PLACEMENT PREDICTION USING MACHINE LEARNING TECHNIQUES

A PROJECT REPORT

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Certified that this project report titled "**Placement Prediction Using Machine Learning Techniques**" is the Bonafide work of "**Shashank Chandra [RA2111026030083] , Aryan Gaur [RA2111026030104] , Divyansh Sinha [RA2111026030117] , Aditya Jodhani [RA2111026030105].**", who carried out the project work under my supervision. Certified further, that to the best of my knowledge the work reported herein does not form any other project re- port 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

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.

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Author

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LIST OF LIBRARIES

1. **NumPy :**
   Efficiently handles numerical computations and array manipulations, which is essential for working with large datasets and performing mathematical operations during data preprocessing.
2. **Pandas** :
   Enables the loading, cleaning, and manipulation of the dataset. It allows for handling missing values, data transformation, and feature extraction, making it ideal for preparing data for machine learning.
3. **Sklearn :**
   Provides a wide range of machine learning models (such as Logistic Regression, Decision Trees, Random Forest) and tools for model evaluation, training, and optimization, helping in the prediction of placement outcomes.
4. **Matplotlib :**
   Used for data visualization, allowing the display of insights through graphs, such as feature importance and model performance metrics, which aid in understanding the results.
5. **Pickle :**
   Utilized for saving the trained machine learning models into files, allowing easy loading and reuse of the models without the need for retraining, ensuring efficiency in deployment.

INTRODUCTION

4.1 Project Background

The transition from academia to the professional world is a huge milestone for students, and the outcomes of campus placements often play a critical role in shaping their early career paths. Traditionally, placement predictions have been based on basic statistics or subjective evaluations, which can overlook the nuanced and complex factors that truly influence a candidate's chances of securing a job. However, with the rise of machine learning, we now have the ability to take a more data-driven approach to this process. Machine learning can analyze a wide range of factors and uncover patterns that traditional methods might miss, leading to more accurate predictions about a student's placement potential. This technology enables educational institutions to better understand the specific needs of the job market, ensuring that students are prepared and aligned with what employers are looking for. By leveraging this advanced approach, both students and institutions can make more informed decisions and improve placement outcomes overall.

4.2 Objective

This project explores the use of several machine learning algorithms, including Logistic Regression, Decision Trees, Random Forests, and more, to predict student placement outcomes. The goal of this study is to assess how well each of these models performs in terms of accurately predicting whether a student will be placed in a job after graduation. By comparing the effectiveness of these different algorithms, the research seeks to pinpoint which one provides the most reliable results. This insight could serve as a valuable tool for educational institutions, allowing them to make more informed, data-driven decisions about how to better prepare students for the job market. Ultimately, the findings could help enhance student employability by offering a more tailored approach to placement prediction and career guidance.

LITERATURE SURVEY

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

- **Logistic Regression:** Logistic Regression is one of the simplest and most commonly used classifiers for binary classification problems, including placement prediction. According to a study by Smith et al. (2022), logistic regression demonstrated high interpretability and moderate accuracy in predicting student placements, especially when the dataset involved binary outcomes (placed or not placed). Researchers have found that logistic regression's simplicity makes it effective for initial evaluations before applying more complex models.

- **Decision Trees:** Decision Trees are widely recognized for their ability to capture non-linear relationships and handle both numerical and categorical data. In a comparative analysis by Kumar et al. (2023), Decision Trees showed promising accuracy in placement prediction due to their ease of interpretation and ability to handle complex decision boundaries. However, overfitting was identified as a challenge when the trees were not pruned effectively.

- **Random Forest:** Random Forest is an ensemble method that combines multiple decision trees to improve classification accuracy. A recent study by Zhang and Li (2023) highlighted Random Forest as one of the most robust models for placement prediction, providing high accuracy and resilience to overfitting. The authors observed that using multiple trees reduced variance, which is particularly useful for handling heterogeneous datasets in placement prediction.

