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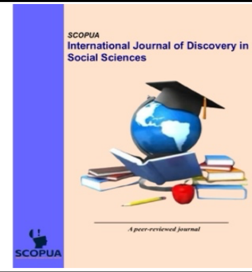

A Data-Driven Approach for Educational Improvement and Quality Enhancement

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ABSTRACT

Despite vast data availability, many organizations struggle to extract actionable insights, often lacking the necessary analytical tools. Sentiment analysis, or opinion mining, has proven effective for understanding user behavior and forecasting trends, particularly in social media. Building on previous research, this study applies sentiment analysis techniques to Quality Enhancement Cell (QEC) data to evaluate teachers' performance and gain insights into student perceptions. The proposed method uses machine learning algorithms to analyze sentiment and predictive patterns, offering objective support for teacher evaluation and fostering informed recommendations for educational development. The results emphasize data-driven improvements in teaching quality, highlighting sentiment analysis as a valuable tool for advancing educational outcomes based on stakeholder feedback.

Keywords*:* Predictive Analysis; Sentiment Analysis; Machine Learning; Educational Improvement

1. Introduction

In the past, education followed rigid frameworks, but today, modernism and technological advancements have reshaped the educational landscape, revolutionizing teaching methods and student engagement by replacing traditional approaches with innovative strategies (Bakar, 2021). One common option is blended learning, which combines online and classroom training so students can progress at their own pace. Project-based learning lets students engage in real-world projects to learn; gamification and other tech-based instructional tools like VR make learning a new language fun (Afzal & Anwar, 2023; Kaliraj et al., 2024; Khatoon, 2025). Instead of just learning a topic, competency-based education demands students to demonstrate their knowledge before moving on. Finally, AI-powered personalized learning adapts to each student's strengths, weaknesses, and development areas to motivate them to study (Rekha et al., 2024). All recognized Higher Education Institutions (HEIs) in Pakistan have been working to enhance their Directorates of Quality Enhancement, achieving a high level of compliance with the Internal Quality Assurance (IQA) framework set by the Higher Education Commission (HEC) (Batool & Qureshi, 2007). The IQA instrument is quantitatively assessed annually using a scorecard, with evaluations beginning on July 1 and concluding on June 30 of the following year. The results are categorized into four quality levels: W, X, Y, and Z. A well-implemented IQA instrument prepares an institution for external evaluations by organizations such as QAA-HEC and other accrediting bodies.

Likewise, data provides the foundation for extracting insights, formulating predictions, and facilitating decision-making across diverse domains, such as finance, healthcare, education, and marketing. Each type of data—structured, unstructured, and semi-structured—plays a unique role in these processes. Structured data, organized in fixed fields within databases, allows for efficient searching and analysis (Mishra & Misra, 2017). In contrast, unstructured data, such as text, images, and social media content, requires advanced techniques like Natural Language Processing (NLP) for effective insight extraction (Gharehchopogh & Khalifelu, 2011). Semi-structured data, represented in formats like JSON, combines elements of both, enabling flexible data sharing with embedded tags or markers(Durner et al., 2021). The emergence of Big Data has introduced the necessity for specialized analytical tools to manage vast and rapidly growing datasets, particularly from sources like the Internet of Things (IoT) (Afzal et al., 2016). Data collected over time facilitates trend and pattern analysis, which is crucial for forecasting and anomaly detection, addressing the broad analytical needs of modern data science. Data mining, an essential aspect of data analysis, involves extracting valuable patterns from large datasets through techniques such as classification, clustering, prediction, and association (Kesavaraj & Sukumaran, 2013). The data mining process encompasses defining the problem, data collection, cleaning, pre-processing, mining, modelling, and testing. Two primary approaches to data mining are directed and undirected; directed mining seeks specific outcomes, such as income levels, while undirected mining uncovers relationships across more generalized data characteristics without predetermined categories.

