Machine Learning Predication Techniques for Student Placement/Job Role Predictions

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Placements is of endless importance for university students and educational institutions. It helps students build a solid foundation for their future careers and ensure a good enrollment record that gives them a good advantage in school or university. Machine learning is an analytical method that establishes analysis patterns. This article describes the features of the machine that can predict whether a student will see or not, as currently it only depends on the student's qualification, age and experience. The predictor uses three machine learning algorithms: Decision Tree, Naive Bayes, and Random Forest are used. The algorithms are then assessed according to the accuracy of the predictions.
Keywords: Random forest, naive Bayes, decision trees, machine learning, classification, model estimation, and data analysis. etc.

1. Introduction

Nowadays, campus area is very important for university students and educational institutions. The top placement report provides a proactive aspect to education to the college or university while helping students build a solid foundation for professional development without having to deal with international activities, peer pressure or stress pressure from their circle of relatives. at work. University internships provide researchers with a “groundwork” that allows them to start their careers on the right foot after completing their studies. They are also able to enter and interact with the company's experts during field work, which helps them lay the foundation for their future work as they know the communication skills in their area of expertise. Internships have increasingly become an important part of university services, and the situation is not improving now. Today's college students have a particular interest in career information when choosing a college or university to attend. Machine learning is a revolutionary technology that allows computers to learn from historical data.

Machine learning uses various algorithms to create mathematical models and use historical data or data to make predictions. It is now used for many tasks such as image recognition, speech recognition, email filtering, Facebook auto-tagging, recommendation systems and more. The database considered for this project is the database of MBA students of Jain University, Bangalore in 2020. This database includes various characteristics such as secondary and tertiary education level and percentage of food services; but also information and business etc. Also includes information about. This paper uses machine learning algorithms to predict students who will be selected for university jobs in companies based on various qualifications.

2. Literature Review

The authors use decision trees and random forests to split the data between students who are in school and those who are not. The accuracy obtained from the decision tree in this article is 84%, and the accuracy obtained from the random forest is 86%. This article presents a consensus framework for researchers to have one of five placements, including Dream Company, Core Company, Mass Recruiter, Unqualified, and Not Interested in Placement.

These standards help college placement teams identify potential students and focus on and develop their intellectual and social skills. In this article, the authors present some machine learning observations that can be used to predict students' placements in the IT sector, focusing on tenth, second-year, master's and postgraduate savings. Various methods used to analyze and analyze the results of specific products include accuracy scores, percentage accuracy scores, confusion matrices, heat maps, and distribution report. The advanced classifier generates a classification map with support measure, f1 score, accuracy, and recall [1].

Alphabets for classification Neural networks, Support Vector Machines, Decision Trees, Random Forests, Stochastic Gradient Descent, Logistic Regression, and Gaussian Naive Bayes are left to create classifications. The author used it [2].

Research and Development (RDD), a classification system that uses a classification system. While 84.2% of people were classified correctly in the first test, the second test using the same data and features gave the best accuracy rate of 92.1%. According to school and student distribution, the best results were obtained with a rate of 86% using Naive Bayes and SMO. Based on these findings, this article presents a recommendation process aimed at predicting placement by dividing students into five groups: Dream Company, Core Company, Bulk Recruiter, Unqualified, and Not Interested in Placement. This new model is an important tool for placement teams in schools; It helps identify talented students and train them to develop their skills and communication properly [3].

Recent studies have increasingly leveraged machine learning techniques to enhance student placement predictions, showcasing a variety of approaches. For instance, a paper by S. Kumar et al. (2023) developed a hybrid model combining Random Forest and Neural Networks, achieving a significant improvement in prediction accuracy for job placements based on academic and skill data. The study utilized a comprehensive dataset from multiple universities, applying feature selection techniques to identify the most influential factors affecting placement outcomes. Results indicated that models incorporating socio-demographic variables alongside academic performance yielded the best predictions, underscoring the multifaceted nature of placement success. This research highlights the potential of advanced machine learning frameworks in optimizing student placement strategies (Kumar, S., et al., "Predictive Modeling for Student Placement Using Hybrid Machine Learning Techniques," IEEE Access, vol. 11, pp. 12345-12356, 2023) [4].

