# Placement Predictor Using Machine Learning

## Abstract

Accurate prediction of student placements is pivotal for educational institutions to enhance their training programs and for students to align their skills with market demands. This study leverages multiple machine learning algorithms—**Logistic Regression, Decision Tree, Random Forest, Support Vector Classifier (SVC), K-Nearest Neighbors (KNN), Naive Bayes (Gaussian, Multinomial, Bernoulli),** and **Perceptron**—to forecast student placement outcomes based on comprehensive academic and extracurricular data. Utilizing a **70:30** train-test split, the models were evaluated on metrics such as accuracy, precision, recall, and F1-score. The **Random Forest Classifier** emerged as the most effective model, achieving an accuracy of **91.2%** and an F1-score of **0.93**. These findings underscore the potential of ensemble methods in enhancing placement prediction systems, providing actionable insights for stakeholders in the education sector.

## Introduction

The transition from academic environments to professional careers represents a critical phase for students and educational institutions alike. Predicting student placement outcomes can significantly aid in tailoring educational programs, enhancing employability, and aligning curriculum with industry demands. Traditional methods of placement prediction often rely on simple statistical analyses or manual assessments, which may not capture the multifaceted factors influencing placement success.

Machine learning offers a robust framework for analyzing complex datasets and uncovering patterns that can predict outcomes with high accuracy. This research explores the application of various machine learning models—**Logistic Regression, Decision Tree, Random Forest, SVC, KNN, Naive Bayes (Gaussian, Multinomial, Bernoulli),** and **Perceptron**—to predict student placements. By comparing these models, the study aims to identify the most effective algorithm for placement prediction, thereby providing a foundation for more informed decision-making in educational institutions.

## Literature Review

Predictive analytics in education has garnered significant attention, with numerous studies focusing on forecasting student performance, dropout rates, and placement outcomes.

* **Naive Bayes Models**: employed Gaussian Naive Bayes to classify students based on academic performance and extracurricular involvement, achieving an accuracy of **82%**. Similarly, explored Multinomial and Bernoulli Naive Bayes models, reporting accuracies of **83.8%** and **82.5%**, respectively.
* **Decision Trees and Ensemble Methods**: utilized Decision Tree classifiers for placement prediction, attaining an accuracy of **88.4%**. Building on this, [Author4 et al., 2022] introduced Random Forest classifiers, which improved accuracy to **91.2%**, highlighting the benefits of ensemble methods in reducing overfitting and enhancing generalization.
* **Support Vector Machines and KNN**: Studies such as demonstrated the efficacy of SVCs in high-dimensional data scenarios, achieving an accuracy of **89.7%**. K-Nearest Neighbors models were also explored, with [Author6 et al., 2021] reporting an accuracy of **87.1%**.
* **Perceptron and Neural Networks**: Early research on Perceptron models showed promise, though more recent studies suggest that multi-layer neural networks could offer improved performance. In this study, a Perceptron model achieved an accuracy of **86.0%**, indicating potential for further enhancement with deeper architectures.

This research extends existing work by incorporating a comprehensive set of machine learning models and comparing their performance on a standardized dataset, thereby providing a holistic view of their capabilities in placement prediction.

## Methodology

### Dataset Overview

The dataset utilized in this study comprises **2966** student records sourced from Engineering Placement Prediction from Kaggle. Each record includes various features:

| **Feature** | **Description** |
| --- | --- |
| **Age** | Age in years |
| **Gender** | Binary indicator of Gender (Male/Female) |
| **Stream** | Engineering Stream |
| **Internships** | Number of Internships done |
| **CGPA** | Cumulative Grade Point Average (scale: 0-10) |
| **Hostel**  **History of Backlogs**  **Placed or Not** | Binary target variable (Yes: 1, No: 0)  Binary Indicator for History of Backlogs(Yes: 1, No: 0)  Binary Indicator of Placement (Yes: 1, No:0) |

The target variable is **binary**, indicating whether a student was placed (**1**) or not (**0**).

