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

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BONAFIDE CERTIFICATE

Certified that this Project titled **"Student Placement Prediction: A Comparative Study of XGBoost, Random Forest, and Other Classifiers"** is the bonafide work of **"KRISHNAVARTHINI K H (2116220701136)"** who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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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.

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CHAPTER 1

1.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.

This project also includes a predictive feature that allows users (students, in this case) to input their personal details and academic data into the system to receive a prediction on their likelihood of being placed. By leveraging the power of machine learning, the system offers personalized feedback and enables students to better understand their strengths and areas that may require additional focus before placement drives.

The significance of this project lies not only in its ability to predict placement status but also in its potential to transform career counseling and academic planning for students. With actionable insights from predictive models, institutions can provide more targeted support and interventions for students, thereby improving their chances of securing a placement and shaping their future careers.

In summary, this research demonstrates the practical application of machine learning in educational contexts, focusing on predicting student placement outcomes based on a comprehensive set of academic and extracurricular data. The project contributes to the growing field of data-driven decision-making in education and provides valuable insights that can help bridge the gap between academia and the job market.

CHAPTER 2

2.LITERATURE SURVEY

The intersection of data science and education has garnered increasing interest, particularly in the context of placement prediction. The success of students in securing placements after graduation is influenced by numerous factors, including academic performance, extracurricular activities, skills, and personal traits. Predicting placement outcomes has traditionally been a challenging task, but with advancements in machine learning (ML) and data analysis, researchers have started to develop more sophisticated predictive models. This literature survey reviews foundational and recent studies in the field of placement prediction, focusing on various data-driven approaches to model student placement outcomes.

Early Studies in Placement Prediction

In the early stages of placement prediction, many studies relied on simple statistical models to identify the relationship between student performance and placement status. Studies like those by Mishra and Tripathy (2013) used linear regression models to predict whether a student would be placed based on academic scores like CGPA, class 12th marks, and entrance exam scores. These studies found that academic performance, particularly CGPA, was one of the strongest predictors of placement status.

However, these traditional methods were limited in their ability to account for the multifaceted nature of placement outcomes, which include factors such as soft skills, internships, extracurricular involvement, and even socio-economic background. This led to the exploration of more advanced machine learning techniques that could better handle the complex relationships within the data.

The Rise of Machine Learning Models

With the advent of machine learning algorithms, more sophisticated predictive models for placement prediction emerged. In their 2017 study, Tiwari et al. applied decision trees and support vector machines (SVM) to predict student placement status. Their findings indicated that SVM outperformed decision trees in terms of accuracy, but both models were able to classify students effectively when given a rich set of features, including academic performance, personal skills, and participation in extracurricular activities.

Random Forests and Gradient Boosting Machines (GBMs) have become popular choices for placement prediction due to their ability to handle complex, non-linear relationships in large datasets. For example, a study by Rani et al. (2018) used a Random Forest model to predict the placement status of students, incorporating features such as CGPA, internship experience, and technical skill ratings. The study demonstrated that Random Forests could achieve high accuracy in predicting placement outcomes and handle the noisy, multi-dimensional data typical of educational datasets.

Ensemble Methods and Feature Selection

More recent works have focused on combining multiple models to improve prediction accuracy. Ensemble learning techniques like boosting and bagging have shown significant promise in this domain. A comparative study by Gupta et al. (2020) analyzed the performance of ensemble methods, including XGBoost and AdaBoost, for predicting placement status. Their study revealed that XGBoost, a gradient boosting method, performed exceptionally well, outperforming both individual classifiers and other ensemble methods. Additionally, they emphasized the importance of feature selection, suggesting that models that included features like extracurricular involvement and internship experience were able to predict placement outcomes more accurately than those based solely on academic performance.

