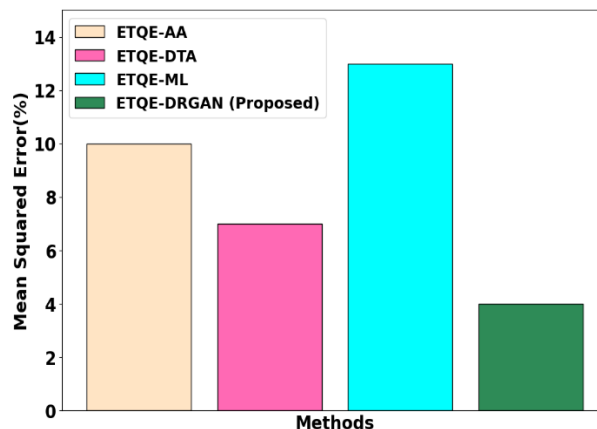


Fig 8: Comparison the mean squad error using the suggested and current approaches

Fig 8 depicts the Comparison the mean squad error using the suggested and current approaches. In ETQE-AA method the mean squad error is 10%. In ETQE-DTA method the mean squad error is 7%. In ETQE-ML method the mean squad error is 13%. In the proposed ETQE-DRGAN method the mean squad error is 4% which is very low compared to other existing methods.

VI. CONCLUSION

The study concludes with the creation of an educational data mining technologies-based Dual Relational Graph Attention Network-based model for assessing the caliber of English instruction in higher education. Based on a count of factors, such as age, gender, education, teaching style, material, and attitude, the DRGAN was utilized to assess how effective a teacher was. English Teaching Quality Evaluation based on DRGAN (ETQE-DRGAN) contributes to the system's ability to analyze and process educational data efficiently. The proposed approach, implemented and validated in MATLAB/Simulink, using the School Database for calculation, the ETQE-DRGAN demonstrates superior performance metrics, with a precision of 98.5%, accuracy of 98%, and the fastest response time of 6.95s. Comparative assessments against existing methods, such as ETQE-AA, ETQE-DTA, and ETQE-ML, affirm the effectiveness and efficiency of the proposed approach.

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