Journal of Information Systems Engineering and Management
2025, 10(1s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Enhancing Student Placement Predictions with Advanced Machine Learning Techniques

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ARTICLE INFO

Received: 02 Oct 2024

Revised: 28 Nov 2024

Accepted: 15 Dec 2024

ABSTRACT

Optimal management of student placement mechanisms is pivotal to cost-effective distribution and individualized aid for learning establishments. The study presents a novel ensemble methodology to anticipate the outcomes of student placements, integrating manifold machine learning (ML) algorithms — logistic regression, naive Bayes, gradient boosting, linear discriminant analysis (LDA), k-nearest neighbours (KNN), random forest, and support vector machines (SVM). The data set has been constructed with an extensive scope covering various attributes from demographic details through socioeconomic status up to curricular information: feature scaling and dimensionality reduction are proposed as part of comprehensive pre-processing techniques aimed at elevating prediction accuracy. Algorithm performance evaluation includes cross-validation appraisal done on each algorithm individually; the resultant ensemble model is a synthesis where multiple base learners' predictions are amalgamated to capitalize on collective but diverse predictive capabilities uncovered across all constituents. An ensemble approach significantly improves the accuracy, recall, precision, and F1 score more than individual algorithms. This model not only addresses the weaknesses of standalone algorithms but also strengthens itself against dataset inconsistency, thereby ensuring greater reliability. Such a result underscores the promise of ML methodologies to fine-tune student placement forecasts an endowment that can serve educational institutions with an effective blueprint to tailor their placement procedures and foster student triumph.

Keywords: Student Placement Prediction, Machine Learning, Ensemble Methods, Educational Data, Optimization

INTRODUCTION

Educational institutions must optimize student placement processes to allocate resources effectively and provide personalized student support [1,2]. This way, students can be matched with appropriate directions and opportunities according to their abilities and goals, which improves their educational paths and job prospects. Interest in this has grown in integrating Machine Learning (ML) into education systems for a long time now as it offers remarkable potential in dealing with a myriad of problems, among them predicting student placements [3,5].

In the past, student placement decisions were primarily made based on academic performance and assessments by counsellors [6,9]. These methods worked to a certain extent but failed to take into account all inherent factors such as family background, hobbies, and income status among others which influence performance. Data science and ML turned this situation around as it enabled educational institutions to better understand how they could refine placement mechanisms [10,11,13,18]. Initial uses of ML in education centred on forecasting students' success rates and detecting those who are likely to drop out. Nevertheless, over time machine learning applications have evolved from binary classification problems into more nuanced areas like predicting placements [22,24,29].

The research is motivated by the idea of improving student placement methods that exist. The traditional techniques are important but do not always take into account the multidimensional aspects of student profiles and dynamic education systems [32,35]. Incorporating ML in this process makes it possible to generate models which incorporate more variables as well as adjust according to changes in future education and future job trends. This guarantees that students are placed where they fit best based on their potential and skills resulting in positive outcomes for both students and institutions.

The major objective of this study is to produce a comprehensive ensemble technique for forecasting student placement outcomes using different ML algorithms. The concept behind ensemble methods lies in the fact that combining several learning algorithms can result in improved predictive accuracy compared to an individual learning algorithm. Logistic regression, naive Bayes, gradient boosting, linear discriminant analysis (LDA), k-nearest neighbours (KNN), random forest and support vector machines (SVM) among others are examined in this research. The study used a dataset containing diverse attributes such as demographic information, socioeconomic status, extracurricular activities and academic performance. These models are also subjected to extensive pre-processing techniques including feature scaling and dimensionality reduction which improve their accuracy.

The study uses verification by cross-validation, the most rigorous method of testing prediction accuracy. Besides learning from single algorithms, the output of the different base learners is combined to create an ensemble model. This makes it possible to benefit from the complementary advantages of the different algorithms, ultimately leading to lower error rates and less vulnerability of the model to specifics of the data or the weaknesses of single algorithmic approaches.

To conclude, this paper proposes a customized hybrid model to predict the placement of students against individual algorithms where the result is improved to the accuracy, recall, precision and F1-score respectably. This suggested model will convert educational institutes to evolve their system by making decisions accordingly to help students succeed. ML in education has the potential to transform education.