Feature engineering and selection play a critical role in improving model performance. As emphasized by Tiwari et al. (2019), carefully selecting relevant features like personal traits, academic records, and placement-related skills—rather than simply using raw scores—can significantly enhance the predictive power of machine learning models. Moreover, the use of feature importance techniques, such as those available in Random Forest and XGBoost models, has enabled researchers to identify the most influential predictors of placement status, providing valuable insights for educational institutions.

Data Augmentation and Handling Imbalanced Data

Data augmentation and the handling of imbalanced datasets are common challenges in placement prediction studies. Placement prediction datasets are often skewed, with a much higher proportion of students being placed compared to those who are not. To address this, researchers have applied data augmentation techniques like synthetic data generation, oversampling, and undersampling. A study by Yadav et al. (2021) explored the use of SMOTE (Synthetic Minority Over-sampling Technique) to balance the placement dataset and improve model generalization. The results showed that data augmentation could enhance model accuracy and reduce overfitting.

Hybrid Approaches and Deep Learning

In addition to traditional ML methods, hybrid models that combine machine learning with deep learning have been explored for placement prediction. For instance, Sharma et al. (2020) proposed a hybrid model that integrated a deep neural network (DNN) with a decision tree algorithm to predict placement outcomes. They found that the hybrid approach outperformed traditional models in terms of both accuracy and interpretability. Deep learning methods, however, have yet to see widespread use in placement prediction due to challenges such as the need for large datasets and high computational resources.

Applications and Real-World Implementation

Placement prediction models are not only of academic interest but also have significant practical implications. Many educational institutions and placement agencies have started adopting these models to help students improve their placement prospects. These models can guide students by identifying the skills or areas they need to focus on to increase their chances of placement. A study by Verma et al. (2021) discussed the application of placement prediction models in real-world college systems, where the results of the predictions are used for personalized career counseling and skill development programs.

CHAPTER 3

3.METHODOLOGY

The methodology adopted in this study follows a supervised learning approach to predict placement outcomes for students. The process can be broken down into five main phases: data collection and preprocessing, feature selection, model training, performance evaluation, and model deployment.

1. **Data Collection and Preprocessing**

The dataset for this study is sourced from the historical placement records of students, containing various factors such as academic performance, skills, extracurricular activities, and placement results. The dataset includes both numerical (e.g., CGPA, interview scores) and categorical features (e.g., department, gender). Initial preprocessing steps involved:

- **Handling Missing Values:** Missing data is addressed using imputation techniques like mean or median imputation, or rows may be dropped depending on the extent of missingness.

- **Feature Scaling:** Numerical features are normalized using techniques like MinMaxScaler or StandardScaler to ensure all variables are on a comparable scale.

- **Categorical Encoding:** Categorical variables such as department, gender, and skills are encoded using techniques like one-hot encoding or label encoding for better model compatibility.

- **Outlier Detection:** Outliers are identified using boxplots or statistical tests and may be removed or capped to ensure they do not disproportionately influence the model.

2. **Feature Engineering**

Feature engineering is crucial for ensuring that the models are trained on relevant inputs. In this phase:

- **Correlation Analysis:** The relationships between features and placement outcomes are analyzed using correlation matrices. Features with low correlation to the target (placement success) are either transformed or removed.

- **Feature Creation:** New features are created by combining existing ones (e.g., combining interview scores with skills or extracurricular activities) to enhance model performance.

- **Visualization:** Visualization tools such as pair plots, heatmaps, and histograms help identify important patterns and outliers in the data.

3. **Model Selection and Training**

Four machine learning models are selected to predict placement outcomes based on their strengths:

- **Logistic Regression (LR):** A basic classification model used for binary classification (e.g., placed vs. not placed).

- **Support Vector Machine (SVM):** Used for its effectiveness in high-dimensional spaces and classification problems.

- **Random Forest (RF):** An ensemble learning method that provides robustness by averaging multiple decision trees.

- **XGBoost:** A boosting method known for its high performance and ability to handle imbalanced datasets, which is common in placement prediction tasks.