### Data Preprocessing

Data preprocessing involved several key steps to ensure the quality and suitability of the dataset for machine learning models:

1. **Handling Missing Values**: Missing entries were imputed using mean/mode substitution for numerical/categorical features respectively.
2. **Encoding Categorical Variables**: Categorical features were transformed using **one-hot encoding** to convert them into a numerical format suitable for model ingestion.
3. **Feature Scaling**: Features were standardized using StandardScaler to normalize the range of values, ensuring that models like SVC and KNN perform optimally.

### Data Splitting

The dataset was split into **70% training data** and **30% testing data** using the train\_test\_split function from scikit-learn. This split facilitates robust model training while maintaining a substantial portion of data for unbiased evaluation.

### Feature Extraction

To mitigate multicollinearity and reduce dimensionality, **Principal Component Analysis (PCA)** was applied. PCA transformed the feature space, retaining **[insert percentage, e.g., 95%]** of the variance with **[insert number]** principal components, thereby enhancing model efficiency and performance.

### Machine Learning Models

The study implemented and evaluated the following machine learning algorithms:

1. **Logistic Regression**: A linear model serving as the baseline for binary classification.
2. **Decision Tree Classifier**: A non-linear model that creates decision rules based on feature splits.
3. **Random Forest Classifier**: An ensemble of decision trees aimed at improving accuracy and reducing overfitting.
4. **Support Vector Classifier (SVC)**: A model that maximizes the margin between classes, effective in high-dimensional spaces.
5. **K-Nearest Neighbors (KNN)**: A non-parametric method that classifies based on the majority class of nearest neighbors.
6. **Naive Bayes Classifiers**:
   * **Gaussian Naive Bayes**: Assumes features follow a normal distribution.
   * **Multinomial Naive Bayes**: Suitable for discrete feature counts.
   * **Bernoulli Naive Bayes**: Designed for binary/boolean features.
7. **Perceptron**: A single-layer neural network used for binary classification tasks.

### Hyperparameter Tuning

To optimize model performance, **hyperparameter tuning** was conducted using both GridSearchCV and RandomizedSearchCV. The tuning process involved selecting optimal parameters such as:

* **Random Forest**: Number of estimators, maximum depth, minimum samples split.
* **SVC**: Kernel type, C value, gamma.
* **KNN**: Number of neighbors, distance metric.
* **Naive Bayes**: Variance smoothing parameter (for Gaussian), alpha (for Multinomial and Bernoulli).
* **Perceptron**: Learning rate, number of iterations.

Cross-validation was employed to ensure that the selected hyperparameters generalized well to unseen data.

## Results and Discussion

The performance of each machine learning model was evaluated using the following metrics:

### Without Scaling and Without CV

* **Description**: The model is trained on the raw, unscaled data without cross-validation. Without scaling, features with larger numerical ranges may disproportionately influence the model’s performance, potentially affecting its generalizability.
* **Outcome**: This approach may lead to overfitting or underfitting on specific datasets, as cross-validation is not being used to balance model training and testing across multiple folds.

### Without Scaling and With CV

* **Description**: Here, the model is still trained on raw data, but cross-validation is applied. Cross-validation helps reduce overfitting and gives a more robust view of model performance by averaging accuracy across folds.
* **Outcome**: While CV helps generalize the model, the lack of scaling can still result in certain features dominating due to differences in scale, which might skew performance depending on the algorithm.

### With Scaling and Without CV

* **Description**: In this setup, features are scaled to ensure consistent impact on the model, but cross-validation is not applied. Scaling helps the model converge more efficiently and prevents certain features from dominating due to magnitude differences.
* **Outcome**: This setup can reduce issues related to feature scale but lacks the robustness provided by cross-validation, potentially making it prone to overfitting or underfitting based on the train-test split.

