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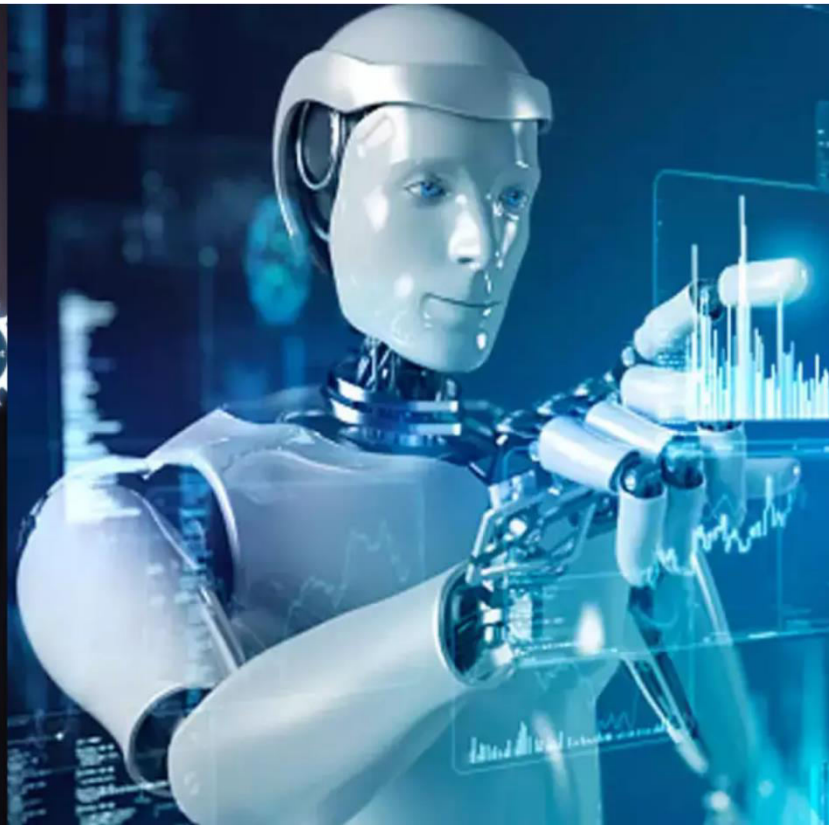

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Teacher Performance Prediction in Education Data Mining: An Analytical Approach

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ABSTRACT: Assessing teacher performance is essential to improving student learning outcomes and the quality of education. Because traditional evaluation techniques frequently have biases and a narrow scope, predictive modeling is a useful substitute. In order to forecast teacher effectiveness based on a variety of behavioral and academic characteristics, this study investigates data mining techniques. The study examines teacher assessment datasets using Decision Tree, Random Forest, and Neural Network i.e. Machine Learning methods, to pinpoint important performance-influencing variables. With an accuracy rate of 92%, the outcome is that The Random Forest's result is better than other models, proving its dependability for predictive analysis. By providing information on teacher efficacy and assisting with institutional decision-making, the study advances educational data mining.

KEYWORDS: Education Data Mining, Teacher Performance, Machine Learning, Predictive Analytics, Evaluation Metrics

I. INTRODUCTION

The teaching assessment system is considered one of the pertinent academic procedures in university instruction, and as such, the internal and external agencies of educational institutions are constantly striving to enhance it. The professional development of instructors in a variety of academic environments was facilitated by the evaluations that the participants completed. [4].

The quality of education is significantly impacted by the efficacy of teachers. Reliable teacher performance evaluation is necessary to improve teaching methods and student learning outcomes. Traditional evaluation methods, such as student feedback and administrative evaluations, usually have subjective biases that limit their effectiveness.

Predictive analytics offers a data-driven approach to assessing teacher performance as data mining in education develops. The primary objective of this project is to predict teacher effectiveness using machine learning models based on measurable variables such as experience, instructional tactics, student interaction, and institutional input.