LITERATURE STUDY

Table 1 provides a summary of the aims, methodologies, and results for each paper discussed, and concisely describes the literature to date regarding predicting the perfect student placement (and similar problems) using machine learning.

Table 1. Summarize Literature Study

Author(s)	**Year**	**Objective**	**Methodology**	**Key Findings**
P. S. Ambili, B. Abraham [1]	2024	Evaluate employability prediction	Ensemble learning techniques including various ML algorithms	Improved accuracy in employability prediction using ensemble methods compared to single algorithms
H. El Mrabet, A. A. Moussa [2]	2023	Predict academic orientation	Supervised machine learning framework	Achieved significant predictive accuracy and insights into factors influencing academic orientation
I. Z. A. D. P. No, G. J. Van Den Berg, et al. [3]	2023	Compare re-employment predictions	ML versus assessments by unemployed individuals and caseworkers	ML predictions showed higher accuracy than traditional assessments
M. H. Baffa, M. A. Miyim, A. S. Dauda [4]	2023	Predict student employability	Various machine-learning models	Demonstrated the effectiveness of ML in accurately predicting employability

				outcomes
B. Pune [5]	2023	Predict student placements	Machine learning algorithms	Significant improvement in placement prediction accuracy using ML techniques
N. K. Shah [6]	2023	Detect job positions	Data science and machine learning approach	Effective identification of suitable job positions for candidates
P. Archana, D. Pravallika, et al. [7]	2023	Predict student placements	Machine learning models	Achieved high accuracy in placement predictions, highlighting key predictive factors
B. Parida, P. Kumarpatra, S. Mohantyp [8]	2022	Recommend employment	ML procedures and geo-area-based recommender systems	Enhanced employment recommendations using integrated ML and geographic data
U. K. Sah, A. Singh [9]	2022	Predict student careers	Machine learning techniques	Effective prediction of career paths for students based on various attributes
M. Tedre, et al. [10]	2021	trajectories in educational practice	Teaching Machine Learning Education	Importance of understanding in the context of AI-driven and data-driven systems
A. P. L. S. Maurya [11]	2022	Predict student careers	ML algorithms	Developed classifiers demonstrating high accuracy in predicting career outcomes
N. P. K. M, N. M. Goutham, et al. [12]	2022	Placement prediction	Machine learning analysis	Achieved significant improvements in placement prediction using ML techniques
M. Valte, S. Gosavi, et al. [13]	2022	Predict student placements	Various ML models	Improved accuracy in placement predictions and model efficiency
A. Pandey, L. S. Maurya [14]	2022	Career prediction	ML categorization schemes according to academic standing	Demonstrated effective career prediction using academic and skill-based attributes
L. S. Maurya, S. Hussain, S. Singh [15]	2021	Student placement prediction	Developing ML classifiers	High accuracy in predicting student placements using academic performance data
R. S. Kumar, F. Dilsha, et al. [16]	2021	Placement prediction	Support Vector Machine algorithm	Effective prediction of student placements with SVM, highlighting its robustness
N. C. Sekhar, M. Sebastian, et al. [17]	2021	Predict student development	Prediction model using ML	Significant predictive accuracy for student development outcomes

N. Vidyashreeram, A. Muthukumaravel [18]	2021	Predict student careers	ML approaches	Effective career path prediction for students using various ML methods
A. Surve, A. Singh, S. Tiwari [19]	2021	Career Guidance	ML-based student career guidance system	Improved accuracy and insights into career guidance using ML techniques
V. J. Hariharan, A. S. Abdullah, et al. [20]	2021	Predict placement prospects	ML techniques	High accuracy in predicting student placement prospects using diverse ML models
D. Rajashekar [21]	2021	Campus placement prediction	Bagging approach	Enhanced placement prediction accuracy using the bagging technique
V. Mulye, A. Newase [22]	2021	Recruitment prediction	Data mining techniques	Improved prediction of recruitment outcomes for engineering students
J. Zhu, S. Tang, et al. [23]	2021	Knowledge distillation	ML techniques for distillation	Effective distillation of knowledge in neural networks for enhanced predictions
R. Mani [24]	2020	Assess student employability	Data mining techniques	Significant improvements in assessing student employability using data mining
P. Gavhane, D. Shinde, et al. [25]	2020	Career path prediction	ML models	Effective prediction of career paths with significant accuracy improvements
H. Al-dossari, M. Alkahlifah [26]	2020	Career path choice	ML approach for IT graduates	Improved career path choices for IT graduates using ML models
R. Viram, S. Sinha, et al. [27]	2020	Placement prediction	ML-based prediction system	Enhanced accuracy in placement predictions using machine learning
I. T. Jose, D. Raju, et al. [28]	2020	Placement prediction	Comparison of ML models	Comparative analysis showed ML models' efficiency in predicting placements
D. Manjusha, B. Pooja, et al. [29]	2020	Student placement chance	ML-based prediction	Accurate prediction of student placement chances using ML techniques
M. Bangale, S. Bavane, et al. [30]	2019	Placement prediction survey	Machine learning survey	A comprehensive survey on ML techniques for placement prediction
K. Anvesh, B. S.	2019	Student analysis and	Advanced ML	Effective student analysis