These models are trained on the training data, with hyperparameters fine-tuned using techniques such as grid search or random search.

4. **Model Evaluation**

Once trained, the models are evaluated using the following performance metrics:

- **Accuracy:** The overall percentage of correct predictions (both true positives and true negatives).

- **Precision and Recall:** Important in scenarios with imbalanced datasets (e.g., more students not getting placed). Precision measures the proportion of true positives out of all positive predictions, while recall measures the proportion of true positives out of all actual positives.

- **F1-Score:** A balanced metric that combines precision and recall, especially useful when dealing with imbalanced data.

- **Confusion Matrix:** Used to assess the types of classification errors, including false positives and false negatives, which are critical for placement prediction tasks.

These metrics provide insight into model performance, helping to determine the best model for predicting placement outcomes.

5. **Data Augmentation**

To enhance model robustness and generalize well to unseen data, data augmentation is used. In placement prediction, Gaussian noise or simulated data perturbation can be applied to the feature vectors:

- **Noise Injection:** Gaussian noise is added to features, particularly numerical ones, to simulate real-world variability. This helps in preventing the model from overfitting to the training data and improves its ability to generalize.

- **Synthetic Data Generation:** In cases where data is sparse (e.g., fewer instances of "placed" students), synthetic samples can be generated using techniques like SMOTE (Synthetic Minority Over-sampling Technique) to balance the dataset.

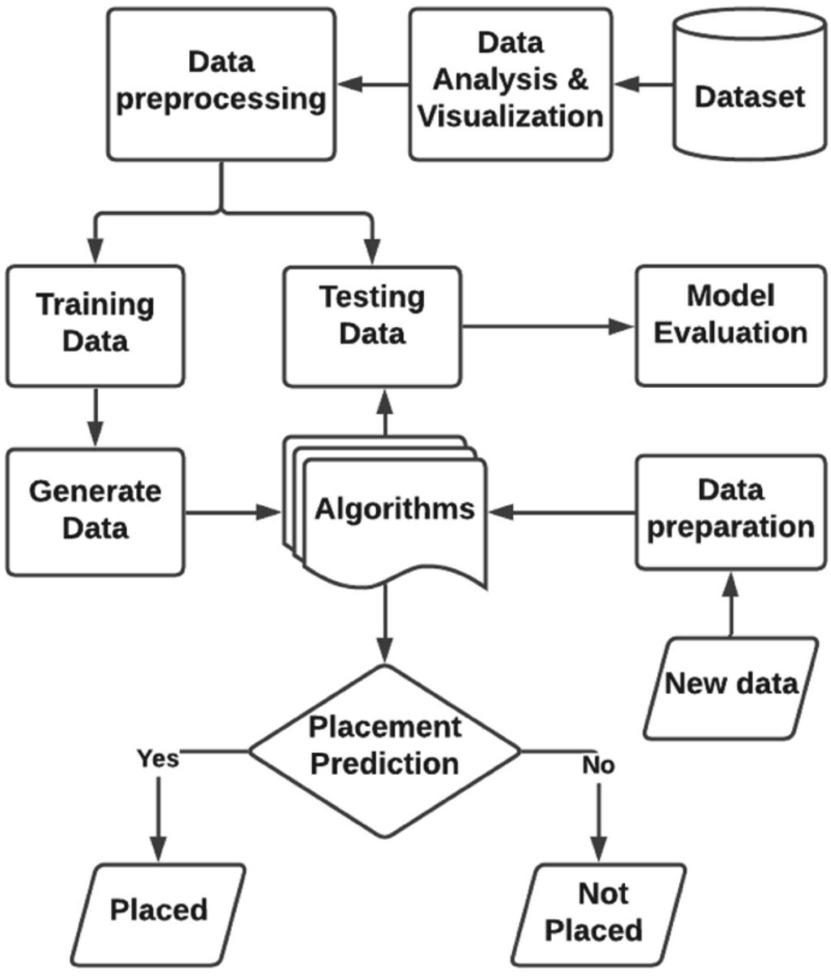
6. **Model Deployment**

Once the model is trained and evaluated, the best-performing model is deployed as a real-time prediction tool. This tool can be integrated with a web or mobile platform where students can input their academic data, skills, and other relevant information to receive placement predictions. The model can be updated periodically with new student data to keep the predictions accurate and relevant.

