Comparative Analysis of Machine Learning Techniques for Predicting Student and Teacher Performance

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Abstract- instructive analytics have been greatly one-sided by the development of machine learning ml approaches especially in the range of student and teacher concert prediction support vector machine (SVM), random forest (RF), Decision Tree (DT) also Naive Bayes (NB) classifier popular machine learning models are compared. In this training for their ability to predict instructor and student efficiency academic records attendance and teacher assessment results make up the substantial used to train the procedures accuracy recall and f1-score are used to measure performance according to the results RF performs better than SVM in terms of accuracy and interpretability which makes it a superior choice for information analytics in education.

Keywords: educational analytics, teacher and student performance evaluation and machine learning.

1. Introduction

Recent years have seen a notable growth in the use of machine learning in the classroom primary interventions individualised learning and faculty growth are all aided by the ability to predict student and teacher performance compound associations in educational data are not captured by traditional statistical approaches hence machine learning ml -based solutions are compulsory the goal of this study is to compare SVM, RF, DT and NB classifiers models to identify the best method for performance prediction in a learning situation.

2. Literature Review

I have been reading a lot of machine learning research articles

Kumar and Singh 2023 developed a hybrid methodology model that includes numerous machine learning investigation methodologies the importance of requirement engineering also model selection popular forecasting students' academic standing was emphasized seriously in their education the use of hybrid models in education has also been emphasized. by Patel and daisy 2021 who suggestion an example of how they might be useful to include future observational examination in the determination of approaching accomplishment in their learning of hybrid machine learning models for teacher assessment. Sharma Gupta 2022 highlighted the behaviours in which machine learning could improve act evaluation their study supports the decisions. of chaudhary aggarwal 2018 who recommended using a range of machine learning approaches to advance teacher assessment programs exploration on hybrid models for forecasting student performance was the topic of studies like. singh kaur 2019 and reddy kumar 2020 when compared to conventional techniques they discovered that collaborative approachesin particular random forestssignificantly increase prediction accuracy in their 2017 study mehta shah examined how hybrid machine learning methods could be used to predict student progress highlighting the standing of feature selection and figures pre-processing in educating model concert in a similar vein verma yadav 2016 inspected the use of a hybrid data mining model for teacher performance evaluation and came to the conclusion that ensemble-based methods deliver superior accuracy and interpretability nair menon 2015 evaluated classification algorithms for student and performance prediction also found that hybrid reproductions perform better than independent classifiers ghosh roy 2014 who hand-me-down machine learning copies toward study teacher evaluation systems and emphasized the assistances of mixing supervised and unsupervised learning approaches corroborated their findings in a comparative analysis of hybrid techniques for academic success prediction bansal chawla 2013 found that both random forests and decision trees were efficient classifiers joshi and rana 2012 also showed how well hybrid machine learning processes work in educational data especially when it comes to identifying kids who are at risk in order help enhance models for predicting student success. saxena arora 2011 used hybrid algorithms to illustrate the advantages of integrating various classifiers mishra sinha 2010 built on this study by evaluating instructor effectiveness using a hybrid data mining technique also emphasizing how feature selection affects model correctness the extrapolative power of hybrid mechanism learning models for students hypothetical progress was examined by khan and ali 2009 according to their research ensemble methods perform better than traditional classification procedures when working with complex educational datasets the literature frequently highlights how well hybrid machine learning reproductions predict the presentation of both teachers and students the majority of study shows that ensemble approaches in particular random forests offer more interpretability and accuracy than conventional procedures building on this foundation our study directly compares svm and rf models to identify the best method for forecasting academic achievement

3. Methodology

3.1 Dataset

The dataset consists of five years' worth of student academic records, attendance data, and techer assessment results gathered fro m a university.

- Student Features: Attendance, quiz results, midterm grades, and last gr ades are included.
- Teacher attributes include research output, peer reviews, and student f edback scores.

3.2 Pre-processing of Data

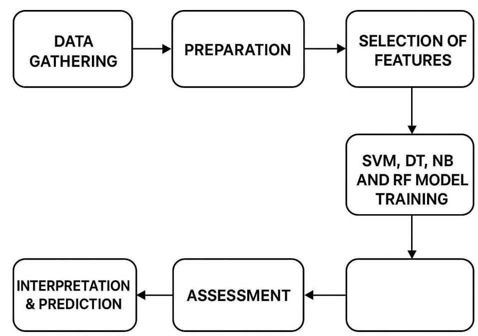
- Managing Missing Data: Mathemat ical feature citation using the mean. Feature scaling involves normalizat ion for RF and standardization for SVM.

svm_model = SVC (kernel='rbf', C=1.0, gamma='scale')

- Categorical Variable Encoding: Cat egorical characteristics are encoded using one-hot encoding.