Recent advancements in machine learning (ML), particularly in the context of sentiment analysis, have significantly improved prediction accuracy compared to traditional statistical methods (Alslaity & Orji, 2024). ML leverages adaptive algorithms to identify patterns within data, offering advantages over parametric methods that rely on predefined assumptions (Wilson & Anwar, 2024). Among the key ML techniques are Supervised Learning, which utilizes labelled data to predict target outcomes, and Unsupervised Learning, which identifies inherent patterns within unlabelled data. Clustering, a common unsupervised technique, groups data based on similarities, thereby uncovering relationships among various data points.

This research focuses on employing sentiment analysis techniques to evaluate teachers based on student feedback.

Specifically, we aim to address the following research questions:

- How do students perceive their teachers based on qualitative feedback?
- What features of the feedback are most predictive of positive or negative evaluations?
- Which feature (method) most influences teaching rank vies?

Our study employs ML algorithms to analyse qualitative data collected from student evaluations, facilitating a deeper understanding of the dynamics between student perspectives and teaching effectiveness.

2. Literature Review

In recent years, the application of educational data mining (EDM) and advanced ML techniques has become central to assessing student performance, teaching effectiveness, and curriculum quality (Fatima et al., 2025; Khan & Ghosh, 2021). These methodologies have emerged as powerful tools for evaluating educational outcomes, predicting academic success, and refining teaching strategies across varied educational settings. This review explores key studies contributing to these domains, examining the methodologies employed, the insights gained, and the identified gaps in knowledge.

Research in EDM demonstrates its impact on predicting academic outcomes and supporting personalized education(Bettahi et al., 2025). Results revealed that interaction with learning resources significantly correlates with academic performance, emphasizing the potential for e-learning platforms to enhance academic outcomes through tailored resources. The study also introduced LMS participation data as a Return on Investment (ROI) metric for teaching assessment, supporting an evaluation approach that considers both student outcomes and instructional quality (Rothwell et al., 2024).

In enhancing teaching quality evaluation, ML models also prove useful, developed a method to evaluate classroom teaching quality by integrating a genetic algorithm with neural networks (NN) (Zhang et al., 2021). Optimizing initial weights and thresholds of the Backpropagation (BP) NN using an adaptive mutation genetic algorithm achieved superior accuracy and convergence speed (Zhang & Qu, 2021). This approach allows institutions to incorporate leader evaluations, expert reviews, peer assessments, and student feedback into a holistic model of teaching quality, presenting an innovative and adaptable framework for instructional assessment. Evaluation models tailored to specific educational contexts also contribute to targeted assessment practices, for example, designed a multi-attribute fuzzy evaluation model for college physical education (PE), addressing the unique objectives and requirements of PE programs (Wang et al., 2021). This multi-dimensional framework captures the physical, developmental, and engagement outcomes critical to PE, advancing the evaluation process by integrating attributes reflective of the discipline's unique demands. Such domain-specific models demonstrate the importance of customization in educational evaluation, recognizing the varied objectives within different areas of study. Data mining applications in admissions decisions are crucial for predicting academic success and aligning admission criteria with institutional outcomes, explored data mining's potential for predicting academic performance based on pre-admission data. Scholastic Achievement Admission Test (SAAT) scores emerged as the strongest predictor of success, emphasizing the importance of standardized testing in admissions processes(Sackett & Kuncel, 2018). Sentiment analysis has emerged as a potent tool for extracting actionable insights from student feedback, applied aspect-based sentiment analysis (ABSA) to assess student comments, analysing sentiments across different levels (document, sentence, object, and aspect) to gauge the sentiment polarity on specific course aspects (Sowndarya et al., 2024). The study illustrated the adaptability of sentiment analysis to educational contexts, allowing educators to tailor course content based on specific student sentiments. This level of analysis provides institutions with critical insights for responsive course design, reflecting a broader trend toward data-driven adaptability in educational strategies.

3. Materials and Methods

3.1 Data Set: The dataset was sourced from the Faculty of Agriculture and Faculty of Sciences at the University of Agriculture, Faisalabad, and an institution with a longstanding history since the early 1980s. Offering courses in over 20 major fields, the faculties comprise numerous PhD-level instructors and annually graduate thousands of students. Data for this study were collected from eight departments within these faculties: Agronomy, CAB (Central Agricultural Biotechnology), Entomology, Forestry, Horticulture, Plant Breeding, Plant Pathology, and Soil Sciences.