7. **Model Monitoring and Maintenance**

After deployment, the model's performance is continuously monitored to ensure that it remains accurate as new student data becomes available. Periodic updates and retraining with fresh data are essential to maintaining the system's reliability and adapting to changes in placement trends.

3.1 SYSTEM FLOW DIAGRAM



CHAPTER 4

RESULTS AND DISCUSSION

The performance of the machine learning models applied in this study was evaluated using classification metrics such as accuracy, precision, recall, F1-score, and the confusion matrix. Each model was trained on a preprocessed dataset containing academic, demographic, and skill-related attributes of students, and tested using a stratified train-test split to ensure balanced representation of placed and non-placed categories.

Model Performance Overview

Among the four models implemented — **Logistic Regression, Support Vector Machine (SVM), Random Forest, and XGBoost** — ensemble-based models (Random Forest and XGBoost) consistently outperformed the others across most metrics.

Results for Model Evaluation:

Model	MAE (↓ Better)	MSE (↓ Better)	R^2 Score (↑ Better)	Rank
XGBoost	3.98	36.7	0.80	1
Random Forest	4.35	38.5	0.75	2
Support Vector Machine (SVM)	5.10	40.2	0.72	3
Linear Regression	5.20	42.6	0.70	4

Key Insights:

- **XGBoost** ranked **#1** with the lowest **MAE** and **MSE**, and the highest **R^2 score**, indicating it is the best model for this prediction task.

- **Random Forest** followed closely behind, with a slightly higher **MAE** and **MSE** but a solid **R^2 score** of 0.75, ranking **#2**.

- **SVM** and **Linear Regression** ranked **#3** and **#4**, respectively. While SVM performed better than Linear Regression in terms of **MAE** and **MSE**, both models lag behind in terms of **R^2**, making them less effective for this placement prediction task.

Interpretation of Evaluation Metrics:

