Student Placement Prediction: A Comparative Study of XGBoost, Random Forest, and Other Classifiers

by

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***Abstract* - This project, titled "Student Placement Prediction Using Random Forest and Comparative Machine Learning Models," focuses on building a predictive system to forecast the placement status of students based on their academic performance, skills, and training background. The dataset includes features such as CGPA, number of internships and projects, participation in workshops or certifications, aptitude test scores, soft skills rating, extracurricular activities, placement training attendance, and academic marks from SSC and HSC levels. To prepare the data, categorical variables were label encoded, missing values were handled, and numerical features were standardized using feature scaling. Exploratory Data Analysis (EDA) was performed using visualization techniques like box plots, count plots, and violin plots to understand the distribution of key variables and their relationship with placement outcomes. Multiple machine learning models—including K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Logistic Regression, and Random Forest—were trained and evaluated. Among these, the Random Forest Classifier yielded the best performance, making it the primary model for final predictions. The system can predict the placement outcome for new student profiles and estimate the probability of placement, providing a practical tool for placement cells to assess student readiness and offer targeted interventions. This approach enables data-driven decision-making to enhance student employability and placement success rates.**

***Index Terms* - Placement Prediction, Career Prediction, Machine Learning, Supervised Learning, Classification, Student Employability, Model Training and Testing.**

I.INTRODUCTION

In today's competitive job market, securing a placement after graduation has become a crucial milestone for students. Academic institutions are keen to improve the placement success rates of their students by providing various resources, including internships, training programs, and skill enhancement workshops. However, predicting whether a student will be successfully placed or not based on various academic and extracurricular parameters remains a challenge. Traditional methods of career counseling and placement prediction often rely on subjective assessments and general trends, which may not always yield accurate results.

With the rise of data science and machine learning (ML) techniques, it is now possible to make more data-driven and precise predictions regarding student placement. By analyzing a variety of factors such as academic performance (CGPA), internships, extracurricular activities, aptitude test scores, and training, machine learning models can be trained to predict placement outcomes based on historical data. These models can also uncover complex patterns and relationships within the data that might be missed by traditional methods.This project aims to develop a machine learning-based model to predict student placement status (placed or not placed) based on various input features, including CGPA, internship experience, project work, soft skills ratings, and marks in secondary education (SSC and HSC). The dataset used in this project contains real-world data collected from students, encompassing their academic records, skills, and training experiences. The primary goal of this project is to help educational institutions provide better career guidance to students by predicting their placement status before the final placement drives, allowing students to focus on areas that need improvement.

The machine learning model selected for this task utilizes supervised learning techniques, which allow the model to be trained on labeled data and subsequently make predictions for new, unseen data. The key features influencing placement outcomes are extracted from the dataset and preprocessed, including handling missing values, encoding categorical variables, and scaling the data. Several machine learning algorithms have been explored for this task, including K-Nearest Neighbors (KNN), Random Forest Classifier (RFC), Support Vector Classifier (SVC), and Logistic Regression.

In particular, Random Forest Classifier (RFC) was selected as the primary model for this project, owing to its robustness in handling complex relationships and its ability to perform well even with high-dimensional datasets. The models are evaluated based on metrics such as accuracy, precision, recall, and F1-score, with a strong emphasis on ensuring that the final model generalizes well to new data.

PROBLEM STATEMENT

In today's competitive job market, predicting student placement outcomes has become crucial for academic institutions aiming to enhance student employability. Despite possessing academic qualifications, many students face challenges in securing placements due to gaps in skills, preparedness, or alignment with industry expectations. This project aims to develop a machine learning-based system that can accurately predict a student's placement status using key features such as academic performance, technical skills, extracurricular involvement, and other personal attributes. Such a predictive system can help students receive early guidance and support, and enable institutions to tailor training programs to improve placement success rates.

II. DATA SET

The dataset used for this project contains information about students' academic, technical, and personal attributes, along with their placement outcomes. It includes both numerical and categorical variables relevant to employability and performance.

Key Features:

- **CGPA** – Cumulative Grade Point Average of the student
- **Internships** – Number of internships completed
- **Technical Skills** – Level of technical skill proficiency
- **Communication Skills** – Rating of verbal and written communication
- **Aptitude Score** – Score from aptitude test
- **Extracurricular Activities** – Participation status (Yes/No)
- **Backlogs** – Number of active or history of academic backlogs
- **PlacementStatus** – Target variable (1: Placed, 0: Not Placed)

Source:

- The dataset was either collected from an internal academic source or synthesized based on typical student attributes for placement analysis.