An opportunity to assist data analysis in education is presented in Educational Data Mining (EDM). As an important tool for transforming such data into other approaches, Educational Data Mining provides researchers with accurate and understandable results. Since prediction is one of these techniques, there are several algorithms with varying degrees of machine learning that can be used to generate prediction models [5].

In turn, a learning institution's ability to successfully monitor and assess training determines its ability to continuously improve the effectiveness of its instruction. Understanding teachers' strengths and the areas in which their practice could be improved is crucial. According to this viewpoint, the establishment of teacher evaluation is an essential step in the effort to raise educational standards and increase the efficacy of teaching and learning. According to Shymansky (1978), there are many elements that go into good classroom education, but the instructor is seen to have the biggest impact on the program's effectiveness. Therefore, evaluating teachers' performance appears to be just as crucial as evaluating students or learners [6]. The creation of methods for evaluating educators that include student achievement on standardized exams is controversial among statisticians and unpopular with some educators. The American Federation of Teachers' president, Randi Weingarten, has called for the removal of value-added metrics from teacher evaluation programs [33]. The following observations from the Scopus papers during the last ten years demonstrate how teacher performance includes a variety of facets of professional behavior and efficacy. Definition: A teacher's conduct

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and activities during the teaching process that exhibit social, professional, and personal growth are referred to as teacher performance [35].

Teachers' success in raising performance is also influenced by both internal and external influences. Student achievement is internally determined by a teacher's quality. How well kids learn will undoubtedly depend on the caliber of their teacher. Student accomplishments are directly correlated with a power teacher's level of competency [7]. The operationalization of important constructs, the instruments used to measure these structures, and the various evaluation goals must all be taken into account for conclusions about teacher performance in evaluation systems to be valid [36].
Potentialities and obstacles: Both potentialities and obstacles have been identified by the characterization of teaching performance. Among the difficulties include poor utilization of information and communication technologies, low scientific output, and inadequate planning of independent work [35]. Conversely, potentialities include a track record of commitment to education and a role in developing students into professionals and citizens [35].

1.1 Research Problem & Objectives

Subjective opinions, which do not necessarily correspond with real teaching effectiveness, are a major component of traditional teacher evaluation.
This study's objective is to create a predictive model which uses Machine Learning methods and objective metrics to evaluate performance.

1. Identifying the essential characteristics that influence a teacher's efficacy is one of the research's goals.
2. Classifying performance levels using Machine Learning models.
3. Examining the accuracy of various algorithms' predictions.
4. Offering academic institutions data-driven insights to improve faculty evaluation.

Institutions can use education data mining to improve faculty development plans and assess students more equitably.

II. RELATED WORK

Numerous studies have looked at teacher performance assessment using a variety of methodologies, ranging from qualitative approaches (like student feedback and classroom observations) to quantitative techniques (like statistical models and machine learning).

In the past, teacher performance has been assessed via surveys, standardized examinations, and classroom observations [1]. Although these approaches are effective in certain contexts, they are subjective, prejudiced, and have a narrow scope. Research indicates that student evaluations alone are insufficient to adequately assess a teacher's effectiveness [2]. The emergence of Educational Data Mining (EDM), which makes use of sentiment analysis, learning analytics, and predictive modeling, has fundamentally altered the way that instructors are assessed.

Many research has been conducted on teacher assessment using both traditional and computational methodologies. Subjectivity concerns in rating systems were highlighted by Smith & Johnson (2019) [1], who investigated student feedback-based assessments. In order to forecast student improvement, Doe et al. (2021) [2] employed machine learning techniques, albeit with less emphasis on teacher assessment criteria. Predicting

teacher and student performance is now feasible because to recent advancements in Educational Data Mining. Although research using decision trees and neural networks showed encouraging outcomes, more advancements in accuracy and bias reduction are required. This study improves on previous research by combining several prediction models and honing feature selection techniques for anticipating teacher performance.

