Computational Sciences and Engineering 3(1) (2023) 33-54

University of Guilan

Computational Sciences and Engineering

journal homepage: https://cse.guilan.ac.ir/

Sentiment Analysis on Student Performance Using Novel Ensemble Machine Learning Technique

Neha Singh [a], Umesh Chandra Jaiswal [a,*]

[a] Department of ITCA, MMMUT, Gorakhpur, India

ARTICLE INFO

Article history:
Received 10 May 2023
Received in revised form 23 May 2023
Accepted 28 May 2023
Available online 28 May 2023

Keywords:
Education
Sentiment Analysis
Machine Learning
Ensemble Model

ABSTRACT

Sentiment inquiry is used in a variety of sectors and has become one of the most popular subjects in academic exploration, with an expanding body of tasks. Maintaining a positive relationship between students requires academic input. Monitoring a student's progress is critical to their growth and helps instructors, parents, and guardians provide more support. Sentiment analysis is extensively used in a variety of fields, like business, social connections, and education. In an educational setting, this strategy allows students' feedback to be analysed, teachers' teaching performance to be monitored, and the learning experience to be improved. In the educational system, teacher assessment is critical to improving the learning experience in institutions. In this research, the authors propose a novel ensemble machine learning technique for figuring out the best ways to help students study in order to boost their academic achievements. This research assesses the effectiveness of techniques using accuracy, recall, precision, and the f-measure. In order to compare the methods used in this study, the authors used several machine learning approaches, like naive bayes, linear support vector machine, random forests, multilayer perceptron, stochastic gradient decent and logistic regression. When comparing several machine learning algorithms, the suggested ensemble technique produces the best results.

1. Introduction

Opinion analysis is the mechanism of extracting and categorising pupils' emotions from a piece of content into unusual emotions like positive, negative, or impartial sentiments or feelings like joy, sadness, anger, or disgust to determine the user's mind-set closest to a given topic. In several domains, such as education, where student opinions are key to assessing the success of mastering technology [1], sentiment analysis plays an important role. Educational data mining is a subset of

* Corresponding author.
E-mail addresses: nehaps2703@gmail.com (U. C. Jaiswal)

https://doi.org/10.22124/cse.2023.24488.1056

record mining software that has emerged to address issues in education. Supporting college students who seek assistance, disposing of and adding garments to the unit in accordance with the college student's understanding, and identifying college students' critiques are all possible outcomes of addressing such issues [2]. Sentiment evaluation is used for instructional improvement. Therefore, coaching assessment has been one of the most essential elements of instructional improvement since it may imply numerous factors of coaching quality [3].

Opinion mining is a method of employing surveys to track people's feelings on any given topic. In general, users’ private emotions, faith, opinions, and goals, for example, may all influence their opinions. Most sentiment mining studies have focused on e-commerce and business applications like product reviews, hotel evaluations, and movie ratings, among other things [4]. Monitoring a student's progress is critical to keeping them on track to achieve their objectives. Parents must be kept up to date on their child's growth through a detailed college progress report that tells them what their child is learning and how far they have come [5].

Various methods have been used to study sentiment in tutor-mastering situations. This is one affective area of a class that desires to progress nicely, whereas another method specialises in the combination of novice feelings in tutor-mastering circumstances and the correct control of these emotions at some point in the gaining knowledge process [6]. Sentiment analysis is a popular way of extracting sentiment from unstructured textual information, and it's used to cut down on the time it takes to gather inspiration and criticism. At the report or sentence level, most of the mastering sets of rules used either lexicon-based or device-based strategies [7].

Figure 1 depicts the sentiment examination techniques, perspectives, and levels used in the domain of education. In this domain, three types of emotion mining techniques are used: machine learning, lexicon-based techniques, and hybrid approaches. Expert system approaches are split into supervised and unsupervised learning techniques. There are a variety of classifiers used in the training region for supervised machine learning approaches, including selection trees, continuous, order-based, and model-based classifiers. The thesaurus-based total method, on the other hand, employs tactics in addition to the thesaurus-based total and core-based total procedures [8]. The machine learning approach employs numerous mastering algorithms to determine sentiment via education on a known dataset. The lexicon-based total strategy entails calculating sentiment scores for an overview [9]. The technique combines the advantages of both rule-based and automated approaches into a single system. Hybrid-based techniques are further classified into elements such as pSenti and SAIL. Another type is the content record stage, determination stage, or word or aspect stage type. A document-stage type of pursuit aims to discover a sentiment polarity for the entire overview, while a sentence-stage or word-stage type can specify a sentiment polarity for every sentence of an overview or even for every word. Our look suggests that most of the strategies tend to focus on the document-stage type. They also divided rating ranges into elements, component rating stages, and international score stages, and these elements were further divided into different sub elements. Most of the answers that specialise in international score types recall only the polarity of the review and depend upon device learning strategies [9]. ***Figure 1*** presents an in-depth type of sentiment analysis.

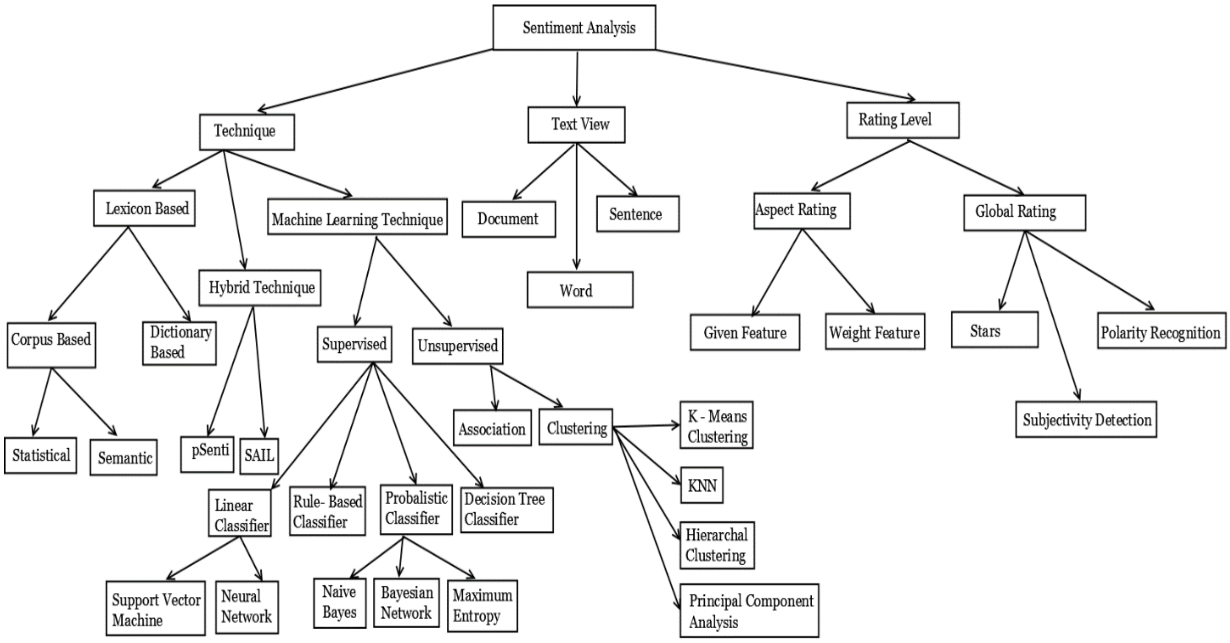

Figure. 1. A taxonomy for sentiment analysis

Understanding people's sentiments is only one aspect of sentiment analysis in numerous fields. In order to understand and enhance the learning process and the context in which it occurs, analytical learning also refers to the collection and analysis of data about people and their surroundings. For e-learning platforms that guide researchers through the learning process in line with their personal requirements and preferences, this information is very important. As a result, this knowledge is equally crucial for instructors because it enables them to understand the psychological state of their pupils.