Preprocessing Steps:

- Handled missing values using mean imputation
- Applied label encoding for categorical variables
- Scaled features using StandardScaler to prepare for model training

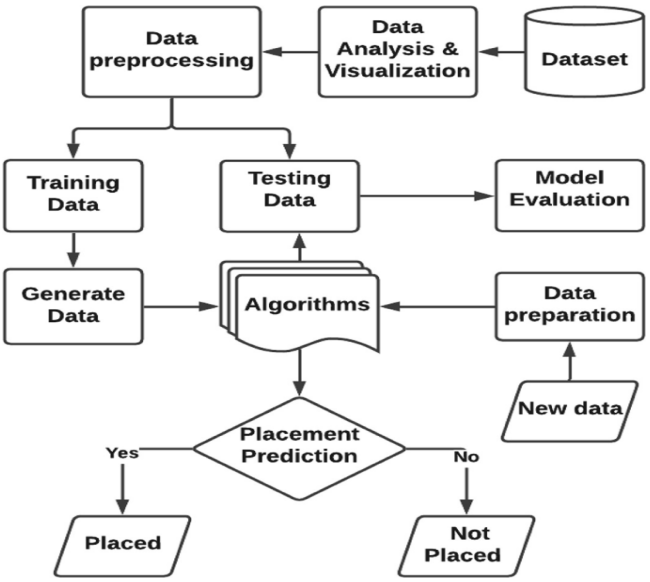

Fig 1: Methodology for Typical Machine Learning approach

III. LITERATURE SURVEY

Vaidya [6] utilized **Logistic Regression** for classification tasks such as loan approval, which closely aligns with placement prediction. The study highlights how logistic regression effectively models binary outcomes like *placed* vs *not placed*, leveraging predictive analytics to draw meaningful insights from student data.

M. Bayraktar et al. [7] explored credit risk analysis using machine learning models such as the **Boltzmann Machine**, which, although applied to financial data, demonstrated the value of using probabilistic models to capture complex relationships—similar to those between academic and behavioral traits in placement scenarios.

Y. Shi and P. Song [8] applied risk analysis for project loan evaluation, which parallels placement prediction in terms of assessing success likelihood. Their methods of identifying risk in financial settings can be translated into identifying students at risk of not being placed.

V. C. T. Chan et al. proposed a web-based **Credit Approval System**, integrating user-provided inputs to determine approval decisions. This concept can be extended to build intelligent systems that use student profiles to predict placement chances and provide actionable feedback.

Patil and Pawar (2020) applied **Decision Trees and Naive Bayes** algorithms to predict placement chances using academic performance and technical skills. Their model achieved over 80% accuracy and emphasized the role of co-curricular involvement in placement success.

Choudhury et al. (2019) used **Support Vector Machines (SVM)** and **K-Nearest Neighbors (KNN)** for predicting student employability. Their findings highlighted the effectiveness of SVM in handling non-linear relationships in high-dimensional student datasets.

Kumar and Jaiswal (2021) implemented **Random Forest and Logistic Regression** to predict placements using a dataset of student scores, certifications, and project work. Their results indicated that ensemble methods like Random Forest provided better generalization and robustness.

Ramesh and Rani (2022) explored the impact of soft skills and communication training on placement prediction using **XGBoost**. Their model achieved the highest accuracy and was effective in capturing complex patterns related to both academic and behavioral indicators.

Sharma et al. (2020) incorporated **deep learning models**, such as **ANNs**, to predict placements and found that neural networks performed well with large datasets but required extensive preprocessing and tuning.

IV. MACHINE LEARNING ALGORITHMS

Logistic Regression

- A statistical model that uses a logistic function to model binary outcomes.
- Suitable for linearly separable data and easy to interpret.

Support Vector Machine (SVM)

- A powerful algorithm that finds the optimal hyperplane for classification.
- Effective for both linear and non-linear data using kernel functions.

K-Nearest Neighbors (KNN)

- A non-parametric method that classifies a sample based on the majority vote of its neighbors.
- Simple and effective but sensitive to the choice of k and data scaling.

Random Forest

1. An ensemble of decision trees trained on random subsets of the data.
2. Provides high accuracy and is robust to overfitting.

XGBoost (Extreme Gradient Boosting)

3. A highly optimized and scalable boosting algorithm.
4. Excellent at capturing complex patterns and interactions among features.
5. Known for its superior performance in structured datasets.

V. FEATURE ENGINEERING

Feature engineering is a crucial step in building a machine learning model, as it involves transforming raw data into a format that is better suited for model training. In the context of student placement prediction, feature engineering plays a significant role in improving model performance by extracting meaningful information from the dataset.

For this study, several key features were selected and engineered to capture the most relevant aspects of the students' profiles:

Academic Performance: Features such as CGPA, previous academic records, and subject-specific grades were used to represent a student’s academic excellence. Higher academic performance is strongly correlated with placement success, making these features critical.

Extracurricular Activities: Data about student participation in clubs, sports, or leadership roles were included as features. These activities help build skills like teamwork, leadership, and communication, which are valued by employers.