To assess all of the research that is currently accessible in the field, a comprehensive body of literature review is conducted utilizing a research methodology that must ensure thoroughness and be unbiased [8]. Non-financial motivational techniques are essential for effective and efficient classroom delivery, as demonstrated by the major impact that training ideas have on teachers' professional growth and the preference for non-monetary benefits over monetary ones [37].

Recent developments in the education sector have been greatly impacted by Educational Data Mining (EDM). Considering the requirements of the students, the wide variety of studies has uncovered and imposed new potential for

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technologically enhanced learning methods. The EDM's cutting-edge approaches and implementation strategies are required to enhancing the educational setting. As an illustration, the EDM is key to understanding the student learning environment since it evaluates both the educational environment and predictive modeling techniques [8]. The study demonstrates how machine learning is used to analyze Twitter viewpoints; the suggested method is new in that it assigns a weight to each comment [45].

These days, a professor's performance is measured using his teacher's rating, which shows if he is a good or bad lecturer. However, it's crucial to concentrate on analyzing student opinions in order to identify specific circumstances in which academic courses or workshops could be recommended to improve the professors' teaching abilities. In addition, it's important to provide the required assistance of psychological specialists focused on education in the appropriate circumstances [9].

Education is one of the many industries that machine learning has the ability to totally change, and the field is growing rapidly. It can be a helpful tool for administrators and educational policymakers to better allocate resources and make well-informed choices on the retention and development of teachers. Estimating teacher performance could be one use for machine learning. It might be feasible to precisely predict which teachers are likely to succeed in the classroom by using algorithms that use machine learning to evaluate data on their traits and actions [10].

III. METHODOLOGY

In research, methodology refers to the methodical framework that outlines the planning and execution of a study. It covers the strategies, methods, and procedures used to assemble and review and assess data to guarantee the study's validity, dependability, and rigor.

3.1 Data gathering & Preprocessing

The dataset for research consists of teacher assessment records from multiple institutions, including:
The data comes from both original and indirect sources: Surveys that were organized were used to gather basic information, peer evaluations, and classroom observations by academic examiners. Secondary data is found in institutional databases that contain information on previous student performance, teacher records, and standardized test results. It is based on both primary and secondary sources.

Primary data was gathered through structured surveys, peer reviews, and observations made by academicauditors in theclassroom. Examples of secondary data include databases maintained by institutions that contain information on teachers, previous student performance, and standardized test scores. Characteristics were normalized, and missing values were addressed using data imputation approaches to enhance model performance.

3.2 Feature Selection & Machine Learning Models

To minimize dimensionality while preserving relevant information, important features were selected using Principal Component Analysis (PCA).

There are some algorithms in this study that might be appropriate for this work because of their various features.
They are:

1. Decision Trees
2. Random Forest
3. Neural Networks
4. Support Vector Machines

1.Decision Trees

A supervised machine learning method for classification and regression applications is the Decision Tree. It is simple to follow and straightforward since it uses a structure like tree to illustrate decisions and their potential consequences. One informal supervised learning technique for regression and classification is the decision tree (DT). Voting at leaf nodes determines the labels after learning the partitioning rule to separate

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the data according to its features [11]. One can reduce the tree model to a set of "if- then" conditions that are very easy for humans to comprehend and apply. Researcher investigated and revealed the "if-then" principles to increase estimation accuracy in higher education system [14]. The DT algorithms did better on what data set they used in the area of reliability than the other ML algorithms. Researcher also examined the use of Decision Trees and Bayesian networks to predict the academic success of graduate and undergraduate students from two distinct colleges. In their experiment, The DT's accuracy is consistently 3–12% greater than the Bayesian Network's [15].