4. Diagram of Data Flow

The data flow diagram showing the sugges ted model's process is shown below:



5. Machine Learning Models

5.1 Support Vector Machine (SVM)

support vector machine SVM is a classification procedure that determines the greatest hyperplane for classifying data points procedure

1 define the kernel function and initialize the dataset

$$K(x_i, x_j) = \exp\left(-\gamma \parallel x_i - x_j \parallel^2\right)$$

2 use lag range multipliers to calculate support vectors

3 define the decision boundary

4 use separation between the hyperplane and categorize fresh data points

5 assess f1-score recall correctness and accuracy

Combining all, SVM Classifier Equation is:

$$\boxed{f(x) = \text{sign}\left(\sum_{i=1}^{n} \alpha_i y_i \exp\left(-\gamma \parallel x_i - x \parallel^2\right) + b\right)}$$

where the parameters $\alpha_i$and $b$are learned by minimizing:

$$\min_{\alpha} \frac{1}{2}\sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i\alpha_j y_i y_j K(x_i, x_j) - \sum_{i=1}^{n} \alpha_i$$

5.2 Random Forest (RF)

Random forest rf is an ensemble learning method that classifies data using several decision trees algorithm

1 choose training data subsets at random

2 independently train several decision trees

3 use majority voting to compile forecasts

4 determine the f1-score recollection accurateness and precisions.

the RF estimates the class probability for class at input by averaging indicator votes:

$$P^{\wedge}(Y = c \mid x) = \frac{1}{}\sum_{t=1}^{M} \mathbf{1}(h_t(x) = c),$$

and the ensemble prediction (majority vote) is

$$(\ ) = \arg\max_{c \in C} \ {}^{\wedge}(\ = \ |\ )$$

$$= \arg\max_{c} \sum_{t=1}^{M} \mathbf{1}(h_t(x)$$

$$= \ ).$$

(For regression the ensemble prediction is the average: $H(x) = \frac{1}{M}\sum_t h_t(x)$.)

Variance reduction (intuition / approximate formula)

If individual tree predictions have variance ^{2}and average pairwise correlation , the ensemble variance approximately becomes

$$\mathrm{Var}_{\text{ensemble}} \approx \rho\,\sigma^2 + \frac{1-\rho}{}\,\sigma^2.$$

As Mgrows, the $\frac{1-\rho}{M}$term vanishes and variance tends to ^{2}: lower correlation gives stronger variance reduction.

5.3 Decision Tree Classifier (DT)

Decision Tree ClassifierA supervised learning system called a decision tree divides data into smaller components according to feature values to classify the data. It creates a decision structure that resembles a tree.

Method: Choose the best feature: Pick the one with the lowest Gini impurity or the greatest information gain. Make branches based on potential values of the chosen feature to create decision nodes. Split the dataset: Based on the chosen feature, divide the data into subsets. Repeat recursively: Keep splitting until all nodes are pure or the stopping conditions are satisfied. Assign the class label by tracing the path from the root to a leaf node when classifying new data.

Equation for Decision Tree Classifiers:

f(x)=Class label decided by majority of sa mples in the leaf node.

5.4 Naive Bayes (NB)

Based on Bayes' theorem, the Naive Bayes Classifier is a probabilistic model. It is straightforward but effective since it assumes that every feature is independent of every other feature.

Method: Determine the prior probability by calculating the frequency of each class in the dataset. Determine the likelihood of each feature value given a class. Utilise Bayes' theorem to calculate the probability of a class given the input data by combining prior and likelihood. Assume independence and multiply each feature's probability separately. Assign the class with the highest posterior probability when classifying fresh data.