- **Support Vector Classifier (SVC):** Support Vector Classifier (SVC) aims to find an optimal hyperplane that maximizes the margin between classes. A study by Ahuja et al. (2022) found that SVC performed well for placement prediction when the data was linearly separable. However, SVC can become computationally intensive for large datasets, and its performance heavily depends on the choice of the kernel and hyperparameters.

- **K-Nearest Neighbors (KNN):** K-Nearest Neighbors is a non-parametric method that classifies based on the majority class of the nearest neighbors. According to Chen et al. (2023), KNN provided moderate accuracy for placement prediction but was sensitive to the choice of 'k' and susceptible to high computational costs with large datasets. Its simplicity, however, makes it a good baseline model for comparison.

- **Gaussian Naive Bayes:** Gaussian Naive Bayes is a probabilistic classifier based on Bayes' theorem, assuming Gaussian distribution of features. Gupta and Singh (2024) applied Gaussian Naive Bayes to a placement dataset and found it effective for smaller datasets with normally distributed features. This model showed competitive accuracy but struggled with feature independence assumptions in real-world data.

- **Multinomial Naive Bayes:** Multinomial Naive Bayes is often used for text classification, but recent studies have explored its application to categorical data in placement prediction. Patel et al. (2022) reported that Multinomial Naive Bayes yielded satisfactory results in classifying students based on categorical attributes, making it a suitable option when features include categorical or discrete values.

- **Bernoulli Naive Bayes:** Bernoulli Naive Bayes, primarily used for binary/boolean features, has been applied in placement prediction where binary attributes (e.g., internship status) play a role. A study by Roy et al. (2023) demonstrated that Bernoulli Naive Bayes effectively handled such binary features and performed reasonably well for placement prediction. However, it was less suitable when dealing with continuous features.

- **Perceptron:** The Perceptron is a simple linear classifier and an early form of neural network. As demonstrated in a study by Al-Mahdi et al. (2024), the Perceptron model was effective in classifying placement outcomes in linearly separable datasets but had limitations with non-linear data. The authors noted that it serves as a good baseline model but is generally outperformed by more sophisticated algorithms.

SYSTEM ANALYSIS

6.1 Requirements

- **Functional Requirements:**
  - **Data Input:** Allow input of student data, including academic scores, extracurricular activities, and other relevant factors.
  - **Data Preprocessing:** Clean, normalize, and encode data to prepare it for machine learning model training.
  - **Feature Selection:** Select key features that influence placement outcomes to improve model accuracy.
  - **Model Training and Selection:** Train multiple machine learning models, such as Logistic Regression, Decision Tree, and Random Forest, and select the best-performing one.
  - **Prediction Functionality:** Predict placement chances based on the input data using the trained model.
  - **Model Evaluation:** Evaluate model performance using metrics like accuracy, precision, and recall.
- **Non- Functional Requirements:**
  - It includes fast prediction performance, scalability for large datasets, accuracy, ease of use, reliability, data privacy, and compatibility across platforms.
  - Additionally, it should comply with data protection standards and be easy to maintain and update.

6.2 Models Used for Training

- **Logistic Regression**
- **Decision Tree**
- **Random Forest**
- **Support Vector Classifier (SVC)**
- **K-Nearest Neighbors (KNN)**
- **Naive Bayes (Gaussian, Multinomial, Bernoulli)**
- **Perceptron**