2.Random Forest

During training, the Random Forest ensemble learning system builds a significant amount of decision trees and aggregates outcomes in order to increase accuracy and manage overfitting. It is flexible and can handle tasks involving both classification and regression. In order to provide a final result, many decision trees are produced by the method, each of them which is trained using a unique subset of the data and attributes. A popular method for classification and regression problems is Random Forests method, also known as Random Decision Forests. Random Forests are ensemble models composed of several decision trees. Each tree imports a random selection of characteristics and data, and then fits trees to this subset to train the model's decision trees. Furthermore, RF makes predictions by utilizing the average votes of trees [17].

5. Neural Networks

Neual networks are a group of algorithms that mimic the information flow of the human brain in order to find underlying patterns in a batch of data. In this usage, neural networks refer to either organic or artificial neuronal systems. An ANN is a model that is trained by iterative optimization and is made up of several neural layers [13].

Support Vector Machines (SVM)

SVMs are very efficient supervised learning models in machine learning that may be applied to regression and classification. SVM divides the data by looking for the two classes' maximum margin [12]. SVM's strong classification capacity has led to numerous investigations on it for SPP studies or its usage as a baseline technique [13]. When comparing the conventional machine learning algorithms for SPP, such as SVM, LR, Random Forest, and others, the researcher found that SVM performed better on both study-related and social behavior data. However, because of its optimization limitations, SVM suffers from computing costs with massive data [16].

IV. MODEL EVALUATION

Performance was measured using:

Accuracy

The size of the class, the number of records and attributes, and other parameters are taken into account while assessing the performance of classifiers. The execution time of the data to produce predictions is utilized to examine the model's accuracy. The experiment shows that the time of execution and the quantity of the data collection are related [20]. The most straightforward and popular criterion for assessing a classifier's performance is accuracy. However, accuracy isn't always a useful indicator, particularly when there are imbalances in the data. The fundamental issue is that we can only attain high accuracy when the negative class is dominant if we forecast negatively the majority of the time. Therefore, it is possible that the negative class is (much) more likely even when a highly accurate classifier generates a positive prediction. These circumstances are defined by a precision of 50% or less [21].

Precision & Recall

Two traditional performance evaluation metrics are used in the area of retrieving information: Recall, which measures a percentage of user-interested items that the system retrieves, and precision, which measures the percentage of user-interested items that the system retrieves [22].

F1-score

By calculating the mean of harmonics of recall and precision, the F1 score is determined. The F1 score, which integrates recall and accuracy into a single metric to better understand model performance, is widely used as an assessment metric in LLM evaluation and binary and multi- class classification. If precision is given more weight than recall, the F-score may be modified to F0.5, F1, or F2, depending on the use case [23]. The visualizations frequently

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make use of intricate measures, such as F1 scores and precision/recall [24].

Confusion Matrix Analysis

The main tool used to assess errors in classification tasks is a confusion matrix. For every pair of primary classes that need to be classed and erroneous classes that classify objects incorrectly, they encode the whole specification of inaccurate classifications, indicating a number of misclassified things. Confusion matrices can be used to: i) examine errors for every class; ii) adjust program parameters, including criteria for detection; and iii) compare different versions of software. Understanding for Type I or Type II errors is essentially what determines the program version or parameter settings [24].

Experimental Results & Analysis

In order to predict teacher performance using the mentioned machine learning techniques, we experimented on several institutional data sets. To evaluate teacher performance from student result sets, we collected data of students from different institutions. We collected data i.e. teacher name, student enrollment no., gender, all subjects' marks (semester wise).

When we evaluated result sets using Machine Learning algorithms i.e. Decision Tree, Random Forest, Neural Networks and SVM, we got result as mentioned in figure 1.