This work makes a significant contribution by analysing and categorising the sentiment of student performance, displaying results using a proposed novel ensemble machine learning approach, and comparing a variety of machine learning classifiers, which are naive bayes, linear support vector machine, random forests, multilayer perceptron, stochastic gradient decent, and logistic regression. The key advantage of the suggested strategy is that it pinpoints the most effective course of action for improving student performance.

The sections of the remaining research are as follows: The review of the literature is in Part 2. The concept and process for the suggested model are described in Part 3. In Part 4, the outcome is covered. The entire paper ends in Part 5.

2. Literature Review

Many types of exploration have been completed in the field of opinion examination. They used a variety of methods, including thesaurus-based approaches, lexicon-based approaches, machine learning classifier algorithms, statistical approaches, long-short-term memory approaches, the nave Bayes algorithm, aspect-based sentiment analysis, and many others.

Pong-Inwong et al. [3] define the pattern of opinion expression in the same way that this study proposes a new method of opinion examination. The proposed methodology extracts responses and remarks from unlocked questions displayed in a learning assessment organisation, allowing student defendants to give comments to their faculty on aspects that change guidance and learning in the lecture room. In comparison to the other classifier algorithms, the SPPM approach gets the best accuracy of 87.94%, according to the data. The proposed model's key contribution is that it uses students' opinions to select the most effective technique for enhancing instruction.

Aung et al. [4] express the level of satisfaction with the result, whether it is outstanding or bad. To overcome this problem, they advocate adopting a lexicon-based total approach to calculate the ranks of coaching progress by automating the research of students' textual content comments. Knowledge of English emotion phrases is used as a grammatical point to regulate the antinomy of phrases. They can figure out how teachers feel by reviewing the opinion records, which include intensifier phrases extracted from student comments and explain the degree of good or bad feelings.

Watkins et al. [5] introduce SENSE, a computer that employs natural language processing to improve secondary school report cards. Through connecting the three main talents that are shared with a pupil's growth, an integer image is generated for easy understanding. Parents and students are less likely to have trouble communicating with each other if teachers, students, and parents or guardians use a better way to share information and talk to each other.

Chauhan et al. [7] say that most of the paintings have been completed to process people's feedback to categorise them as high-quality or low-quality opinions using dictionary-based or system-based learning techniques at a high level. It has been proposed that emotion evaluation plays a significant role in locating critiques of a specific point of view while using a wearable gadget in educational situations. In this study, they used system learning and lexicon-based methodologies to perform a view-based, completely emotional evaluation.

Mite-Baidal et al. [8] give a thorough overview of the literature on opinion examinations in the field of learning. The target of this observation is to identify the methodologies and digital academic materials benefits of opinion examination, among other things, and the additional advantage of applying opinion examination in the education sector. The findings show that Naive Bayes is the most commonly used opinion examination method, and MOOC conferences and civil chain are the most commonly used digital academic tools for data collection for opinion analysis.

Onan et al. [10] utilise ensemble learning and deep learning paradigms to provide an efficient sentiment categorization strategy with good prediction performance in MOOC reviews. In this contribution, they seek to solve various issues related to sentiment analysis of educational data.

Barron-Estrada et al. [11] provide a sentiment analyzer for recognising polarity and emotions based on studies using textual expressions penned in Spanish in the field of computer science, which may be utilised in an ITS to detect students' feelings and/or emotions. They also show the sentiment analyser’s results, which are quite promising, with an accuracy rate of 88.26%.

Hasib et al. [12] present a prediction model for secondary school student success based on data and five categorization algorithms. The test results show that it outperforms other models. Therefore, it is critical to consider whether a model makes a certain forecast. As a result, they train interpretable models for all the classifiers. This has the primary benefit that the models can be trusted, and their transparency makes it easier to comprehend how they operate.

Kandhro et al. [13] define the proposed model as a time-saving method for sentiment analysis in teacher evaluations. The approach employs input as content to calculate the content. Furthermore, by using a pre-trained word vector model, the machine was able to acquire considerable semantic and syntactic data. As a result, this approach has the potential to affect various problems in classic approaches, such as n-gram, naive bayes, and the base vector tool approach, where word regulation and data are lost. Learning helps to improve the quality of guidance in educational organizations. Furthermore, the dataset will be upgraded by boosting the information patterns of inactive remarks.

Lee et al. [14] propose a strategy for identifying pupils who are expected to fail an educational career early on. To improve predictive accuracy, an opinion examination is used to classify emotional data from content-based, automatically evaluated comments given by students. Experiments revealed that combining collected opinion data from pupil automatic appraisal significantly improved early-stage prediction quality. Due to data scarcity at the start of the course, the results also show that measured information, like drill completion, attendance, and examination grades, has limited early prognostic value.

Vital et al. [15] analyse the many categories of students' learning styles, including "very rapid," "fast, moderate, and "slow." They used attributes including ability, knowledge level, reasoning, and key subject abilities in their training and testing for this. In this study, researchers are employing several machine learning approaches, conducting statistical analysis, classifying students into four categories of learners, and selecting the most effective algorithm for forecasting students' learning rates.

Yousafzai et al. [16] examine deep neural network strategies to effectively forecast students' progress based on previous data. By examining current research issues that are founded on sophisticated feature classification and prediction, they have used the most advanced BiLSTM in this paper, together with an attention mechanism model. To anticipate success early on, this work is extremely important for academics, universities, and government agencies. BiLSTM improved sequence learning skills outperformed performance when combined with attention mechanisms. An efficiency score of 90.16% was attained by the suggested strategy.

Saravanan et al. [17] found a productive learning environment by analysing and contrasting various machine learning algorithms for the academic success of the learner. This study examines deep learning techniques and suggests approaches. The suggested algorithms can more accurately depict students' academic achievement.

Kaur et al. [18] define this study as a continuation of a previous study that looked at the emotions and sentiments of students. Pupils were biased towards assignments and tests as these would support them better, and the desire for details for the examination was extra for supervision and transmission compared to others, which had extra numerically related calculations, according to data analysis.

Al Shibli et al. [19] the goals are to comprehend the variety of techniques employed to forecast student outcomes and to suggest various machine learning techniques for forecasting academic achievement.

Ouatik et al. [20] use educational data mining and artificial intelligence techniques to predict students' academic progress. The results after utilising big data are fairly good at completion and were able to reach a recognition accuracy of 87.32% by the SVM classifier when they were compared to the findings before and after.

Misuraca et al. [21] describe an approach that can be used in an educational setting to process student feedback with the goal of assessing the instructor's effectiveness and improving the learning experience. This paper will compare the armed approaches, talk about their features, and show how they work with a simple example to review the many R packages that can be used to do opinion analysis.

Relucio et al. [22] focused mostly on instructional posts found on the microblogging social media site. The web analytics technique was used to obtain and analyse insights about community behaviours and sentiments by collecting, preprocessing, categorising, and analysing results.

Nikoli et al. [23] present an ABSA method for free content revision based on Serbian students' perspectives. The opinion examination was performed at the most detailed level of content granularity, at the sentence segment level. All NLP approaches, tool learning approaches, traditional actions, and languages are all used in the system.

Shrotriya et al. [24] propose a unique and controllable education system. This concept was made possible because of the opinion examination approach implemented using an advanced form of neural grid planning called PMM networks. They have further developed a feasibility technique for national ministries of education to use in putting such a preferred system in place.

Kandhro et al. [25] give a way for opinion analysis to enhance the calibre of instruction at universities and other educational institutions. The goal of this analysis is to look into various tool research methods in order to regulate their value and generate concern in this field of analysis. When compared to other types of performance, MNB and MLP were shown to be the most effective.