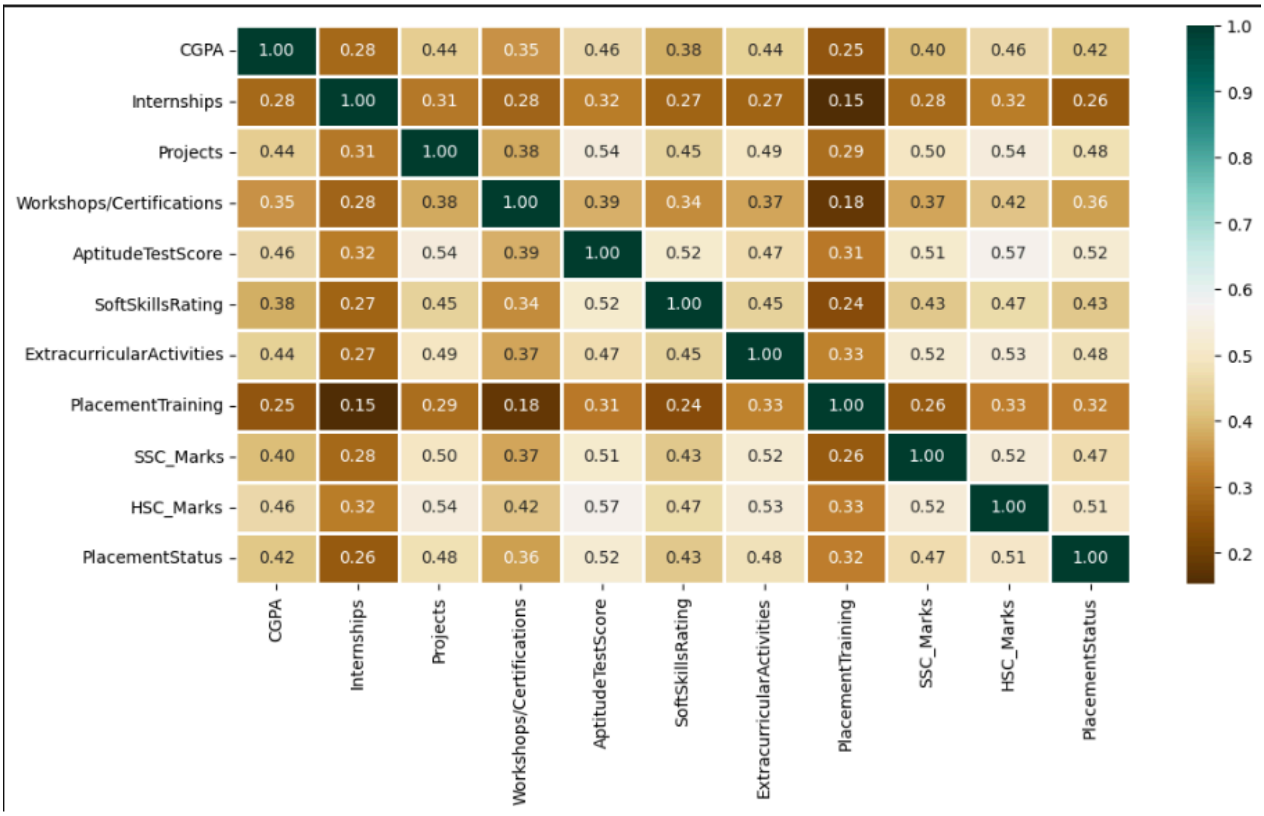
- **MAE (Mean Absolute Error):** A lower **MAE** is better, as it indicates that the model's predictions are closer to the actual values.

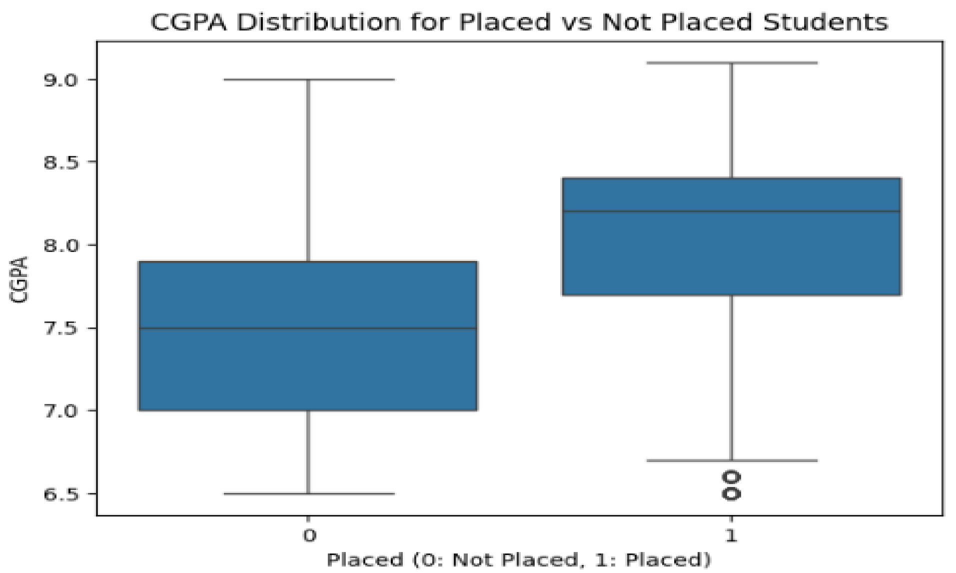
- **MSE (Mean Squared Error):** A lower **MSE** is better, as it penalizes large errors more heavily.