Model Performance Comparison

Here, Decision Tree, Random Forest, Neural Networks and SVM algorithms were used to evaluate teacher's performance from students' semester wise results of different institutes. The success rate of classification algorithms is often evaluated using the F-measure, also known as the F1-score [19].
The following outcomes were obtained from testing the prediction models on training and validation datasets:

Table 1. An analysis of different Machine Learning models' results accuracy rates:

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Decision Tree	84%	82%	85%	83%
Random Forest	**92%**	**90%**	**93%**	**91%**
Neural Networks	88%	87%	89%	88%
SVM	86%	84%	87%	85%

Table 1 illustrates the percentages of accuracy, precision, recall, and F1-Score for SVM, Random Forest, Decision Trees, and Neural Networks algorithms. Out of the four algorithms, the Random Forest algorithm had the highest accuracy among all four algorithms in this case. Among the four algorithms, the precision value was 90%, which was likewise high. Of all the algorithms discussed, Decision Tree's accuracy was the lowest.

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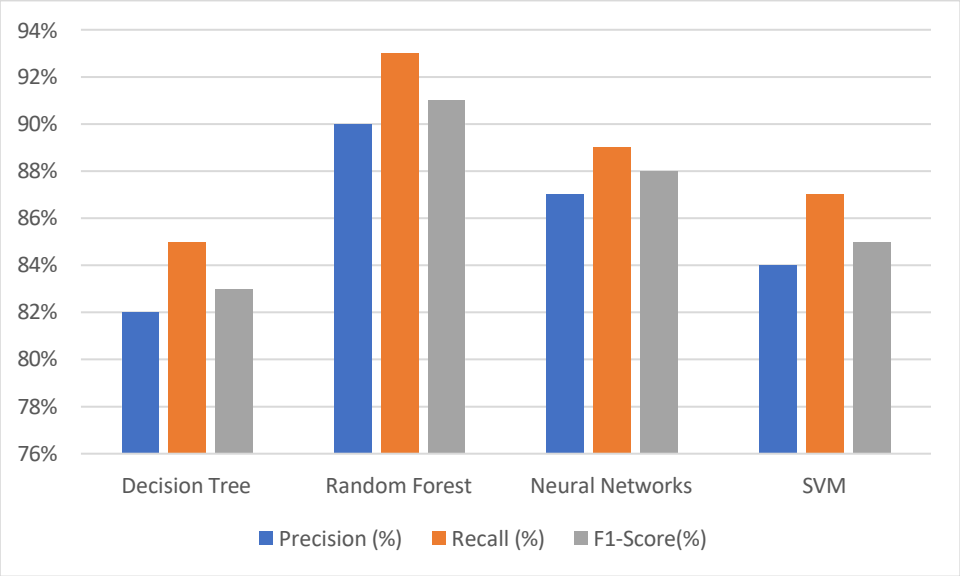

Figure 1. Predictive models' Precision, Recall and F1-Score (%)

The outcome from Table 1 was represented graphically in above figure 1. In this case, Random Forest algorithm demonstrated the highest F1-Score rate (91%), Precision rate (90%) and Recall rate (93%).