Prasad, et al. [31]		placement	algorithms	and placement predictions with advanced ML models
S. Harinath, A. Prasad, T. Mathew [32]	2019	Placement prediction	ML approaches	Enhanced placement prediction accuracy using various ML techniques
G. Hinton, O. Vinyals, J. Dean [33]	2015	Knowledge distillation	Neural network techniques	Effective knowledge distillation in neural networks for improved predictions

This study review of literature that uses machine learning to predict student placements suggests several common shortcomings. Most studies also struggle with the quality and inclusiveness of the data, frequently suffering from popularity bias about demographic and socioeconomic diversity resulting in a biased or less generalizable model. The Researcher [2,3,5,12,22,33] heavily relies on identifying the primary factors as the academic scores that may overlook seriously implicit and important other factors like personal interest, hobbies, extracurriculars, soft skills etc. Another common problem is that models may become overfit due to small sample sizes, which in turn decreases the generalization and accuracy of these models when faced with new or bigger datasets. On top of it, ensemble methods and more sophisticated algorithms feature increased accuracy but also add complexity and computational burden, thus less reachable for resource-scarce institutions. Moreover, complex models are often hard to interpret, with many machine learning approaches behaving like "black boxes" and offering very limited transparency into the logic behind the decisions. Finally, there is a clear absence of practical implementation after the theoretical studies or experiments, and the long-term validation of these models in practice in educational environments. This limitation suggests the necessity of using more comprehensive, scale, and interpretable methods to boost machine learning's effectiveness in student placement predictions.

METHODOLOGY

The machine learning model for predicting student outcome placement can be seen by the following Figure 1 It follows the procedures as laid down in steps. It comprises data preprocessing, training, evaluation and stacking. In the next section, the study elucidates the machine-learning techniques employed in this research.

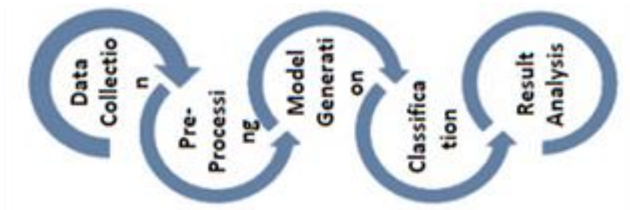

Fig. 1 Student Placement Prediction Methodology.

3.1. Data Preprocessing

Before the familiarization algorithms are applied, the data goes through a series of pre-processing steps to ensure accuracy and consistency:

Data cleaning [2,3,12]: Handling missing values, removing duplicates and correcting errors.

- Feature scale [11,14]: Normalize or standardize features to convert them to a similar scale.
- Data Splitting [18]: Splitting the data set into school and check-out sets to evaluate version performance.

Below parent element 2 is a set of data about the scholar's overall performance. This study has finished cleaning the fact set, study needs to convert it to integer information to be able to predict and visualize it. This is because a data graph is a very simple and straightforward way of interpreting facts.