The dataset focuses on student evaluations of instructor performance, collected via the QEC questionnaires. These evaluations include 14 questions covering various dimensions of teaching effectiveness. The questionnaire data capture student perspectives on teaching quality and are intended to provide feedback for continuous educational quality improvement within the institution. Each student completed the questionnaire independently, rating instructors on a range of criteria established by the QEC, serving as an evaluative tool for teacher performance, similar to QEC standards. Data were collected from undergraduate and postgraduate students during the academic years 2017–2018, based on their experiences with their instructors. The collected data span two key faculties and reflect both general feedback on educational practices and specific areas of instructional quality. The questionnaire contains the following 13 attributes assessing instructional quality from students' viewpoints: whether the instructor provides a lesson plan in the first lecture; the instructor's adherence to scheduled arrival and departure times; the instructor's level of preparation for each lecture or practical session; the instructor's demonstrated knowledge of the subject matter; the effectiveness with which the instructor conveys the topic; the availability of additional resources provided beyond the course textbook; the instructor's role in creating a conducive learning environment; whether the instructor completes the syllabus as planned; the encouragement of student participation in class activities; fairness of the instructor's evaluation methods; the prompt return of graded assignments, tests, and answer sheets within the specified timeframe; and the instructor's accessibility for consultations during designated office hours.

3.2 Manuscript formatting requirements: The QEC survey data was collected for analysis, which was a total of thirteen questions. Existing dataset was paper based survey and it was digitally available in image format. The first task was to shape this image-based data into process able form. We did this transformation in four steps: (i) Converting the data into the CSV format, (ii) generating identification numbers that would serve as a representation of the various instructor classes and semesters that ensure every data point is separately identified and monitored. (iii) To high quality and consistency, the weighted formula is applied which can be seen in equations 1 & 2 and is a visual representation in Figure 1 for every characteristic. This is an essential step in the process of normalizing and cleaning the data. Different weighted ratings were provided to the responses throughout this procedure. These scores were determined how relevant the responses were to the restructured responses and how each answer impacted the entire study. The following Figure 1 shows the attribute Weightage.

$$Wi = \sum_{I=1} N\,(Xi * Wi) \,/\, \sum_{I=1} N\,(Wi) \qquad (1)$$

$$Wi- = \sum_{I=1} N\,(Xi * Wi) \qquad (2)$$

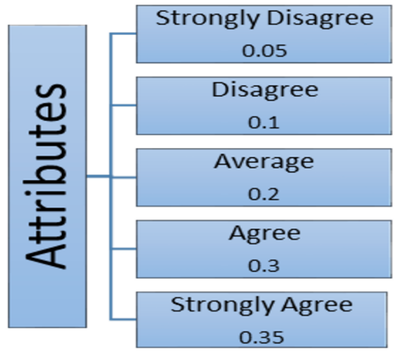

Figure 1: Attribute Weightage Given to Attributes Options

(iv) Completeness investigation the completeness of the data by checking for values that were either null or missing. Through the use of the mean imputation approach, which involves filling in the missing entries with the mean of the identical entry value, we are able to account for the data gap to the greatest extent possible. After going through above sequence of stages, the data became clean, trustworthy, and prepared for some additional statistical and machine learning techniques.

After pre-processing and cleaning the data we applied the three most popular machine learning algorithms and got the results. Details are shown in Figure 2.

Algorithm 1: J48 algorithm using C4. It uses decision-tree classification models to interpret complex datasets and visualize decision-making. J48 is strong because it can process continuous and discrete attribute values and missing values, which are prevalent in practical datasets. Information gain is used for attribute selection to maximize tree structure while balancing accuracy and computational efficiency. Furthermore, it prunes decision trees to reduce overfitting and increase generalization to fresh data. J48 is an excellent candidate for data analysis and decision-making in data-driven research publications because of its precision, ease of use, and adaptability.