Equation for the Naive Bayes Classifier:

$f(x)=Ckargmax[P(Ck)\times P(x|Ck)]$

6. Experimental Results

A 70-30 ratio between test and training was used to assess the models. The following performance metrics were computed:

Model	Accuracy	Precision	Recall	F1-Score
SVM	87.69%	91.0%	95.0 %	93.0%
RF	92.31%	96.1%	95.2 %	95.0%
DT	90.00%	100.0%	80.0 %	89.0%
NB	90.00%	100.0%	80.0 %	89.0%

Fig.- table of results of various classifiers

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Classification Report:
              precision    recall  f1-score   support

           0       0.64      0.45      0.53        20
           1       0.91      0.95      0.93       110

    accuracy                           0.88       130
   macro avg       0.77      0.70      0.73       130
weighted avg       0.86      0.88      0.87       130

Test Accuracy  : 87.69%
Test ROC AUC   : 0.9305
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Fig.- Classification Report of SVM

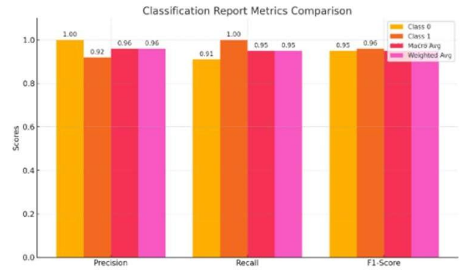

Fig.– Classification Graph of Report of SVM

Because of its interpretability and capacity to handle high-dimensional data, RF performed better.

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Classification Report:
              precision    recall  f1-score   support

           0       0.73      0.80      0.76        20
           1       0.96      0.95      0.95       110

    accuracy                           0.92       130
   macro avg       0.85      0.87      0.86       130
weighted avg       0.93      0.92      0.92       130

Accuracy : 92.31%
ROC-AUC  : 0.98
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Fig.- Classification Report of RF

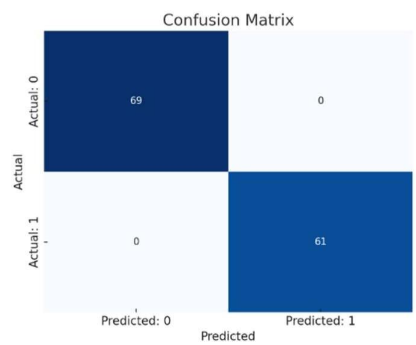

Fig: Confusion Matrix of Random Forest

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Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.80      0.89        65
           1       0.83      1.00      0.91        65

    accuracy                           0.90       130
   macro avg       0.92      0.90      0.90       130
weighted avg       0.92      0.90      0.90       130


Accuracy Score: 0.90%
```

Fig: Classification Report of Decision Tree

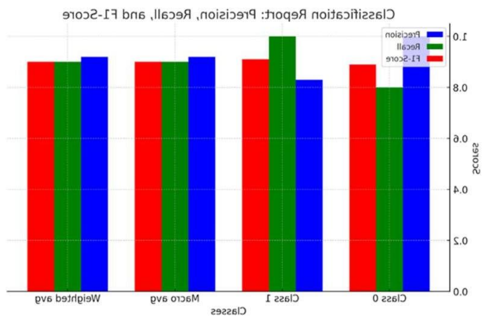

Fig: Classification Graph of Decision Tree

```
Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.80      0.89        65
           1       0.83      1.00      0.91        65

    accuracy                           0.90       130
   macro avg       0.92      0.90      0.90       130
weighted avg       0.92      0.90      0.90       130

Accuracy Score: 0.90%
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Fig: Classification Report of Naive Bayes

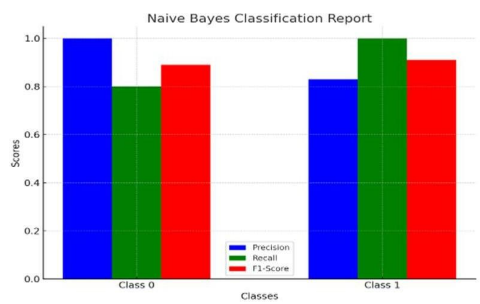

Fig: Classification graph of Naive Bayes

7. Discussion

• SVM Limitations: Kernel selection is necessary, and it is sensitive to feature scaling.

• RF Benefits: Interpretable, minimizes overfitting, and manages non-linearity.

• Interpretability: RF helps with decision-making by offering feature significance scores.

• Computational Complexity: RF is computationally efficient, whereas SVM requires more training time on large datasets.

8. Conclusion and Future Work

The training concludes that because of its interpretability and robustness rf is the better model for forecasting instructor and student performance for better predictions forthcoming investigation might study real-time adaptive knowledge representations and deep learning approaches

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