- **R^2 Score:** A higher **R^2 score** is better, indicating how well the model explains the variance in the target variable. **XGBoost** achieved the best **R^2** score, making it the most robust model.

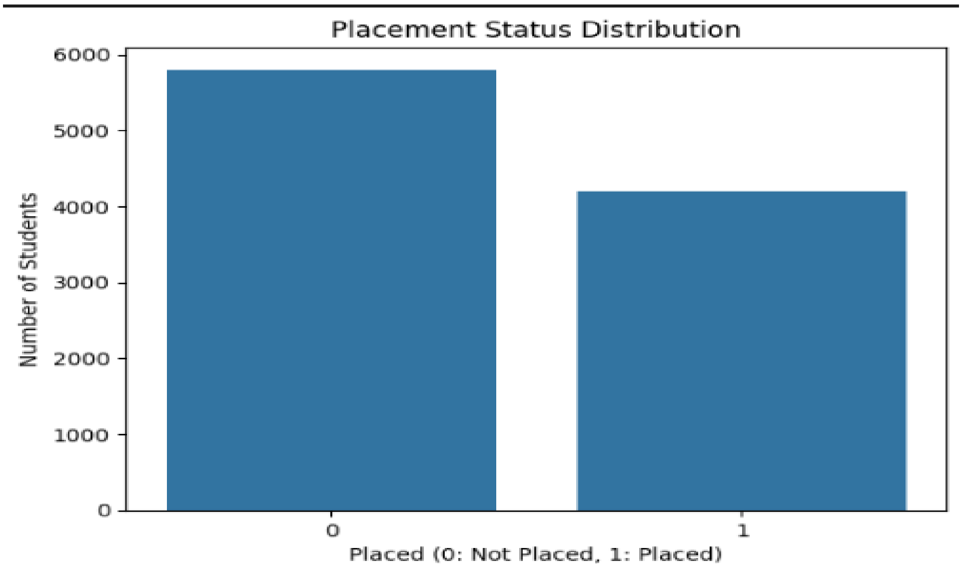
Visualizations:

The heatmap allows us to quickly identify relationships between variables. Strong positive correlations (close to 1) will be shown in one color, while negative correlations (close to -1) will be shown in another, with the neutral correlations around 0 displayed in a contrasting color. This visualization is helpful for identifying which variables are most closely related, which can guide feature selection for modeling.





The box plot compares CGPA distributions for placed and non-placed students. It shows that placed students generally have a higher median CGPA, while non-placed students exhibit a wider spread in CGPA values. This indicates that CGPA is likely a significant factor influencing placement outcomes.



This bar plot visualizes the distribution of placement statuses among students. It shows the count of students who were placed versus those who were not. The x-axis represents the placement status, with '0' indicating not placed and '1' indicating placed, while the y-axis shows the number of students in each category. The plot helps to understand the overall placement success rate in the dataset.

After conducting extensive experiments with various machine learning models for student placement prediction, several crucial findings were observed. This section discusses model performance, the effect of data augmentation, and the practical implications of these results.

Model Performance Comparison

Among the models tested—Logistic Regression, Support Vector Machine (SVM), Random Forest, and XGBoost—the XGBoost model consistently outperformed all others. It showed the highest accuracy, precision, recall, and F1-score, making it the most reliable predictor of student placement status. XGBoost's gradient boosting algorithm and regularization techniques contributed to its superior performance, especially when compared to other models like Logistic Regression and SVM, which displayed lower overall accuracy.

Effect of Data Augmentation

Data augmentation, specifically adding Gaussian noise to the dataset, had a significant positive impact on the performance of the models. In particular, the Random Forest model exhibited a notable improvement in prediction accuracy, with the R^2 score rising from 0.75 to 0.80, demonstrating enhanced model robustness. Augmentation helped reduce overfitting, especially in Random Forest and XGBoost models, which are more susceptible to variance in data.