Multani et al. [26] define the examination of feelings and their patterns, which are discussed in this survey research. They also suggested a method for predicting user-specific feelings and categorising them as "negative" or "positive". They have utilised the "Twitter" dataset to create this method in Java environments. It offers a method for studying social information for academic purposes that considers the considerable drawbacks of the standard qualitative study.

Jang et al. [27] suggest a realistic approach to predicting students' success in the classroom. To discover the opinions of professional educators, they carried out qualitative research. Additionally, they tested multiple machine learning methods. The research's findings indicated that logistic regression performed the best all around.

Rakhmanov et al. [28] in this experiment, a huge dataset of over 52 000 comments was used to construct a modernization classification approach. The findings of a correlation test among opinion examinations and scale-graded survey responses demonstrate that opinion examinations can be recognised as a reasonable tool for procedure and instructor assessment. A comparison of alternative vectorization and classification algorithms was conducted. The experiment results show that the arbitrary forest classifier was the more appropriate and efficient analysis approach.

Gaftandzhieva et al. [29] explain how to use statistical and machine learning approaches to forecast students' exam results and presence in online courses. Four machine learning methods are used to estimate the pupils' final grades. Also used was five-fold cross-validation.

Sultana et al. [30] establish a deep learning-based approach for opinion categorization based on educational data samples. In this study, they concentrated on the precision and consistency of the learning data set sample in order to estimate the best model.

Berrar et al. [31] define the processes leading to one of the greatest powerhouses of learning algorithms. The publication serves as an encyclopaedia for bioinformaticians, machine learners, and statisticians and includes an explanation of certain cautions and dangers in developing a Bayesian approach.

Abu et al. [32] show that the range used has a significant impact on the algorithms' effectiveness, with huge differences in performance between different distances. On most data sets, they discovered that a newly proposed non-convex optimization range significantly outperformed the other ranges.

Jantakun et al. [33] identify a machine's model for forecasting student results using data science methods. The two steps of the research process are context evaluation and assessment. Education professionals and learners can enhance their teaching and learning processes by predicting student achievement.

Cambria et al. [34] emulating human intelligence requires an understanding of sentiments, which is one of the crucial components of personal growth and evolution.

Table 1. Compare various sentiment analysis existing techniques to proposed model.

Ref. No.	Year	Description	Techniques	Best Technique	Prediction Result
[3]	2019	Provide a strategy for teaching sentiment categorization.	ID3, OneR, Logistic, Naïve Bayes, Hoeffding tree, Support Vector Machine, Ada Boost, BFTree, SimpleLogistic, BayeNet, ZeroR, Stacking	Sentiment Phrase Pattern Matching	87.94%
[10]	2021	The objective of the work is to apply the paradigms to develop a sentiment categorization scheme that is efficient and has high prediction accuracy for MOOC reviews.	Deep Learning, Supervised Learning and Ensemble Learning Techniques	Deep Learning Methods	95.80%
[11]	2019	It presents a sentiment analyzer for the detection of polarity and emotions related to learning.	Bernoulli NB, Multinomial NB, SVC, Linear SVC, SGD Classifier, K-Nearest Neighbors, CNN -LSTM	CNN -LSTM	88.26%.
[12]	2022	This study provides a prediction model for students' progress in secondary education.	Support Vector Machine, XGBoost, Naive Bayes, Logistic Regression, K-Nearest Neighbors	Support Vector Machine	96.89%
[13]	2019	It is meant to improve the educational system's teaching quality.	CNN, LSTM	LSTM	90%
[15]	2021	Analyse the many student-leaning categories in this paper.	Classification Trees, k-NN, C4.5, SVM, and Naive Bayes	k-NN	0.94%

[16]	2021	Predict student achievement in this research using prior data.	Deep Neural Network Model	BiLSTM	90.16%
[17]	2022	To evaluate and improve students' academic performance.	ANN, LSTM, MLP, and IP-LSTM	IP-LSTM	91%
[18]	2020	This study is a development of a prior investigation that examined the emotions and feelings expressed in student responses.	Naïve Bayes and Support Vector Machine	Naïve Bayes	94.5%
[19]	2022	This study forecasts student performance.	Support Vector Machine, Linear Regression, Naive Bayes, Random Forest	Linear Regression	0.81%
[20]	2022	They employ techniques for predicting pupils' achievement in education.	KNN, C4.5, SVM	SVM	87.32%
[23]	2020	In this definition at the phrase segment level, they proposed a strategy for the ABSA in Serbian.	KNN, Naïve Bayes, SVM, DB, SVM-DB	SVM-DB	0.89%
[27]	2022	This study's objective is to predict students' achievement.	Machine Learning and Artificial Intelligence Techniques	Logistic Regression	0.951%
[28]	2020	In this study's experiment, a large dataset was used to build a state-of-the-art classification model.	Tf-Idf and Count vectorization Random Forest, Naïve Bayes, Gradient Boosting, Support Vector Machines	Tf-Idf, Random Forest	88%
[29]	2022	This research provides a case study for predicting the students' exam results.	XGBoost, Random Forest, KNN, SVM	Random Forest	78%
----	-----	In this research, authors propose a novel ensemble machine learning technique for figuring out the best ways to help students study in order to boost their academic achievements.	Naïve Bayes, Logistic Regression, Random Forest, Linear SVC, Ensemble Model	Ensemble Model	98%

The papers examined in the literature review are listed in ***Table 1***. The above table includes the author's techniques, opinion mining method, classification algorithm, and year of publication. The purpose of this table is to list the most frequently used instructional materials for sentiment examination. The outcomes of all of the preceding surveys reveal the various sentiment analysis methodologies used in education, such as J48, artificial neural networks, decision trees, random forests, logistic regression, support vector machines, naive bayes, multilayer perceptrons, and many others. In the survey, many different types of researchers utilised diverse ways to improve teaching and learning practises. In comparison to ***Table 1***, we found that the proposed ensemble model is the most accurate at predicting whether a student will be successful.

3. Methodology

In this work, the student's performance is classified using sentiment analysis, and records are analysed using ensemble machine learning methods. In this research, the main objective is the prediction of student performance using sentiment analysis and comparing the techniques with novel ensemble machine learning techniques. We use the Jupyter Notebook Platform for the implementation of the methodology. ***Figure 2*** represents the suggested methodology.

3.1. Proposed Model Process

The proposed model process is depicted in ***Figure 2*** and is broken down into nine major phases: data acquisition, sentiment classification, representation of marks, classification of marks percentage, display sentiment polarity, split dataset, techniques used, performance evaluation, and result. These phases are described below:

- In the first part, gather the student's mark datasets.
- In the second section, determine the student sentiment category by using some fundamental criteria. ***Table 2*** shows the classification of the collected data.

Table 2. Collected data classification.

Class	Basics of Classification
Excellent	80-100
Very Good	60-79

- In the third part, show all students’ marks.
- In the fourth part, display all marks in the form of percentages.
- In the fifth part, we display sentiment polarity in graphical form.
- In a six-part split, the dataset is split into two parts: training data and testing data.
- In the seventh part, present the technique used in the student sentiment classification.
- In an eight part display comparison of classifiers, accuracy results in the form of precision, recall, and f-measure.
- In the ninth part, the best result is displayed, which is used in student sentiment classification.