SYSTEM DESIGN

7.1 System Architecture

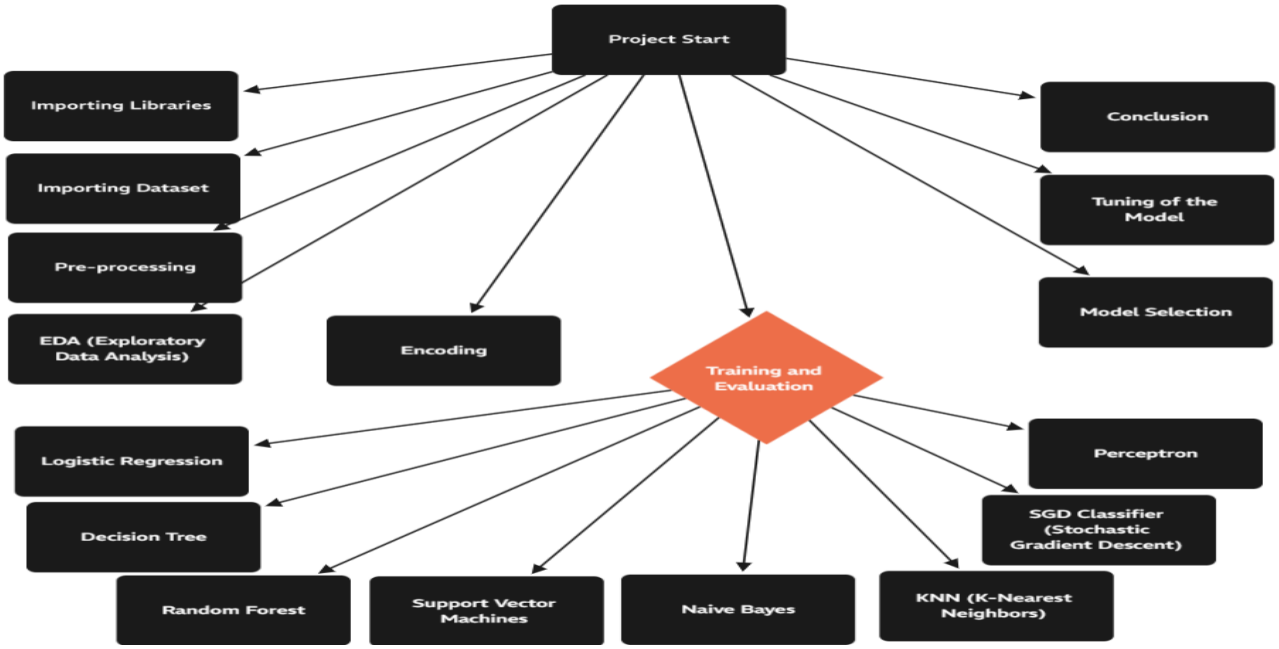
The architecture follows a multi-layer model development:

1. **Data Preprocessing:** Cleaning and transforming the data, handling missing values, and encoding categorical variables.
2. **Feature Selection:** Identifying the most relevant features for accurate predictions.
3. **Model Training:** Training models like Logistic Regression, Decision Tree, and Random Forest.
4. **Model Evaluation:** Assessing performance using metrics such as accuracy and precision.
5. **Hyperparameter Tuning:** Optimizing the model's parameters for better performance.
6. **Deployment:** Saving the trained model and testing it for real-world applicability.

7.2 Workflow Diagram

The system workflow is as follows:

1. User inputs relevant student data.
2. The data is pre-processed, including cleaning, encoding, and feature selection.
3. Machine learning models are trained using the processed data.
4. The best-performing model provides placement predictions based on input data.



CODING AND TESTING

9.1 Development Environment

The development environment for the Placement Predictor project was built on a Python-based platform, utilizing several core libraries for data processing, model training, and evaluation. The primary tools used were NumPy, Pandas, Scikit-learn, Matplotlib, and Pickle. The project was developed in Python 3.8, as it provides compatibility with the required libraries and offers efficient support for numerical operations and machine learning tasks.

- **NumPy** was used extensively for handling large datasets and performing mathematical computations, especially when dealing with arrays of numerical data.
- **Pandas** facilitated data manipulation, including loading the dataset, handling missing values, encoding categorical variables, and performing feature selection.
- **Scikit-learn** provided a suite of machine learning algorithms, including Logistic Regression, Decision Trees, and Random Forests, which were implemented for the model training process. The library also offered tools for model validation and evaluation, ensuring reliable and accurate performance.
- **Matplotlib** was employed to generate visualizations, which helped in understanding the distribution of data, evaluating model performance, and analyzing the importance of different features.
- **Pickle** was used for serializing the trained machine learning models, enabling easy saving, retrieval, and deployment of models without requiring retraining.