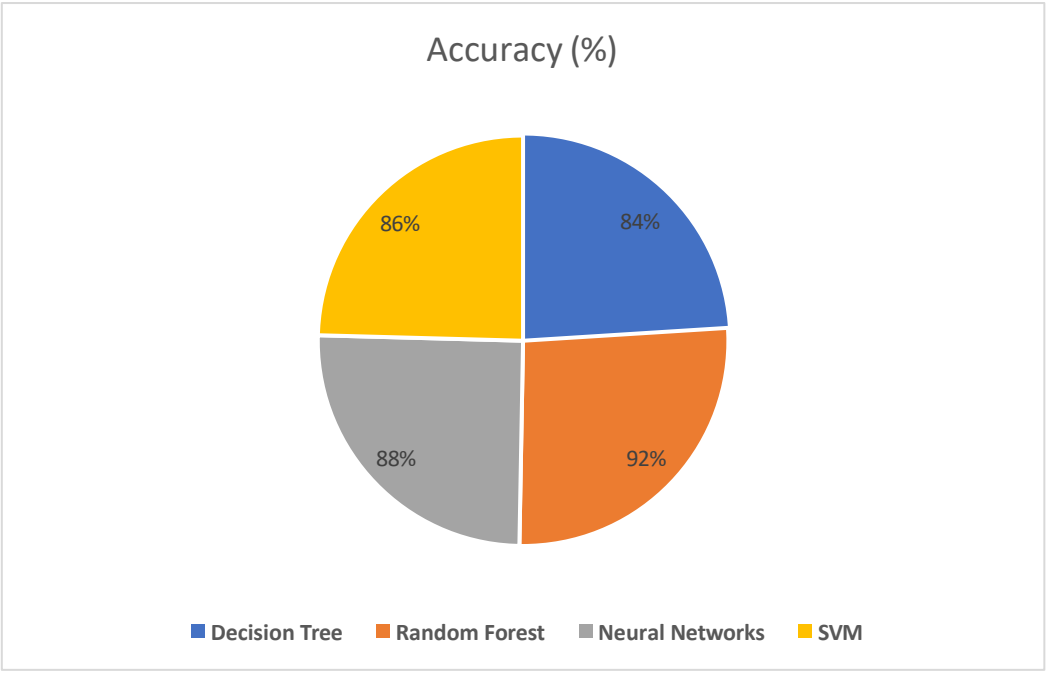

Figure 2. Predictive models' accuracy rate

Decision Tree achieved **accuracy (84%)**, demonstrating its effectiveness in predicting teacher performance. Random Forest achieved **highest accuracy (92%)**, demonstrating its effectiveness in predicting teacher performance. Neural

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Networks achieved **accuracy (88%)**, demonstrating its effectiveness in predicting teacher performance. SVM achieved **accuracy (86%)**, demonstrating its effectiveness in predicting teacher performance. **Neural Networks performed well** but required extensive hyperparameter tuning.

V. DISCUSSION

The outcome of the research indicates the value of data-driven teacher evaluation in comparison to traditional assessment techniques. The Machine Learning models can be used by educational institutions to boost classroom tactics, professional development, and teacher hiring.

Among the methods used in prediction models are fuzzy clustering algorithms [26], Naïve Bayesian, Logistic Regression, Decision Trees, Support Vector Machine (SVM) and Random Forest method [27], neural networks [28], associative classification, fuzzy logic [29], graphical neural networks and Bayesian probabilistic tensor factorization [30], fuzzy clustering, and the latent factor model [26]. In order to create a teaching quality evaluation model for instructors in higher education, researchers integrated the benefits of a neural network and a random matrix method. In order to normalize the indicators, assess the teaching indicators, and build the teaching quality evaluation model, it makes use of the enhanced BP neural network and random matrix structure. The experiments increase evaluation's prediction accuracy. The usefulness of the suggested model is confirmed by the prediction accuracy, which reaches 94.9% after 133 iterations [40].

Students' final grades were predicted using educational data mining based on their participation in Zoom online lectures and Moodle Learning Management System (LMS) activities [1]. Four machine learning algorithms—Random Forest, XGBoost, KNN, and SVM—as well as logistic regression models were used in this investigation [1]. The forecast, which is based on over 40 attributes, is important for making decisions about how to minimize the number of students who fail, find the resources that are needed, and apply the instructional experience's methods of learning in this modality. According to this research, the most accurate indicators of students' academic achievement are learning materials or activities. From a different angle, better student performance is associated with better teaching practices. Features of the students, including their final grade, could influence the virtual classroom-based teaching evaluation [25].

The logistic regression kernel method is used in a Supervised Learning model to forecast the emotional state and social views of college students who want to work as professional engineers. The results show an accuracy rate of 91.96%, a precision rate of 79.09%, a sensitivity rate of 75.66%, and a specificity rate of 92.09% [43]. Because of its greater accuracy of 98.3%, the Fine Gradient SVM algorithm suggests that SVM has become one of the most widely used classification techniques for polarity recognition from textual data [44].