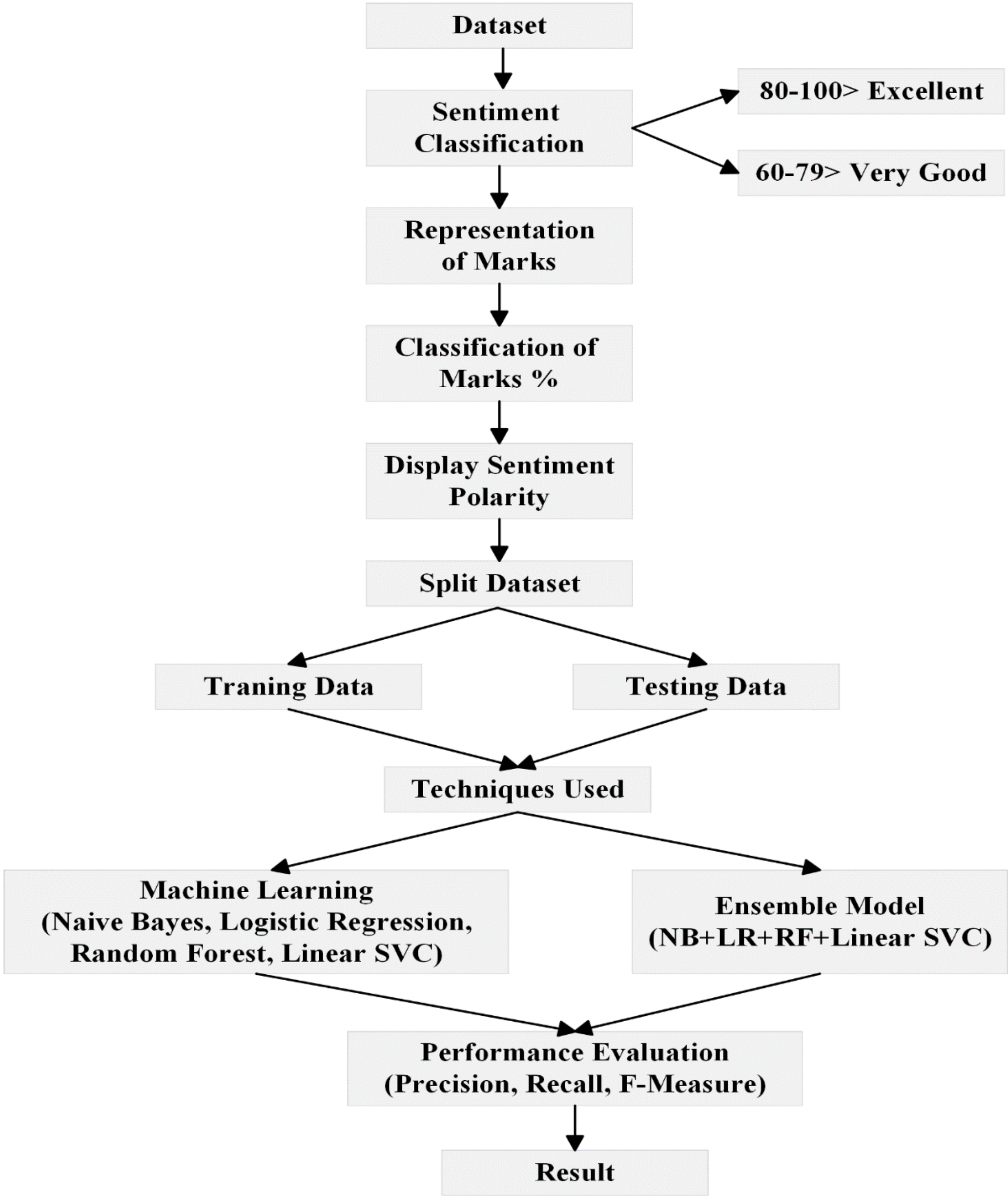

Figure. 2. Proposed Model

3.2. Dataset Details

In this experiment, the dataset collected from Kaggle (https://www.kaggle.com/datasets/erqizhou/students-data-analysis) is dated 2/03/2023. The dataset consists of 17 attributes, but we add one more attribute, which is sentiment. In this sentiment attribute, determine the student sentiment category by using some fundamental criteria. We classified student sentiment into two groups: excellent and very good. The sentiment attribute is classified based on one of the attributes, GPA. If a student's GPA is between 80 and 100, their sentiment is excellent, and if it is between 60 and 79, their sentiment is very good. ***Table 3*** shows the collected data's classification.

Table 3. Dataset details

Attributes	Statistic / Label	Value
ID	Minimum	1141
	Maximum	1245
	Mean	1193
	StdDev	30.455
Class	A	76
	B	29
Gender	Male	37
	Female	68
Race	Minimum	1
	Maximum	7
	Mean	1.79
	StdDev	1.674
GPA	Minimum	63.49
	Maximum	93.71
	Mean	82.957
	StdDev	6.053
Algebra	Minimum	46
	Maximum	98
	Mean	76.057
	StdDev	11.723
Calculus 1	Minimum	38
	Maximum	100
	Mean	71.962
	StdDev	12.197
Calculus 2	Minimum	17
	Maximum	99
	Mean	78.943
	StdDev	14.997
Statistics	Minimum	51
	Maximum	100
	Mean	85.133
	StdDev	10.27
Probability	Minimum	29
	Maximum	97
	Mean	83.876
	StdDev	10.514
Measure	Minimum	54
	Maximum	100
	Mean	80.762
	StdDev	10.296
Functional Analysis	Minimum	9
	Maximum	100
	Mean	75.324
	StdDev	13.003
From 1	A-Z	102
	AA	2
	BB	1

From 2	A	32
	B	73
From 3	A-D	99
	S	6
From 4	Minimum	0
	Maximum	3
	Mean	0.505
	StdDev	0.899
Y	Minimum	0
	Maximum	2
	Mean	0.714
	StdDev	0.829
Sentiment	**Excellent**	**76**
	Very Good	**29**

3.3. Sentiment classification

In this part, classify student sentiment, which is based on student GPA attributes. Student sentiment is excellent if the student's GPA is between 80 and 100, and very good if the student's GPA is between 60 and 79.

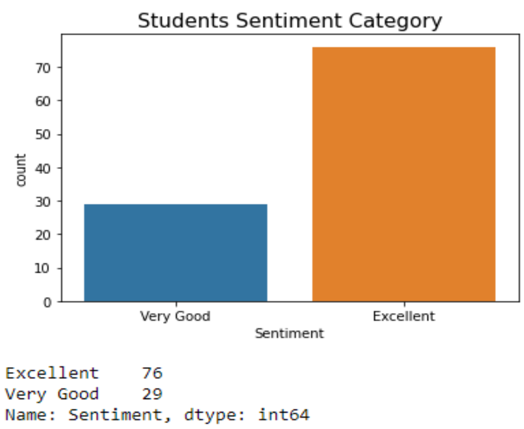

Figure. 3. Shows student sentiment

Figure 3 represents the categories of student sentiment, and the range of excellent sentiments is 76 and the range of very good sentiments is 29.

3.4. Techniques Used

In this proposed method, we use logistic regression, multilayer perceptron, linear SVC, random forest, naive bayes, stochastic gradient decent and proposed ensemble machine learning techniques.