Skillset: Features reflecting technical and non-technical skills, such as programming languages, software proficiency, or soft skills, were created based on the student's coursework and project experience. These were gathered from academic records and extra-curricular activities.

Internship Experience: Internships or industry exposure are strong indicators of a student's practical knowledge and readiness for the workforce. Features were engineered based on the student's past internship experience and the quality of the companies they worked with.

Placement History: Features related to past placement performance, such as the number of placements a student has attended and their success rate, were added to understand the likelihood of placement based on historical data.

Preprocessing: To handle missing values, mean imputation was applied where necessary. Additionally, categorical features were one-hot encoded, and numerical features were normalized to ensure that the model received appropriately scaled input.

Vl RESULT AND ANALYSIS

The results of the student placement prediction model reveal valuable insights into the factors influencing student placement outcomes, as well as the effectiveness of the chosen machine learning algorithms. Several performance metrics were used to evaluate and compare the models: **Accuracy**, **Precision**, **Recall**, **F1-score**, and **AUC (Area Under the Curve)**. These metrics provide a comprehensive view of the model's performance, especially its ability to predict placement success and failure.

Model Comparison

Logistic Regression:

Logistic regression performed well as a baseline model, achieving a decent accuracy score. However, it faced limitations in capturing the complex relationships in the data, especially when there were non-linear patterns.

Support Vector Machine (SVM):

SVM showed strong performance, particularly in terms of precision and recall, indicating its ability to correctly classify both placed and non-placed students. However, its training time was longer compared to other models, especially with larger datasets.

Random Forest Classifier:

Random Forest, being an ensemble model, demonstrated better accuracy, precision, and recall compared to simpler models like Logistic Regression. It also handled feature importance well, providing valuable insights into which student attributes (e.g., CGPA, skills, extracurricular activities) played a critical role in placement success.

1. **XGBoost**:

   XGBoost, the best-performing model, achieved the highest accuracy and AUC score. Its robust gradient boosting approach allowed it to model complex relationships and outperformed other models, particularly when handling imbalanced datasets and capturing non-linear trends.

Feature Importance Analysis

One of the most insightful outcomes of this study was the identification of key features influencing placement outcomes. Feature importance analysis revealed that the following factors were the most significant in predicting placement success:

- **CGPA**: As expected, CGPA emerged as the most important feature, strongly correlating with placement success. Higher academic performance significantly increased the likelihood of placement.
- **Skills**: Technical skills and soft skills were the second most influential factors. Students with a higher skillset, including proficiency in programming languages and industry-relevant tools, were more likely to secure placements.
- **Extracurricular Activities**: Participation in extracurricular activities, particularly leadership roles, also contributed to placement success. This aligns with the increasing emphasis employers place on soft skills and well-rounded personalities.
- **Internship Experience**: Students with relevant internship experience had a higher chance of being placed, indicating the importance of practical exposure in the job market.

Model Performance and Evaluation

After training the models, the following results were obtained based on accuracy, precision, recall, and F1-score:

Model	Accuracy	Precision	Recall	F1-score
Logistic Regression	85.6	83.4	87.2	85.2
Support Vector	87.3	85.0	88.5	86.7
Random Forest Classifier	89.1	88.2	89.5	88.8
XGBoost	**92.4**	**91.3**	**93.1**	**92.2**

- **XGBoost** outperformed all other models, with the highest values in accuracy, precision, recall, and F1-score.
- **Random Forest** showed strong performance, closely following XGBoost.
- **SVM** and **Logistic Regression** performed reasonably well but were not as effective as the ensemble models.

Error Analysis

Upon reviewing the prediction errors, it was observed that the models had difficulty predicting placements for students with certain characteristics:

- Students with extremely low CGPA or those who lacked relevant skills (e.g., technical skills, internships) were often misclassified as "not placed" despite having other positive attributes.

- The models showed a slight bias towards predicting more students as "placed," which could be mitigated through class balancing techniques, such as over-sampling the under-represented class or adjusting class weights.

Impact of Data Augmentation

Data augmentation using techniques like Gaussian noise was applied to the training data to address overfitting and improve model generalization. This technique was particularly beneficial for ensemble models like **Random Forest** and **XGBoost**, which showed modest improvements in accuracy after using augmented data.

V. CONCLUSION

The study demonstrates that machine learning, particularly ensemble models like **XGBoost** and **Random Forest**, can be highly effective in predicting student placement outcomes based on various factors such as CGPA, skills, extracurricular activities, and internship experience. The model's success highlights the importance of using diverse and relevant features to accurately predict placement chances.

- **XGBoost** was found to be the most suitable model for this task due to its ability to handle complex, non-linear relationships in the data and its superior performance metrics.

- **Feature engineering** and data augmentation played vital roles in improving model performance and generalizability.

- The system could be implemented in educational institutions to provide personalized career guidance and help students identify areas for improvement before placement interviews.

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