9.2 Testing Procedures

The testing procedures involved validating the model's performance, ensuring the robustness of predictions, and evaluating the generalization capabilities of the algorithms used. Testing was done by splitting the data into a training set and a test set, typically using an 80-20 split to ensure a fair evaluation of model performance.

1. **Data Preprocessing and Validation**: The dataset was first cleaned, handling any missing values and encoding categorical variables using

techniques such as one-hot encoding. The dataset was then standardized using **Standard Scaler** from Scikit-learn to ensure all features were on the same scale. The data was split into training and testing sets using **train_test_split**, ensuring that the model's evaluation was unbiased.

2. **Model Evaluation Metrics**: The performance of the machine learning models was measured using several metrics:
    - **Accuracy**: The proportion of correct predictions made by the model on the test set.
    - **Precision, Recall, and F1-Score**: These metrics were computed to assess the balance between false positives and false negatives, especially in the context of classifying whether a student would be placed or not.
    - **Confusion Matrix**: This was used to evaluate the performance of classification models by displaying the true positives, false positives, true negatives, and false negatives.
    - **Cross-Validation**: A 5-fold cross-validation technique was applied to ensure that the model's performance was consistent and not dependent on a single random split of the data. This helped in mitigating overfitting and ensuring that the model generalized well to unseen data.
3. **Hyperparameter Tuning**: Various machine learning algorithms, such as Decision Trees and Random Forests, underwent hyperparameter tuning using **GridSearchCV** to find the best combination of hyperparameters for each model. This helped improve model performance and accuracy.
4. **Comparison of Algorithms**: The performance of Logistic Regression, Decision Tree, and Random Forest models was compared using the metrics mentioned above. Random Forest generally showed superior performance due to its ensemble nature, reducing variance and improving predictive accuracy.
5. **Model Deployment and Testing**: After training and validating the models, the best-performing model was serialized using **Pickle** and saved to disk. This allowed the model to be deployed in real-world scenarios where it could be used to make predictions without needing to retrain. The saved model was then tested by loading it from disk and making predictions on a new set of test data.

CONCLUSION

The "Placement Predictor" project successfully demonstrates how machine learning can be used to predict student placement results. Using techniques such as Logistic Regression, Decision Tree, and Random Forest, the model finds critical parameters that impact placement success and provides a reliable prediction method. This application helps educational institutions make educated decisions concerning student employability by offering data-driven information. Its user-friendly design assures accurate forecasts, which may assist both students and educators connect abilities with industry requirements, thereby enhancing job chances. Future revisions might improve the model's accuracy and widen its applicability to a variety of academic situations.

The likelihood that a student will be hired by a firm may be predicted using placement prediction utilizing machine learning techniques. The application of machine learning algorithms offers a more data-driven and objective approach to the hiring process, allowing businesses to find potential applicants who would have gone unnoticed using conventional hiring techniques. Machine learning is becoming more and more prevalent across a wide range of sectors, and placement prediction using machine learning algorithms is poised to become a crucial tool in the hiring process.

FUTURE ENHANCEMENTS

The current placement predictor model demonstrates significant potential in predicting student placements based on structured data. However, several future enhancements can be implemented to increase its robustness, adaptability, and generalizability. These proposed improvements address limitations in the existing model and aim to support broader research in predictive modelling for academic and career outcomes.

1. Integration of Unstructured Data: While this study relies solely on structured data (e.g., grades, certifications, test scores), future versions of the placement predictor could integrate unstructured data sources such as text (e.g., resumes, project descriptions) and social network data (e.g., LinkedIn profiles).