- **Naïve Bayes (NB):** The term "naive Bayes learning" describes the method of building a Bayesian predictive model that, when applied to a given instance, gives a posterior class probability $P(Z = z_a \mid Y = y_b)$. These probabilities are used by the straightforward Bayes classification algorithm to categorise an instance [31]. By using Bayes' theorem and somewhat condensing the syntax, we obtain:

$$P(z_a \mid y_b) = \frac{P(y_b \mid z_a)\, P(z_a)}{P(y_b)} \tag{1}$$

It should be noted that the combined probability of y_b and z_a is the numerator in ***Eq. (1)***. Therefore, the numerator can be expressed as follows; for clarity, we'll just use y and leave out the index b :

$$\begin{aligned} & P(y|z_a)P(z_a) = P(y, z_a) \\ & = P(y_1, y_2, \ldots\ldots, y_p, z_a \\ & = P(y_1|y_2, y_3, \ldots\ldots.., y_{p,} z_a)P(y_2, y_3, \ldots\ldots, y_p, z_a) \\ & = P(y_1|y_2, y_3, \ldots\ldots.., y_{p,} z_a)P(y_2, y_3, \ldots\ldots, y_p, z_a)P(y_3, y_4, \ldots\ldots, y_p, z_a) \\ & = P(y_1|y_2, y_3, \ldots\ldots.., y_{p,} z_a)P(y_2, y_3, \ldots\ldots, y_p, z_a)\ldots\ldots..P(y_p|z_a)P(z_a) \end{aligned} \tag{2}$$

- **Random Forest (RF):** Both classification and regression problems can be solved using this method. The forest is made up of a variety of different decision trees. A class prediction is made by each individual tree. Finally, the class with the most votes is evaluated for prediction. It makes a forest by putting together a group of decision trees with a bagging strategy [35].
- **Logistic Regression (LR):** This is the most straightforward method for solving regression and classification tasks. It determines the likelihood of a certain output, which can be binomial or multinomial. The data and connections between the variables are described using the sigmoid function. It is currently being used in studies to determine whether a transaction is fraudulent.
- **Linear Support Vector Machine (SVC):** When the data is anticipated to be linearly separable, one of the algorithms that is frequently utilised is linear SCV. "The goal of a linear SVC (support vector classifier) is to match the data provided, returning a "best fit" hyperplane that divides, or categorises, the data," states the article. After obtaining the hyperplane, users can give the algorithm some variables to identify what the "predicted" class is [36].
- **Multilayer Perceptron (MLP):** A type of feedforward network is the multilayer perceptron (MLP). Alternatively, it is referred to as a nonlinear and robust artificial neural network. The MLP, as it has been suggested, consists of three layers: input, hidden, and output. There are neurons with nonlinear activation functions in every node or layer. Therefore, it makes sense to learn how the variables relate to one another.
- **Stochastic Gradient Decent (SGD):** SGD is a straightforward and effective technique for differentiable learning in linear classifications under convex loss functions, such as logistic regression and SVM. In content-scale learning for machine learning, SGD recently received positive attention. Additionally, the performance of the classifier is excellent, and its implementation on text is fairly simple. It is mostly employed for sparse and large-scale machine issues, particularly with text categorization. A straightforward application of the vanilla model fixes its learning rate [25].
- **Proposed Ensemble Technique:** When classifying unique examples, an ensemble of individually trained classifiers combines their predictions. The ensemble method provides improved prediction capability and a high level of stability by combining numerous

"individual" (diversity) models. Ensemble is essentially a supervised learning strategy for merging several weak formative assessments to create a strong learner. When combining models with weak correlation, ensemble methods perform better. Each student's data is classified by the ensemble methods using the majority vote approach. The four classifiers are given equal weight in the majority voting process. The student records were classified separately by all four models; however, the overall sentiment is assigned to the group that received the most votes among the four classifier outcomes [37].

- This research contains an ensemble technique by merging four techniques: Nave Bayes, logistic regression, random forest, and linear SVC. With the help of this ensemble technique, maximum results are achieved. Naive Bayes is employed for both categorization and training purposes. Based on Bayes' theory, this classifier uses probabilistic data [38]. It is possible to use a logical technique to demonstrate the likelihood of a specific group or the absence of recurrence [39]. The random forest approach combines tree predictors. The same application is used to build each tree in the forest using random vector values that are sampled independently. By using hyperplanes, linear SVC examines data and establishes decision boundaries. The hyperplane divides the document vector in one class from the other class in the case of two categories, keeping the separation as wide as possible [38]. In this research, an ensemble technique with multiple parameters is used that has used four individual techniques: linear SVC, naive Bayes, random forest, and logistic regression. Ensemble technique can be explained as follows:

$$z = argmax \sum_{i}^{n} NB_i, \quad \sum_{i}^{n} LR_i, \sum_{i}^{n} RF_i, \sum_{i}^{n} SCV_i \tag{3}$$

- Four variables $\sum_i^n NB_i$, $\sum_i^n LR_i$, $\sum_i^n RF_i$, and $\sum_i^n SCV_i$ will provide prediction probabilities for each training sample. The probabilities for every test sample using NB, LR, RF and SVC then pass through the ensemble criterion, as illustrated in ***Figure 4***.

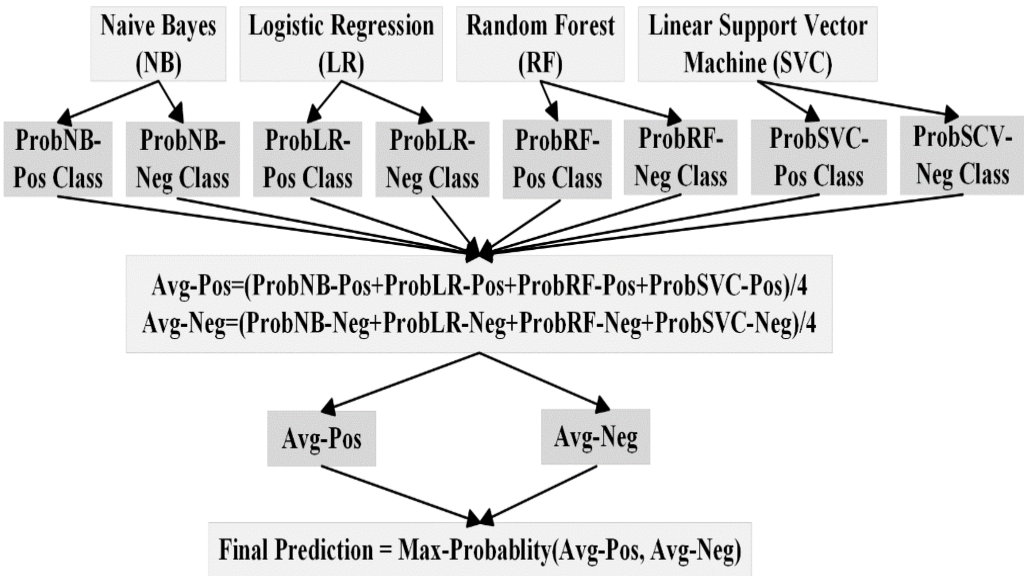

Figure. 4. Proposed ensemble technique architecture (NB+LR+RF+SVC)

- An explanation can be used to demonstrate how the ensemble works. Each class is given a probability score when a given sample travels through the NB, LR, RF, and SVC (that can be positive or negative).

- The ultimate choice is made by the suggested ensemble technique, which combines the classifiers' predicted probabilities. the probability for each class separately using NB, LR, RF, and SVC models that are trained on the dataset. The probability predicted by the four methodologies is used to compute the average probability for each class. After that, depending on the highest average probability for a class, the decision function selects the final class for the evaluation.

3.5. Evaluation Parameters

The term "confusion matrix" on a set of test data can be used to assess how well a supervised ML system performs. There are four terms that make up the confusion matrix: “True Positive (TP)”, “False Positive (FP)”, “True Negative (TN)”, and "False Negative (FN)" [40]. The assessment matrices of precision, recall, and accuracy are calculated ***Eqs. (4)***, ***(5)***, and ***(6)*** to assess the performance measure of any classifier based on the importance of these components.

$$Precision = \frac{TP}{TP + FP} \quad \textbf{(4)}$$

$$Recall = \frac{TP}{TP + FN} \quad \textbf{(5)}$$

$$F - Score = \frac{2 * Precision * Recall}{Precision + Recall} \quad \textbf{(6)}$$

3.6. Proposed Algorithm

Algorithm 1. Sentiment Analysis on Student Performance Algorithm Representation for Proposed Ensemble Methods

Input: Traning on dataset using ensemble machine learning technique

Output: Classification of student sentiment and prediction of student marks

1. Load dataset
2. Apply sentiment classification
   If
   80-100 > Excellent
   Else
   60-79 > Very Good
3. Display all students’ marks.
4. Display student marks percentage (%)
5. Display all student sentiment polarity.
6. Split dataset into train and test set
7. Techniques used (Logistic Regression, Linear SVC, Random Forest, Naive Bayes, Multilayer Perceptron, SGD and Ensemble Machine Learnig Model)
8. Measure performance by using Accuracy, Precision, Recall and F-Score
9. Display result

4. RESULTS

In this experiment, six methods linear SVC, multilayer perceptron logistic regression, SGD, random forest, and naive bayes are utilised to forecast student performance on sentiment examination tests. The objective was to create an ensemble machine learning technique that would be more effective than existing machine learning classifiers. Results from this experiment were used to predict students' performance.