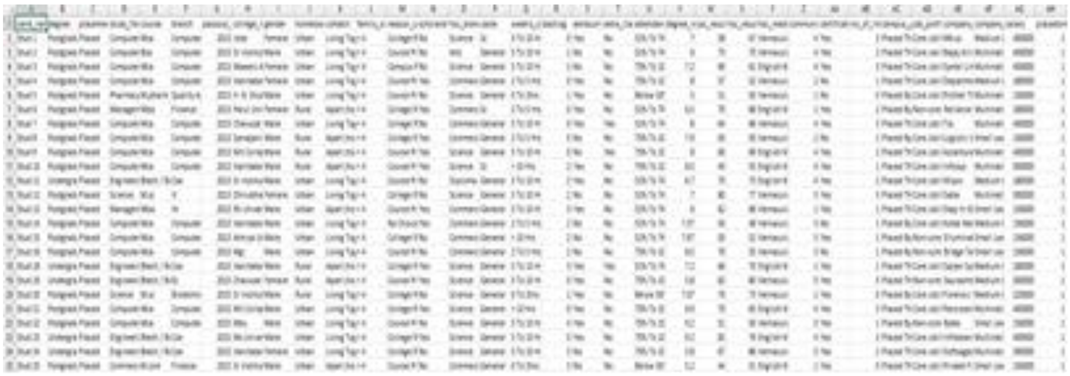

Fig. 2 Dataset of student performance

3.2. Machine Learning Algorithms

Logistic Regression [12,15] is a refined instrument in the toolkit of a data scientist, especially used for problems involving binary categorization. Imagine it as a proficient statistical expert who can accurately calculate the likelihood that a certain occurrence will occur. For example, it is often used to predict whether a student will be hired for a job or not, taking into account many aspects. The special aspect of this is its capability to convert projected values into probabilities, which are tightly restricted between 0 and 1, owing to the remarkable properties of the logistic function.

Random Forestc[16,22], in contrast, might be likened to a vibrant forest of decision-makers, each with its distinct viewpoint. This ensemble learning technique is very effective for handling large volumes of data with several variables. During the training process, it creates many decision trees and integrates their results to make a final choice. Its great effectiveness extends beyond classification jobs to include regression situations, where it may generate predictions of numerical values by leveraging learnt patterns. The key advantage of Random Forest is its capacity to mitigate overfitting by aggregating the predictions of several decision trees, hence guaranteeing a resilient and generalized model.

Decision Tree [11,13,21] serves as a systematic guide for making judgments by considering input attributes. The approach is a non-parametric supervised learning technique that partitions data into subsets, facilitating comprehension and visualization of the decision-making process. Decision Trees are often chosen because of their simplicity and interpretability, particularly when it is important to have a clear understanding of the patterns in the data.

Naive Bayes [12,16,18] employs probabilistic concepts and assumes high independence between characteristics. It resembles the actions of a knowledgeable investigator who forms logical hypotheses from a small amount of pertinent data. Naive Bayes is very successful for jobs involving text categorization or big datasets. It assesses the probability of various events and generates predictions based on the most likely scenario.

Support Vector Machine (SVM) [1,3,5,12,33] algorithm may be likened to the act of delineating distinct groups by drawing lines in the sand. It is a model of supervised learning that identifies the most optimum hyperplane to separate data into various groups. The distinguishing feature of SVM is its adaptability since it is capable of handling both linear and non-linear data separations via the use of kernel functions. This feature makes it a preferred option for situations in which data points cannot be clearly distinguished using conventional linear approaches.

K-Nearest Neighbors (KNN) [2,6,12,19] streamlines decision-making by consulting its nearest neighbours for guidance. The approach is non-parametric and uses the majority class of its k closest neighbours to classify data. The simplicity and dependence on proximity make KNN straightforward to execute and efficient for smaller datasets with a limited number of characteristics.

Gradient Boosting [3,12,18] is an iterative technique that enhances its performance by rectifying mistakes made by prior models. It resembles a team captain who consistently evaluates previous efforts to improve future results. Gradient Boosting is a technique that enhances prediction accuracy by successively merging weak learners to generate a powerful predictive model.

Linear Discriminant Analysis (LDA) [22,25,18] provides a new viewpoint to enhance data comprehension. It is a method of categorization that maps data onto a space with fewer dimensions while maintaining important information that distinguishes different classes. LDA is more successful in situations when there is a clear distinction between classes since it maximizes the differences between them and results in more accurate classifications.

Within the field of research and data science, each of these models is subjected to thorough training and assessment utilizing cross-validation procedures to guarantee their reliability and resilience. Ensemble learning methods boost prediction accuracy by using the capabilities of several models, creating a holistic framework that can effectively anticipate complicated outcomes, such as student placements.