Algorithm 2: Random Forest using multiple trees. Random Forest is an ensemble learning method that mixes many decision trees to create more accurate and robust predictions. It reduces decision tree overfitting via community wisdom. It is a supervised ML approach that works well with huge datasets with many features or missing values for classification or regression. It automatically handles non-linear relationships and variable interactions, making it appropriate for many applications.

Algorithm 3: Naive Bayes using probability. It is used for text classification, spam detection, sentiment analysis, and document categorization due to its strong feature independence assumption, which simplifies computation and scales well. Despite this simplistic assumption, Naïve Bayes delivers impressive results in practice. It utilizes the Bayes theorem to calculate the probability of various classes. It solves binary and multiclass classification problems quickly. It works well with little training data, making it useful when data is scarce. The ease of use and interpretability of Naïve Bayes makes it a popular choice for machine learning applications.

4. Results and Discussions

The total number of data was (214 files) classified into three categories 80% of data is used for training, 10% is used for validation, and remaining 10% is utilized for testing.

In this analysis, we applied 3 ML algorithms. First is j48 which is based on a decision tree. In this study, a tree was built to display the categorization approach. From the given figure we have come to know that the J48 algorithm is providing us with 98% accuracy. Out of 82 instances, it correctly identified 81 instances and incorrectly identified only one instance. 42 teachers were good but we nominated 41 teachers as good and 40 teachers were bad and have been nominated as bad. Results and graphical representation show in Table 1 and Figure 2.

J48	
Correctly Classified Instance	98.78%
Incorrectly Classified Instance	1.21%
Mean absolute error	0.0238
Root mean Squared error	0.1091
Relative absolute error	4.7618%
Root Relative Squared error	21.8218 %

Table 1: J48 Decision Tree Results

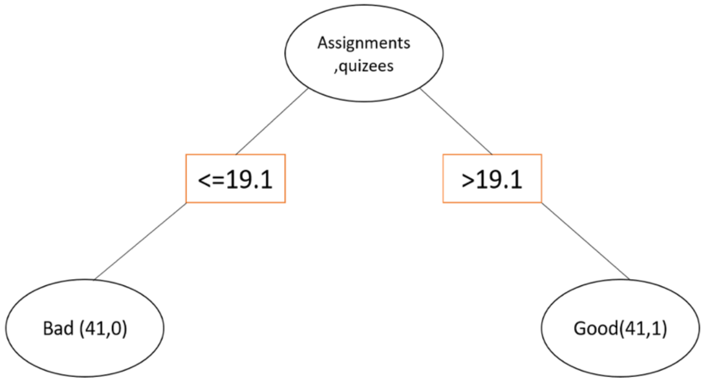

Figure 2: Decision Tree Graphical Representation

The second algorithm was a random forest which is based on multiple decision trees. The total time taken to build this model was 0 seconds, which explains the detailed accuracy by class. From the given Table () we have come to know that Random Tree is providing us 100% accuracy. Out of 82 instances, all the instances were correctly identified, and no one instance we incorrectly identified. So we can say that this algorithm is providing us more accuracy rather than other algorithms that we had applied to it. 42 teachers were identified as good and 40 teachers were considered as bad. Results and graphical representation are shown in Table 2 and Figure 3.

Random Forest	
Correctly Classified Instance	100%
Incorrectly Classified Instance	0%
Mean absolute error	0
Root mean Squared error	0
Relative absolute error	0
Root Relative Squared error	0