The result showed that prediction of student performance and data analysis in sentiment analysis were achieved using the proposed ensemble machine learning techniques. This resulted in datasets being subjected to sentiment analysis. The number of students is classified into two sentiment categories: excellent and very good, and all these classes are classified under certain conditions, like if 80–100 > excellent and 60–79 > very good.

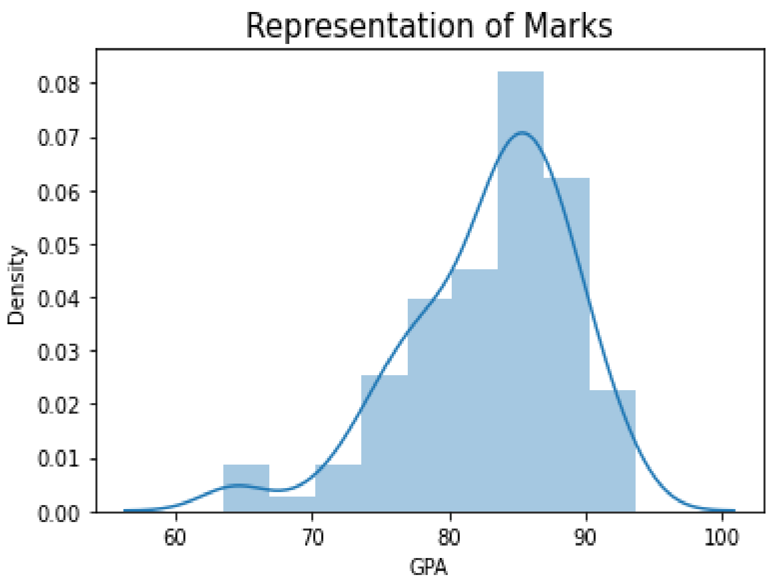

Figure. 5. Shows the students marks

Figure 5 represents student marks obtained in exams, and students' marks range from 60 to 95.

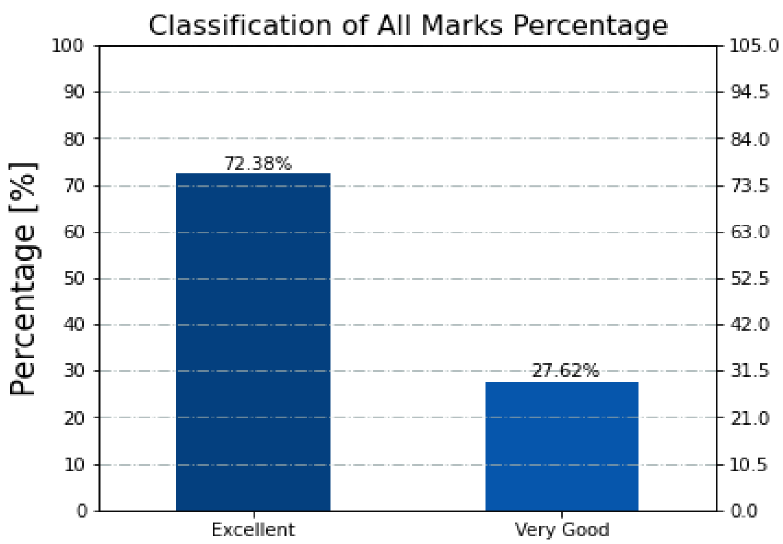

Figure. 6. Shows the students marks percentage

Figure 6 represents the students' mark percentages and shows an excellent sentiment category mark percentage of 72.38% and a very good sentiment category mark percentage of 27.62%.

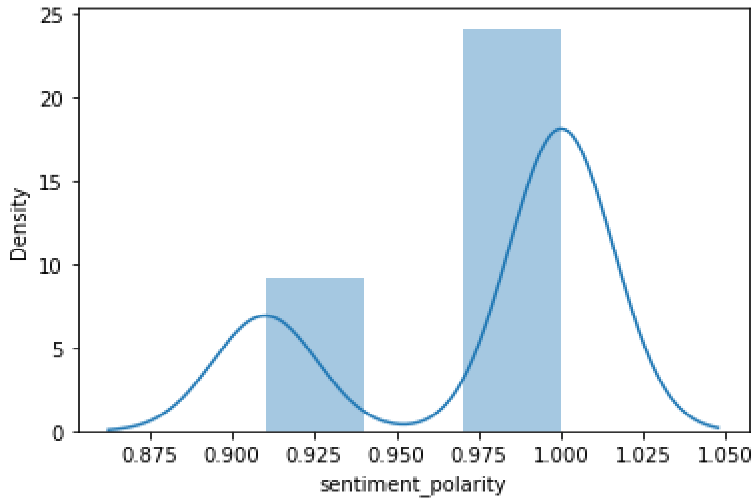

Figure. 7. Shows students sentiment polarity

Figure 7 shows students' sentiment polarity, which ranges from 0.91 to 1.

Table 4. Cross validation outcomes for various models

Techniques Name	**Predicated Class→** / **Actual Class↓**	**Very Good**	**Negative**
Naïve Bayes	Very Good	27	2
	Excellent	9	67
Logistic Regression	Very Good	17	12
	Excellent	11	65
Random Forest	Very Good	26	3
	Excellent	2	74
Linear SVC	Very Good	25	4
	Excellent	6	70
Multilayer Perceptron	Very Good	23	6
	Excellent	5	71
Stochastic Gradient Decent	Very Good	21	8
	Excellent	6	70
Proposed Ensemble Model	Very Good	28	1
	Excellent	1	75

In the above ***Table 4***, show the confusion matrix outcomes for NB, LR, RF, Linear SVC, MLP, SGD and the proposed Ensemble Model. In the above confusion matrix, the model's name, predicted class, actual class, very good value and negative value are shown.

The outcome from each classifier model is displayed in ***Table 5***. In this performance comparison, the authors use the parameters accuracy, precision, recall, and f-measure.

Table 5. Comparison of all techniques

Techniques	Accuracy	Precision	Recall	F-Score
Naïve Bayes	89.52	0.910	0.895	0.831
Logistic Regression	78.09	0.779	0.781	0.780
Random Forest	95.23	0.952	0.952	0.952
Linear SVC	90.47	0.907	0.905	0.906
Multilayer Perceptron	89.52	0.894	0.895	0.895
Stochastic Gradient Decent	86.66	0.864	0.867	0.865
Proposed Ensemble Model (NB+LR+RF+SVC)	**98.09**	**0.981**	**0.981**	**0.981**

4.1. Statistical Result

- **Accuracy:** Proposed ensemble model performance improves by 2.86% using random forest, 7.62% using linear SVC, 8.57% using naive bayes, 20% using logistic regression, 8.57% using multilayer perceptron, and 11.43% using SGD, all in terms of accuracy value.
- **Precision:** In terms of precision, ensemble model performance is better by 0.029% than random forest and provides a 0.074% increment with linear SVC. The percentages are 0.202% for logistic regression, 0.071% for naive Bayes, 0.087% for multilayer perceptron, and 0.117% for SGD.
- **Recall:** In the case of recall, ensemble model performance is 0.029% in comparison with Random Forest. Moreover, it improves performance by 0.2% in comparison with logistic regression, and it also improves performance by 0.086%, 0.076 percentage points, when using naive bayes and linear SVC, and by 0.086%, 0.0114%, for multilayer perceptrons and SGD.
- **F-Measure:** In the case of f-measure, ensemble model performance provides an increment of 0.029%, which is better than random forest, as well as 0.075% with linear SVC, 0.201% with logistic regression, 0.15% with naive bayes, 0.116% with SGD, and 0.086% with multilayer perceptron.