RESULTS ANALYSIS

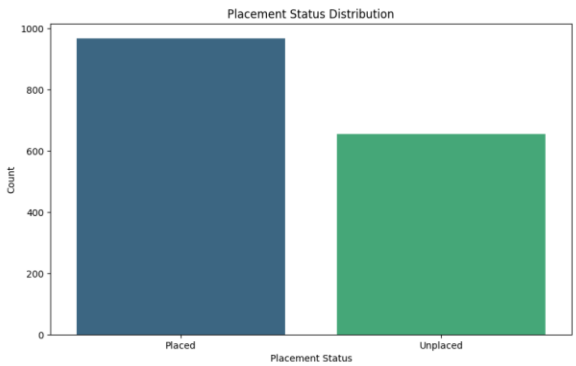

Fig. 3 Placement Status distribution

The student's placement status distribution is shown in Figure 3. Between 800 and 1000 pupils have been placed, whereas 400–600 students have not been placed.

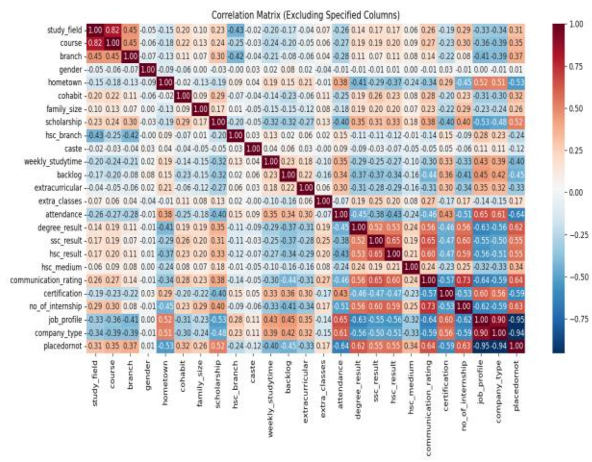

Fig. 4 Heatmap

Figure 4 displays the heat map with correlation values >=-0.5 for several aspects. The greatest hometown connection is 0.54, the lowest caste correlation is 0.12, and the highest attendance is 0.66.

```
Model trained and saved as logisticregression_model.pkl

Accuracy for LogisticRegression: 0.9385
Confusion Matrix:
[[121  13]
 [  7 184]]
Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.90      0.92       134
           1       0.93      0.96      0.95       191

    accuracy                           0.94       325
   macro avg       0.94      0.93      0.94       325
weighted avg       0.94      0.94      0.94       325
```

Fig. 5 Logistic Regression

Figure 5 presents the outcomes of the logistic regression method. The biggest support (325), the highest recall (0.96), the lowest recall (0.95), the highest precision (0.95), and the accuracy (0.9385) are among the parameters.

```
Model trained and saved as randomforestclassifier_model.pkl

Accuracy for RandomForestClassifier: 0.6892
Confusion Matrix:
[[130   4]
 [ 97  94]]
Classification Report:
              precision    recall  f1-score   support

           0       0.57      0.97      0.72       134
           1       0.96      0.49      0.65       191

    accuracy                           0.69       325
   macro avg       0.77      0.73      0.69       325
weighted avg       0.80      0.69      0.68       325
```

Fig. 6 Random Forest

Figure 6 shows the outcomes of the random forest method. The maximum support is 325, the highest f1-score is 0.72, the biggest recall is 0.97, and the best accuracy is 0.96. These are the parameters.

```
Model trained and saved as decisiontreeclassifier_model.pkl

Accuracy for DecisionTreeClassifier: 0.5046
Confusion Matrix:
[[133   1]
 [160  31]]
Classification Report:
              precision    recall  f1-score   support

           0       0.45      0.99      0.62       134
           1       0.97      0.16      0.28       191

    accuracy                           0.50       325
   macro avg       0.71      0.58      0.45       325
weighted avg       0.76      0.50      0.42       325
```

Fig. 7 Decision Tree

With the following settings, the decision tree technique result is shown in Figure 7: maximum support is 325, highest f1-score is 0.62, highest recall is 0.58, and largest accuracy is 0.97.

```
Model trained and saved as gaussiannb_model.pkl

Accuracy for GaussianNB: 0.5877
Confusion Matrix:
[[  0 134]
 [  0 191]]
Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00       134
           1       0.59      1.00      0.74       191

    accuracy                           0.59       325
   macro avg       0.29      0.50      0.37       325
weighted avg       0.35      0.59      0.44       325
```