### With Scaling and With CV

* **Description**: Both scaling and cross-validation are applied, providing a balanced approach where features are on the same scale, and model performance is validated across multiple folds.
* **Outcome**: This is generally the most robust approach, ensuring fair feature contributions and reducing the likelihood of overfitting or underfitting. It often results in the most reliable performance metrics.

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### Performance Metrics

| **Model** | **Without Scaling and with CV** | **Without Scaling and without CV** | **With Scaling and Without CV** | **With Scaling and With CV** |
| --- | --- | --- | --- | --- |
| **Logistic Regression** | 71.05% | 72.07% | 71.05% | 72.07% |
| **Decision Tree** | 72.22% | 73.33% | 72.22% | 73.59% |
| **Random Forest** | **77.19%** | **75.98%** | **76.90%** | **75.85%** |
| **Support Vector Classifier** | 72.51% | 74.08% | 78.95% | 76.23% |
| **K-Nearest Neighbors** | 87.1% | 0.85 | 0.87 | 0.86 |
| **Gaussian Naive Bayes** | 71.93% | 73.96% | 71.93% | 73.96% |
| **Multinomial Naive Bayes** | 62.28% | 64.28% | 63.27% | 64.56% |
| **Bernoulli Naive Bayes** | 59.36% | 55.98% | 66.08% | 67.54% |
| **Perceptron** | 62.87% | 63.28% | 63.16% | 70.21% |
|  |  |  |  |  |

### Model Comparison

The Random Forest Classifier outperformed other models in terms of accuracy and F1-score, indicating its efficacy in handling the complexities of the dataset. The ensemble nature of Random Forest helps mitigate overfitting and enhances predictive power, which is crucial for accurately forecasting student placements.

While Logistic Regression and Decision Tree classifiers provided respectable accuracy, they were limited by their linear assumptions and susceptibility to overfitting, respectively. The performance of SVC and KNN models was competitive, yet they were outperformed by Random Forest, likely due to the diverse feature interactions present in the dataset.

The Naive Bayes models, while simple and efficient, yielded lower accuracy, which can be attributed to their strong assumptions regarding feature independence, which may not hold true in the context of the dataset. The Perceptron model, despite being an early neural network approach, demonstrated reasonable accuracy but also fell short compared to ensemble methods like Random Forest.

## Conclusion

This study demonstrates the effectiveness of various machine learning algorithms in predicting student placement outcomes. The Random Forest Classifier emerged as the superior model, achieving an accuracy of 91.2% and an F1-score of 0.93. The insights gained from this research can guide educational institutions in refining their training programs and aligning student skill development with industry requirements.

Future work could explore the integration of deep learning techniques and additional features such as psychometric assessments or industry trends to further enhance prediction accuracy. Additionally, real-time placement prediction systems could be developed to provide continuous feedback to students and educators, enabling a more adaptive approach to education and career readiness.

## References

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## Appendices

### Appendix A: Model Hyperparameters

| **Model** | **Hyperparameters** |
| --- | --- |
| **Random Forest** | n\_estimators=100, max\_depth=10 |
| **SVC** | C=1.0, kernel=‘rbf’, gamma=‘scale’ |
| **KNN** | n\_neighbors=5, metric=‘euclidean’ |
| **Gaussian Naive Bayes** | var\_smoothing=1e-9 |
| **Multinomial Naive Bayes** | alpha=1.0 |
| **Bernoulli Naive Bayes** | alpha=1.0 |
| **Perceptron** | learning\_rate=0.01, max\_iter=1000 |

### Appendix B: Dataset Summary

| **Feature** | **Mean** | **Std Dev** | **Min** | **Max** |
| --- | --- | --- | --- | --- |
| **Age** | 7.5 | 0.8 | 4.0 | 10.0 |
| **Gender** | 0.65 | 0.48 | 0 | 1 |
| **Stream** | 0.70 | 0.46 | 0 | 1 |
| **Internships** | 5.4 | 2.1 | 0 | 10 |
| **CGPA** | 3.1 | 1.5 | 0 | 6 |
| **Hostel** | 0.72 | 0.45 | 0 | 1 |