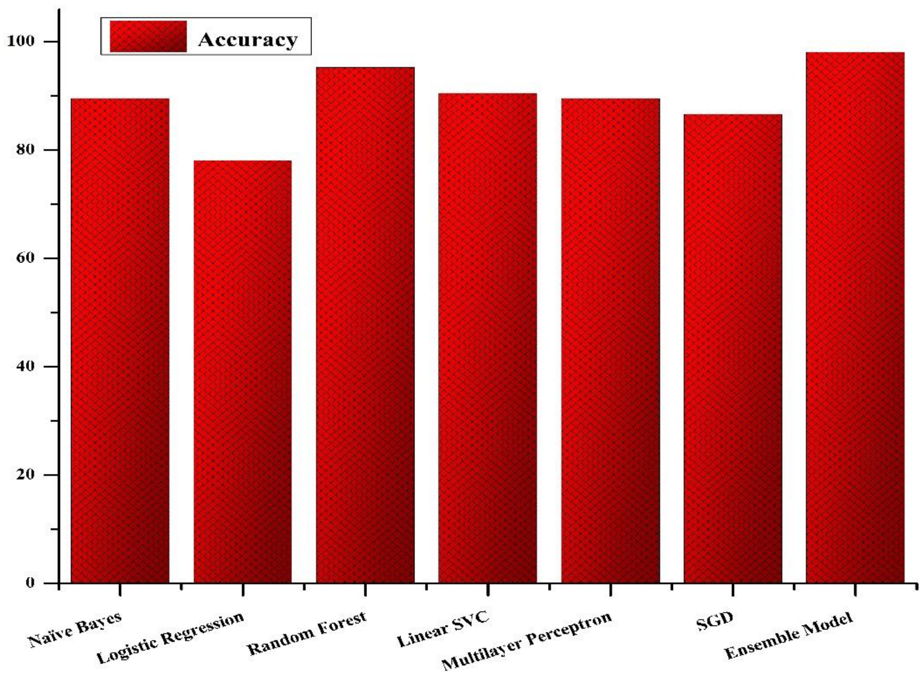

Figure. 8. Performance comparison of various techniques

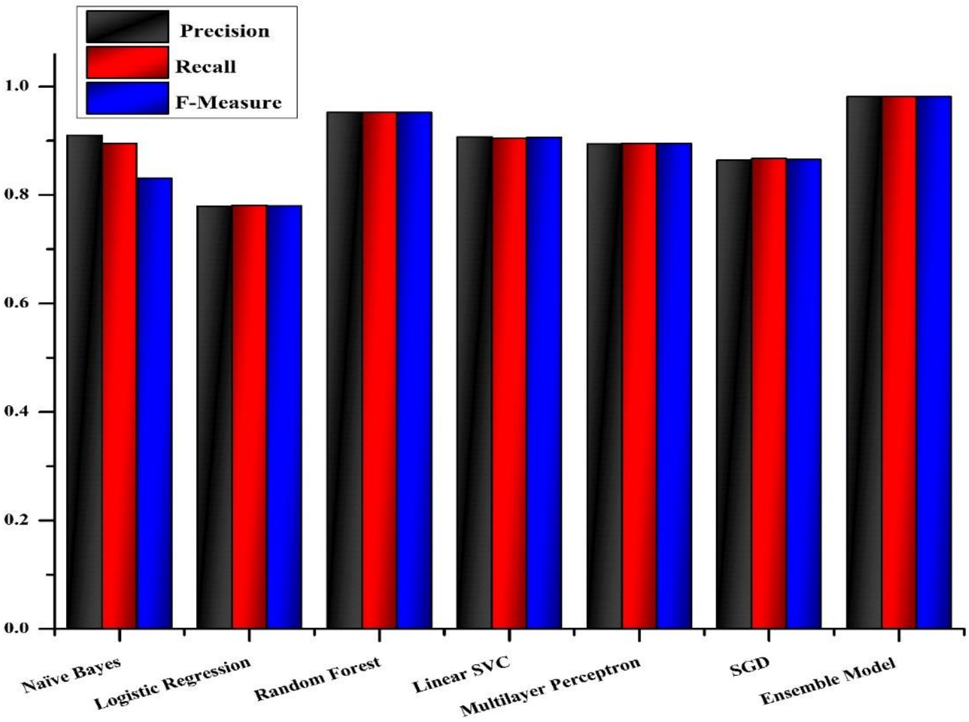

Figure. 8. Comparison of different parameters for selected classification algorithms

In ***Figures 8 and 9***, all techniques perform well in predicting student marks. When compared to other methodologies, ensemble model performance performs the best overall in terms of accuracy, precision, recall, and f-measure results.

5. CONCLUSION

The improvement of the educational process and the achievement of the students are the main advantages of opinion analysis in the educational sector. This study developed a novel ensemble machine learning technique for classifying student sentiment and performance and compared the proposed approach to other machine learning techniques. In comparison with other techniques, the proposed ensemble techniques give the best results in predicting student performance. In this research, classify the student sentiment category, which is based on students’ performance. These student sentiment categories are excellent and very good. This study can assist us in locating the problems and challenges that have an impact on students' academic performance. The following is the future range of our research: improved professional decision-making, the development of efficient teaching techniques, and testing datasets with several machine learning approaches to increase the persuasiveness and service of the organisation for one and all other students.

Declaration

Ethical Approval: Not Applicable

Competing Interests: The authors have not any competing interest.

Funding: Not Applicable

Availability of data and materials: The detail of dataset is provided in the dataset description section.

Acknowledgements

I sincerely appreciate Prof. Umesh Chandra Jaiswal's unceasing guidance.