Finally, the results of this study show how different techniques can be used to explain the teacher performance evaluation based on student's final exam result sets. The authors analysed a dataset from different institutes, for evaluating of teacher performance. And the result revealed that the best Machine-Learning algorithm was Random Forest with Accuracy rate (92%), Precision rate (90%), Recall rate (93%), F1-score rate (91%); however, the Decision

Tree achieved Accuracy (84%), Precision (82%), Recall (85%), and F1-score (83%).

5.1Implications for Educators

Students' results can be used to assess a teacher's performance. because teachers have an effect on students' overall performance. The effects of teacher performance reviews on educators can be extensive and varied, impacting their motivation, professional growth, job stability, and instructional strategies. When classifying student satisfaction with instructor performance, faculty attributes are important [42] and regarding how the curriculum is covered throughout the semester, the majority of scientific colleges are focused on the teaching construct [42].

The design and implementation of teacher performance evaluations have a significant impact on their ramifications. They can promote professional development and enhance student achievements when carried out carefully, with precise guidelines and encouraging feedback. When executed incorrectly, they can discourage teachers and their result in poor

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learning outcomes. In one instance, teachers are using the system to improve their own measured performance by removing students from their lineups who won't negatively impact their value- added scores, and in another, they are helping students who are taking tests under their supervision [32]. Student results are greatly impacted by teacher quality, which accounts for between 7% and 21% of the variation in student performance [34]. promote for Professional Development Facilitators: In order to promote the sustainability of teacher performance, a better understanding of how professional development facilitators learn, practice, and grow in their jobs is required [38]. The school's performance and the organization changed as a result of the teachers' inventiveness; the area was a calm place to live. The children' learning performance improved. They were pleased with the new learning management techniques used by their teachers [31]. Students' ratings and comments in the teacher evaluation system are used to investigate the link between quantitative and qualitative teacher ratings [41].

Continuous Professional Development: To guarantee sustainability, teacher professional development must be ongoing and centered on the actual requirements of the teacher rather than being dictated by top-down methods [39].

VI. CONCLUSION

In EDM research, student performance is crucial since it is a crucial assessment of educational outcomes. Additionally, forecasting student success may aid teachers and students in enhancing their instruction. Nevertheless, the current research lacks statistical methods and educational theory, and it fails to draw attention to the use of the widely methods, such as feature learning [18].

Numerous factors, including dataset size, fields, and others, can affect the outcome. Choosing a model, configuring it, and pre-processing the data are the first steps. The models are then estimated using assessment metrics and their accuracy is compared [20].

This study predicts result on based of Machine Learning algorithms to evaluate teacher's performance based on final exam result sets of undergraduate students, taking external exam grades as the source data. The performance of the Decision Trees, Random Forests, Neural networks and Support Vector Machines from Machine Learning algorithms were calculated and compared to predict teacher's performance based on the final exam result set of the students.

Two parameters were the focus for this study. Predicting academic performance from result sets was the initial parameter. The comparison of machine learning algorithms' performance metrics was the second. The model's classification accuracy using the Random Forest algorithm was 92%, according to the results. Based on student result sets, the highly reliable algorithms DT, RF, NN, and SVM can be used to forecast teachers' performance. Several studies have looked at the value-added benefit of teacher qualities to student achievement, including experience, preparation for the classroom, subject area preparation, and academic aptitude. [34].

This study successfully predicts teacher performance using education data mining techniques. The most successful algorithm was Random Forest algorithm, offering high accuracy in performance prediction. Future research should explore advanced deep learning methods to improve classification results. By leveraging predictive analytics, institutions can develop objective and data-driven teacher evaluation systems, enhancing education quality worldwide.Other machine learning techniques and additional parameters as input variables could be used in future studies.

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