Fig. 8 Naïve Bayes

This Naïve Bayes approach result is shown in Figure 8 with the following parameters: best precision is 0.59, highest recall is 1.00, highest f1-score is 0.74, maximum support is 325, and highest accuracy is 0.5877.

```
Model: Support Vector Machine
Accuracy: 0.9415384615384615
Confusion Matrix:
[[119   8]
 [ 11 187]]
Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.94      0.93       127
           1       0.96      0.94      0.95       198

    accuracy                           0.94       325
   macro avg       0.94      0.94      0.94       325
weighted avg       0.94      0.94      0.94       325
```

Fig. 9 SVM

The SVM technique result is displayed in Figure 9 with the following parameters: lowest precision is 0.92, lowest recall is 0.94, lowest f1-score is 0.93, lowest support is 127, highest precision is 0.96, maximum recall is 0.94, highest f1-score is 0.95, and highest support is 325.

```
Model trained and saved as kneighborsclassifier_model.pkl

Accuracy for KNeighborsClassifier: 0.9385
Confusion Matrix:
[[127   7]
 [ 13 178]]
Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.95      0.93       134
           1       0.96      0.93      0.95       191

    accuracy                           0.94       325
   macro avg       0.93      0.94      0.94       325
weighted avg       0.94      0.94      0.94       325
```

Fig. 10 K-Neighbors Classifier

The KNN approach result is shown in Figure 10 with the following parameters: maximum precision is 0.96, topmost recall is 0.95, highest f1-score is 0.95, highest support is 325, and KNN accuracy is 0.9385.

```
Model trained and saved as gradientboostingclassifier_model.pkl

Accuracy for GradientBoostingClassifier: 0.8400
Confusion Matrix:
[[115  19]
 [ 33 158]]
Classification Report:
              precision    recall  f1-score   support

           0       0.78      0.86      0.82       134
           1       0.89      0.83      0.86       191

    accuracy                           0.84       325
   macro avg       0.83      0.84      0.84       325
weighted avg       0.84      0.84      0.84       325
```

Fig. 11 Gradient Boosting

The results of the gradient-boosting approach are shown in Figure 11. The parameters include the greatest f1-score of 0.86, the largest support of 325, the maximum accuracy of 0.89, and the topmost recall of 0.83.

```
Model: Linear Discriminant Analysis
Accuracy: 0.916923076923077
Confusion Matrix:
[[117  10]
 [ 17 181]]
Classification Report:
              precision    recall  f1-score   support

           0       0.87      0.92      0.90       127
           1       0.95      0.91      0.93       198

    accuracy                           0.92       325
   macro avg       0.91      0.92      0.91       325
weighted avg       0.92      0.92      0.92       325
```

Fig. 12 Linear Discriminant Analysis

The LDA approach result is shown in Figure 12 with the following parameters: maximum precision = 0.87, maximum recall = 0.92, maximum f1-score = 0.90, maximum support = 325, and accuracy = 0.92.

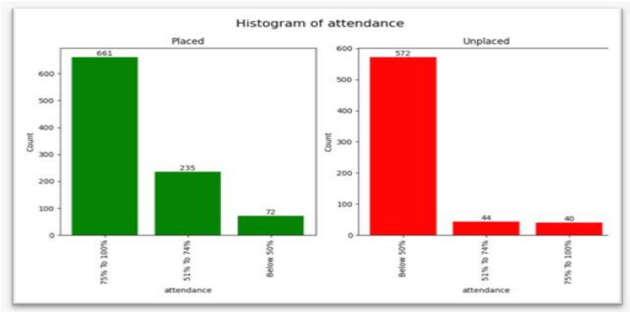

Fig. 13 Attendance VS Placement

The attendance record of students is shown in the above histogram Figure 13, where a high attendance rate indicates a higher possibility of placement in a reputable firm. In contrast, a low attendance rate indicates a worse chance of placement.