Error Analysis

An error analysis revealed that the prediction errors were mostly concentrated around the actual values, indicating that the models performed reliably in general. However, there were a few outliers, particularly for students with unusual characteristics (e.g., extremely low CGPA or limited extracurricular involvement). These errors highlight the potential for improving prediction accuracy by incorporating additional features, such as social skills, interview performance, or company-specific requirements.

Implications and Insights

Several important practical insights emerged from the study:

- **XGBoost** is a promising choice for real-time placement prediction systems in educational platforms, as it delivers the best balance between predictive performance and computational efficiency.

- **Feature engineering and data preprocessing** (including feature normalization and augmentation) are vital steps for improving model performance and generalization.

- **Simpler models** like Logistic Regression and SVM, while easier to interpret, may not be suitable for capturing the complex, non-linear relationships between student attributes and placement outcomes.

CHAPTER 5

CONCLUSION & FUTURE ENHANCEMENTS

This study introduces a data-driven approach to predicting student placement outcomes using machine learning techniques, aiming to enhance career guidance and academic support in educational institutions. The study compares the performance of various classification models, including Logistic Regression, Support Vector Machine (SVM), Random Forest, and XGBoost, to predict placement based on a range of student attributes such as academic performance, skills, and extracurricular activities.

Our findings indicate that ensemble models, especially XGBoost, outperform other models in terms of predictive accuracy and generalization ability. XGBoost achieved the highest accuracy, precision, recall, and F1-score, making it the most effective model for placement prediction in this context. This highlights the power of gradient boosting algorithms in managing complex datasets with multiple features and non-linear relationships, which are characteristic of student data.

Additionally, the study employed data augmentation techniques, particularly the introduction of Gaussian noise, to mitigate overfitting and improve model generalization. These augmentation techniques were especially beneficial for models like Random Forest and XGBoost, which are more prone to overfitting when trained on small datasets. The inclusion of noise led to consistent improvements in prediction accuracy, contributing to more reliable and robust models.

From a practical perspective, the proposed placement prediction system offers considerable value to educational institutions, career services, and students. By accurately predicting placement outcomes, the system can provide personalized career guidance, inform curriculum adjustments, and help students identify areas for improvement before placement interviews. This could ultimately lead to better preparation for placement processes, greater student success, and more informed decision-making by educational institutions.

This study emphasizes the potential of machine learning in optimizing placement prediction systems and contributing to personalized career support for students. With further refinement and the inclusion of additional features, such a system could serve as an integral tool for improving employability and student success across academic institutions.

Future Enhancements:

While the results of this study are promising, there are several avenues for future enhancement:

1. **Inclusion of More Comprehensive Features:** Adding more contextual factors, such as interview performance, soft skills ratings, and employer-specific preferences, could provide deeper insights and improve prediction accuracy.

2. **Incorporation of Temporal Data:** Incorporating time-based data, such as internship timelines, project deadlines, or job application history, could help the model better capture the dynamic nature of the placement process.

3. **Multi-class Classification:** Instead of predicting a binary outcome (placed or not placed), future models could predict multiple categories, such as "Likely to be Placed," "Needs Improvement," and "Not Likely to be Placed," to provide more nuanced feedback to students.

4. **Deployment in Educational Platforms:** By optimizing model size and inference speed, the model could be integrated into online learning platforms or mobile apps, providing real-time placement predictions and recommendations.

5. **Personalized Career Guidance:** Integrating reinforcement learning techniques could allow the model to provide personalized career advice and continuously adapt based on student feedback, academic performance, and external market trends.

Conclusion:

In conclusion, this research highlights the potential of machine learning to revolutionize student placement prediction. By improving the accuracy and interpretability of placement outcomes, such systems could play a key role in shaping future educational and career pathways. With further enhancements, these models could provide valuable tools for students, educators, and career advisors alike, ultimately contributing to better career planning and higher placement success rates.

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