Table 2: Random Forest

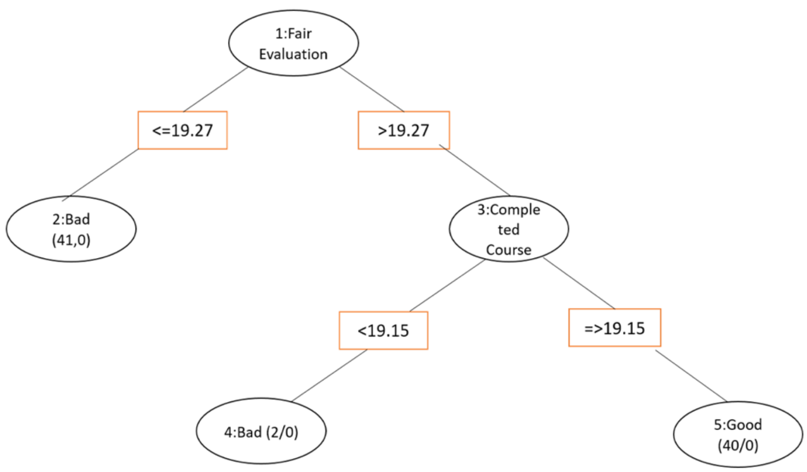

Figure 3: Random Forest Graphical Representation

The third and the last one was Naïve Bayes which is based on probability or likelihood. The total time taken to build this model was 0.01 seconds because we performed the sample test at that time, which explains the detailed accuracy by class. From the given table we have come to know that out of 82 instances, Naïve Bayes correctly identified the 75 instances, and 7 instances were incorrectly identified. 42 teachers were good and all the teachers were correctly identified and a total of 40 teachers were bad out of these 40 teachers only 33 were correctly identified as bad and 7 teachers were incorrectly identified as good. Results representation are shown in Table 3.

Naïve Bayes	
Correctly Classified Instance	91.46%
Incorrectly Classified Instance	8.53%
Mean absolute error	0.089
Root mean Squared error	0.275
Relative absolute error	17.91%
Root Relative Squared error	55.05%

Table 3: Naive Bayes Results

4.1 Comparisons of Algorithm

Table 4 is the Comparisons of Algorithms (J48, Random Forest and Naïve Bayes)

Classification Model	Correctly Instances	Incorrectly Instances	Percentage of Accuracy	Test Data Instances
J48	81	1	98.78%	82
Random Forest	82	0	100%	82
Naïve Bayes	75	7	91.46%	82

Table 5: Comparisons of Algorithms

4.2 Ranking of Attributes:

Using a model that analyses the relative relevance of thirteen different characteristics, this analysis that was conducted for this study aimed to evaluate and rank the impact that many characteristics have on the performance of teachers. The following aspects were evaluated: the delivery of a lesson plan, the timing of classes, the preparation of lectures, the knowledge of the subject matter, the ability to communicate effectively, the provision of additional materials, the creation of a healthy learning environment, the delivery of the course, the participation of students in activities, the fairness of grading, the standards for assignments and quizzes, the feedback from instructors, and the moral and ethical behaviour of teachers. The analysis of these characteristics resulted in the production of percentage scores that indicated their influence on the effectiveness of teaching. This information provides clarity regarding which characteristics greatly boost educational impact. The investigation brought to light specific areas that require targeted professional development to improve teaching practices. Each percentage score and ranked of attributes are shown in Table 5.

Sr No	Attributes	Score
1	Assignment and Quiz	91%
2	Instructor Feedback	86%
3	Activity Involvement	85%
4	Fair Evaluation	85%
5	Completed Course	85%
6	Communication	85%
7	Learning Environment	80%
8	Knowledge of Subject	80%
9	Provide Lesson Plan	72%
10	Additional Material	71%
11	Lecture Preparation	68%
12	Timing	68%
13	Instructor Moral and ethical norms	58%

Table 6: Ranking of 13 Attributes basis on Scores

5. Conclusion

In this study, we presented a data-driven approach to educational improvement, utilizing ML techniques—specifically decision-tree analysis and Naive Bayes—to QEC data for insights into teacher performance and student sentiment. This method effectively highlighted key factors influencing educational outcomes, demonstrating the potential of sentiment analysis and predictive modelling in evaluating teaching effectiveness and shaping future educational strategies. Our findings underscore the utility of data analytics in educational settings, revealing valuable insights that can support targeted improvements in teaching quality based on objective data. While our approach successfully identified performance indicators, further advancements could enhance its impact. Future research might explore more sophisticated techniques, such as cluster ANN, to provide a deeper, multidimensional understanding of academic achievement factors. By integrating these advanced methods, educators and policymakers could gain more nuanced insights, potentially leading to robust early warning systems, optimized lesson planning, and enhanced educational management. This study reinforces the role of data-driven strategies in advancing educational outcomes, positioning sentiment analysis and machine learning as pivotal tools for continuous improvement in education.

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