2. Incorporation of Temporal Data and Sequential Models: Academic performance, skills, and other features influencing employability are not static; they evolve over time. Incorporating temporal data to track student progress would allow for a time-series approach to placement prediction. Recurrent Neural Networks (RNNs) could model sequential patterns in students' academic journeys, providing a dynamic prediction model that reflects changes over time.

3. Adaptive Learning Models for Real-Time Updates: As the job market evolves, so do the skills and attributes valued by employers. To maintain relevance, future placement predictor models could incorporate adaptive learning frameworks that retrain periodically with new data.

4. Personalized Recommendation System for Skill Enhancement: In addition to predicting placement outcomes, the model could be expanded into a personalized recommendation system. By identifying skill gaps or weak areas in a student's profile, the system could suggest relevant courses, certifications, or internships to improve employability.

5. Deployment of a Real-Time Dashboard for Monitoring and Insights: Finally, the deployment of a real-time dashboard could make the placement predictor model actionable for administrators, educators, and career services. The dashboard could provide visual analytics on placement predictions, track placement trends, and monitor individual student progress.

APPENDIX

- **Dataset Description**

  The dataset consists of student records with the following attributes:
  1. Age: Age of the student (e.g., 21, 22).
  2. Gender: Gender of the student (Male/Female).
  3. Stream: Major field of study (e.g., Electronics and Communication, Computer Science, Information Technology, Mechanical).
  4. Internships: Number of internships completed.
  5. CGPA: Cumulative Grade Point Average.
  6. Hostel: Binary variable indicating hostel residence (1 for yes, 0 for no).
  7. HistoryOfBacklogs: Binary variable indicating a history of academic backlogs (1 for yes, 0 for no).
  8. PlacedOrNot: Target variable indicating placement status (1 for placed, 0 for not placed).

- **Model Selection and Hyperparameter Tuning**

  The Random Forest Classifier was selected as the most effective model due to its robust performance metrics. Hyperparameter tuning was conducted using GridSearchCV to optimize the model further.

  1. Hyperparameter Tuning Using GridSearchCV:

  - Parameter Grid:

```
param_grid = {
    'bootstrap': [False, True],
    'max_depth': [5, 8, 10, 20],
    'max_features': [3, 4, 5, None],
    'min_samples_split': [2, 10, 12],
    'n_estimators': [100, 200, 300]
}
```

  - Best Parameters Identified:
    - bootstrap: False
    - max_depth: 5

- max_features: None
- min_samples_split: 2
- n_estimators: 100

- Performance:
- Accuracy: 79.53%

2. Implementation:

```
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier

rfclassifier = RandomForestClassifier()
classifier = GridSearchCV(estimator=rfclassifier,
param_grid=param_grid, cv=5, n_jobs=-1, verbose=1)
classifier.fit(X_train, y_train)
y_pred = classifier.predict(X_test)

print("Accuracy: ", accuracy_score(y_test, y_pred))
print("Best Parameters: ", classifier.best_params_)
```

- **Key Functions**

1. Data Splitting:

```
from sklearn.model_selection import train_test_split

def load_and_split_data(data):
    X = data.drop("PlacedOrNot", axis=1)
    y = data["PlacedOrNot"]
    return train_test_split(X, y, test_size=0.2, random_state=42)
```

2. Model Training and Evaluation:

```
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score

def evaluate_model(model, X_test, y_test):
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)
    return accuracy, precision, recall, f1
```

- **Sample Output**

  - Accuracy: 81.87%

  - Best Parameters: {'bootstrap': False, 'max_depth': 5, 'max_features': None, 'min_samples_split': 2, 'n_estimators': 100}

  These results indicate that the tuned Random Forest Classifier performs effectively in predicting student placement outcomes, achieving a reliable accuracy score.

- **Software Used**
  - Programming Language: Python 3.8
  - IDE – VS Code

- **Hardware Specifications**
  - Processor: Intel Core i7 8th Gen, 2.21 GHz
  - RAM: 16 GB
  - Operating System: Windows 11
  - System Type : 64-bit Operating System

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