References

[1] Rani, S., & Kumar, P. (2017). A sentiment analysis system to improve teaching and learning. Computer, 50(5), 36-43.
[2] Altrabsheh, N., Gaber, M. M., & Cocea, M. (2013). SA-E: sentiment analysis for education. Frontiers in Artificial Intelligence and Applications, 255, 353-362.
[3] Pong-Inwong, C., & Songpan, W. (2019). Sentiment analysis in teaching evaluations using sentiment phrase pattern matching (SPPM) based on association mining. International journal of machine learning and cybernetics, 10, 2177-2186.
[4] Aung, K. Z., & Myo, N. N. (2017, May). Sentiment analysis of students' comment using lexicon based approach. In 2017 IEEE/ACIS 16th international conference on computer and information science (ICIS) (pp. 149-154). IEEE.
[5] Watkins, J., Fabielli, M., & Mahmud, M. (2020, July). Sense: a student performance quantifier using sentiment analysis. In 2020 International Joint Conference on Neural Networks (IJCNN) (pp. 1-6). IEEE.
[6] Dolianiti, F. S., Iakovakis, D., Dias, S. B., Hadjileontiadou, S., Diniz, J. A., & Hadjileontiadis, L. (2019). Sentiment analysis techniques and applications in education: A survey. In Technology and Innovation in Learning, Teaching and Education: First International Conference, TECH-EDU 2018, Thessaloniki, Greece, June 20–22, 2018, Revised Selected Papers 1 (pp. 412-427). Springer International Publishing.
[7] Chauhan, G. S., Agrawal, P., & Meena, Y. K. (2019). Aspect-based sentiment analysis of students' feedback to improve teaching–learning process. In Information and Communication Technology for Intelligent Systems: Proceedings of ICTIS 2018, Volume 2 (pp. 259-266). Springer Singapore.
[8] Mite-Baidal, K., Delgado-Vera, C., Solís-Avilés, E., Espinoza, A. H., Ortiz-Zambrano, J., & Varela-Tapia, E. (2018, October). Sentiment analysis in education domain: A systematic literature review. In Technologies and Innovation: 4th International Conference, CITI 2018, Guayaquil, Ecuador, November 6-9, 2018, Proceedings (pp. 285-297). Cham: Springer International Publishing.
[9] Collomb, A., Costea, C., Joyeux, D., Hasan, O., & Brunie, L. (2014). A study and comparison of sentiment analysis methods for reputation evaluation. Rapport de recherche RR-LIRIS-2014-002.
[10] Onan, A. (2021). Sentiment analysis on massive open online course evaluations: a text mining and deep learning approach. Computer Applications in Engineering Education, 29(3), 572-589.
[11] Barron-Estrada, M. L., Zatarain-Cabada, R., & Bustillos, R. O. (2019). Emotion Recognition for Education using Sentiment Analysis. Res. Comput. Sci., 148(5), 71-80.
[12] Hasib, K. M., Rahman, F., Hasnat, R., & Alam, M. G. R. (2022, January). A machine learning and explainable ai approach for predicting secondary school student performance. In 2022 IEEE 12th Annual Computing and Communication Workshop and Conference (CCWC) (pp. 0399-0405). IEEE.
[13] Kandhro, I. A., Wasi, S., Kumar, K., Rind, M., & Ameen, M. (2019). Sentiment analysis of students' comment using long-short term model. Indian Journal of Science and Technology, 12(8), 1-16.
[14] Yu, L. C., Lee, C. W., Pan, H. I., Chou, C. Y., Chao, P. Y., Chen, Z. H., ... & Lai, K. R. (2018). Improving early prediction of academic failure using sentiment analysis on self-evaluated comments. Journal of Computer Assisted Learning, 34(4), 358-365.
[15] Vital, T. P., Sangeeta, K., & Kumar, K. K. (2021). Student classification based on cognitive abilities and predicting learning performances using machine learning models. International Journal of Computing and Digital Systems, 10(1), 63-75.
[16] Yousafzai, B. K., Khan, S. A., Rahman, T., Khan, I., Ullah, I., Ur Rehman, A., ... & Cheikhrouhou, O. (2021). Student-performulator: student academic performance using hybrid deep neural network. Sustainability, 13(17), 9775.

[17] Saravanan, T., Nagadeepa, N., & Mukunthan, B. (2022). The Effective Learning Approach to ICT-TPACK and Prediction of the Academic Performance of Students Based on Machine Learning Techniques. In Communication and Intelligent Systems: Proceedings of ICCIS 2021 (pp. 79-93). Singapore: Springer Nature Singapore.
[18] Kaur, W., Balakrishnan, V., & Singh, B. (2020, April). Improving teaching and learning experience in engineering education using sentiment analysis techniques. In IOP Conference Series: Materials Science and Engineering (Vol. 834, No. 1, p. 012026). IOP Publishing.
[19] Al Shibli, K. S., Al Abri, A. S. S., Sunny, L., Ishwar, N., & Cherian, S. P. (2022). Model for Prediction of Student Grades using Data Mining Algorithms. European Journal of Information Technologies and Computer Science, 2(2), 1-6.
[20] Ouatik, F., Erritali, M., Ouatik, F., & Jourhmane, M. (2022). Predicting Student Success Using Big Data and Machine Learning Algorithms. International Journal of Emerging Technologies in Learning (Online), 17(12), 236.
[21] Misuraca, M., Forciniti, A., Scepi, G., & Spano, M. (2020). Sentiment Analysis for Education with R: packages, methods and practical applications. arXiv preprint arXiv:2005.12840.
[22] Relucio, F. S., & Palaoag, T. D. (2018, January). Sentiment analysis on educational posts from social media. In Proceedings of the 9th international conference on E-education, E-business, E-management and E-learning (pp. 99-102).
[23] Nikolić, N., Grljević, O., & Kovačević, A. (2020). Aspect-based sentiment analysis of reviews in the domain of higher education. The Electronic Library, 38(1), 44-64.
[24] Shrotriya, S., & Kumari, N. (2018). Smart Education System Developed by Sentiment Analysis of Students Using PMM Neural Networks. International Journal for Research in Applied Science & Engineering Technology (IJRASET), 6.
[25] Kandhro, I. A., Chhajro, M. A., Kumar, K., Lashari, H. N., & Khan, U. (2019). Student feedback sentiment analysis model using various machine learning schemes: a review. Indian Journal of Science and Technology, 12(14), 1-9.
[26] Multani, A., & Agrawal, A. (2019). Sentiment Analysis for Understanding Students' Learning Experiences: A Survey Paper. International Journal of Scientific Research & Engineering Trends, 5(2).
[27] Jang, Y., Choi, S., Jung, H., & Kim, H. (2022). Practical early prediction of students' performance using machine learning and eXplainable AI. Education and Information Technologies, 1-35.
[28] Rakhmanov, O. (2020). A comparative study on vectorization and classification techniques in sentiment analysis to classify student-lecturer comments. Procedia Computer Science, 178, 194-204.
[29] Gaftandzhieva, S., Talukder, A., Gohain, N., Hussain, S., Theodorou, P., Salal, Y. K., & Doneva, R. (2022). Exploring online activities to predict the final grade of student. Mathematics, 10(20), 3758.
[30] Sultana, J., Sultana, N., Yadav, K., & Alfayez, F. (2018, April). Prediction of sentiment analysis on educational data based on deep learning approach. In 2018 21st Saudi computer society national computer conference (NCC) (pp. 1-5). IEEE.
[31] Berrar, D. (2018). Bayes' theorem and naive Bayes classifier. Encyclopedia of Bioinformatics and Computational Biology: ABC of Bioinformatics, 403, 412.
[32] Abu Alfeilat, H. A., Hassanat, A. B., Lasassmeh, O., Tarawneh, A. S., Alhasanat, M. B., Eyal Salman, H. S., & Prasath, V. S. (2019). Effects of distance measure choice on k-nearest neighbor classifier performance: a review. Big data, 7(4), 221-248.
[33] Jantakun, K., Jantakun, T., & Jantakoon, T. (2022). The Architecture of System for Predicting Student Performance Based on Data Science Approaches (SPPS-DSA Architecture). Int. J. Inf. Educ. Technol, 12(8), 778-785.
[34] Cambria, E., Das, D., Bandyopadhyay, S., & Feraco, A. (Eds.). (2017). A practical guide to sentiment analysis.
[35] Sadineni, P. K. (2020, October). Detection of fraudulent transactions in credit card using machine learning algorithms. In 2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC) (pp. 659-660). IEEE.
[36] Sadineni, P. K. (2020, October). Detection of fraudulent transactions in credit card using machine learning algorithms. In 2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC) (pp. 659-660). IEEE.
[37] Lalata, J. A. P., Gerardo, B., & Medina, R. (2019, June). A sentiment analysis model for faculty comment evaluation using ensemble machine learning algorithms. In Proceedings of the 2019 International Conference on Big Data Engineering (pp. 68-73).

[38] Tripathy, A. (2017). Sentiment analysis using machine learning techniques (Doctoral dissertation).
[39] Yousaf, A., Umer, M., Sadiq, S., Ullah, S., Mirjalili, S., Rupapara, V., & Nappi, M. (2020). Emotion recognition by textual tweets classification using voting classifier (LR-SGD). IEEE Access, 9, 6286-6295.
[40] Ghosh, M., & Sanyal, G. (2018). Performance assessment of multiple classifiers based on ensemble feature selection scheme for sentiment analysis. Applied Computational Intelligence and Soft Computing.