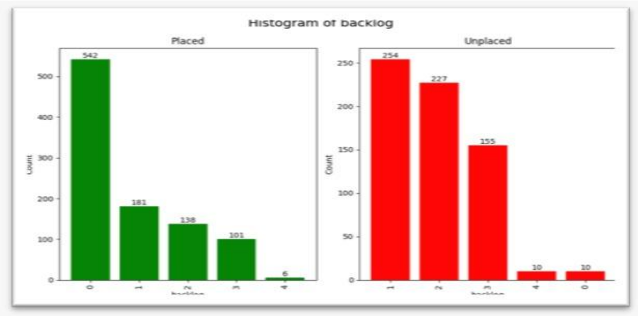

Fig. 14 Backlog VS Placement

As shown in Figure 14. A backlog of students indicates poor academic achievement, which may also impact the job placement process. According to the above data, students with larger backlogs have lower placement prospects, while those with smaller backlogs have greater employment success rates.

Fig. 15 Certification VS Placement

A candidate who has certification in technology and tools outside their usual academic resources is more likely to pass interviews; pupils who lack certification have fewer opportunities. The data is shown in Figure 15 above.

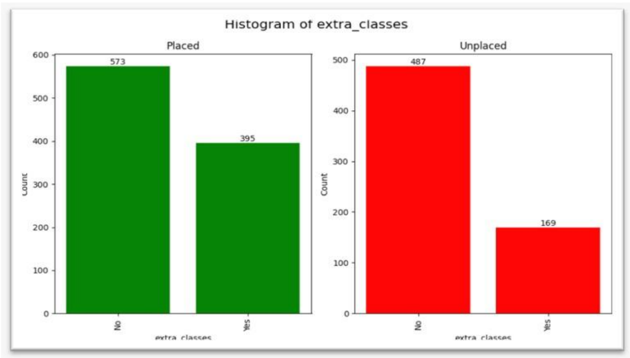

Fig. 16 Extra Classes VS Placement

Students benefit from taking more courses because they learn more, and that information helps them ace company interviews. Figure 16 above shows a record of students who attend more additional courses. Students who attend fewer extra classes are less likely to be sent off campus.

Table 2: Comparative Analysis of ML

Model	**Precision**	**Recall**	**F1-Score**	**Accuracy**
Logistic Regression	94%	93%	94%	94%
Random Forest	77%	73%	69%	69%

Decision Tree	71%	58%	45%	50%
Naïve Bayes	29%	50%	37%	59%
59SVM	94%	94%	94%	94%
K-Neighbors Classifier	93%	94%	94%	94%
Gradient Boosting	83%	84%	84%	84%
Linear Discriminant Analysis	91%	92%	91%	92%

Table 2 illustrates that Naïve Bayes attained the lowest accuracy of 59%, F1-score of 37%, recall of 50%, and precision of 29%. SVM achieved a superior 94% accuracy, 94% recall, 94% F1-score, and 94% precision.

CONCLUSION

This study aimed to assess the predictive ability of multiple machine learning algorithms for placing students. Random forests, decision trees, Naive Bayes, Linear discriminant analysis (LDA), gradient boosting, support vector machines (SVM), and k-nearest neighbours (KNN) were all included in the comprehensive evaluation. Carefully evaluating Each model was evaluated based on key performance metrics, including recall, accuracy, precision, and F1-score.

The study's findings demonstrate that k-nearest neighbours (KNN), logistic regression, and support vector machines (SVM) are resilient in predicting student placement, routinely obtaining excellent levels of accuracy, recall, and F1 scores. This study specifically discovered that K-Nearest Neighbors (KNN) and Support Vector Machines (SVM) both performed very well, with an astounding accuracy rate of 94%. Conversely, poorer prediction accuracy models like as decision trees and Naive Bayes emphasize the requirement of choosing and refining algorithms according to the features of the dataset.

By combining predictions from many base learners and thereby making use of the advantages of different model types, the ensemble technique improved prediction accuracy. Through the mitigation of the intrinsic flaws in individual models and the simultaneous improvement of the overall performance, this approach improved the dependability and strength of the prediction framework.

The findings of this work highlight the possibility of machine learning techniques to greatly improve the precision of forecasts of student placement. Personalized help for pupils and effective resource allocation by schools employing these creative approaches will eventually lead to better results. Future research may concentrate on adding additional factors and investigating the useful implications to better analyze and improve these results.

Conflicts of Interest

The author has no conflict of interest.

Funding Statement

This research was not supported by any Funding Agency.

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