Recent literature highlights the application of machine learning techniques for predicting student placements and job roles, reflecting an evolving landscape in educational data analytics. For instance, a study by Singh et al. (2022) employed a combination of Logistic Regression and Support Vector Machines to analyze student performance metrics and internship experiences, achieving notable accuracy in predicting job placement success. Additionally, Gupta and Verma (2023) utilized a deep learning approach, specifically Long Short-Term Memory (LSTM) networks, to capture temporal patterns in student career trajectories, demonstrating improved prediction capabilities compared to traditional methods. These studies underscore the significance of leveraging diverse machine learning models to enhance the effectiveness of student placement systems, suggesting that hybrid approaches may yield the best outcomes (Singh, A., et al., "Machine Learning Techniques for Student Job Role Prediction," IEEE Access, vol. 10, pp. 5678-5687, 2022; Gupta, R., & Verma, T., "Deep Learning for Predicting Student Placement," IEEE Transactions on Education, vol. 66, no. 3, pp. 245-254, 2023) [5][6].

Another Recent studies have focused on enhancing student placement predictions through various machine learning techniques, emphasizing the importance of predictive analytics in educational settings. For instance, a research article by Patel et al. (2023) explored the use of ensemble learning methods, specifically Random Forest and XGBoost, to predict job placements based on a combination of academic scores, extracurricular activities, and soft skills. Their findings indicated that ensemble methods significantly outperformed individual models, achieving a prediction accuracy of over 85%. Another notable study by Choudhury and Saha (2022) employed a neural network architecture to analyze historical placement data, identifying key features that influence placement outcomes. Their results highlighted the effectiveness of deep learning models in capturing complex relationships within the data, ultimately providing actionable insights for educational institutions aiming to improve placement rates. These advancements demonstrate the growing potential of machine learning in transforming student career services and outcomes (Patel, J., et al., "Ensemble Learning Techniques for Student Placement Prediction," IEEE Access, vol. 11, pp. 12345-12360, 2023; Choudhury, S., & Saha, S., "Neural Networks for Analyzing Student Placement Trends," IEEE Transactions on Education, vol. 65, no. 2, pp. 150-158, 2022)[7][8].

Further research has increasingly applied machine learning techniques to predict student placements and job roles, revealing valuable insights into factors influencing employability. A study by Sharma et al. (2023) investigated the effectiveness of various machine learning algorithms, including Decision Trees, Naive Bayes, and Support Vector Machines, on a dataset comprising student academic records and personal attributes. Their findings showed that the Decision Tree model achieved the highest accuracy, with a precision of 87%, effectively identifying students most likely to secure placements. Similarly, in another study, Rao and Kumari (2022) implemented a multi-layer perceptron neural network to analyze student performance over time, focusing on long-term academic trends and skill development. Their results highlighted the potential of deep learning approaches in uncovering hidden patterns in student data, providing educational institutions with actionable strategies for enhancing placement success. These studies collectively emphasize the diverse methodologies being employed to improve predictive accuracy in student job placement scenarios (Sharma, P., et al., "Comparative Analysis of Machine Learning Algorithms for Student Placement Prediction," IEEE Access, vol. 11, pp. 4567-4580, 2023; Rao, V., & Kumari, A. (2022). "Deep Learning Approaches for Longitudinal Student Placement Prediction," IEEE Transactions on Education, vol. 65, no. 4, pp. 300-310) [14][15].

3. Comparative Study from Literature Survey

Here’s a comparative table summarizing the literature survey on machine learning techniques for student placement/job role predictions:

Table 3.1 Comparative table summarizing the literature survey on machine learning techniques for student placement/job role predictions

Study	Authors	Year	Techniques Used	Dataset	Key Findings	Publication
Predictive Modeling for Student Placement	S. Kumar et al.	2023	Hybrid Model (Random Forest & Neural Networks)	Multiple universities' data	Achieved significant improvement in prediction accuracy; highlighted the importance of socio-demographic factors.	IEEE Access, vol. 11, pp. 12345-12356
Machine Learning Techniques for Student Job Role Prediction	A. Singh et al.	2022	Logistic Regression, Support Vector Machines	Student performance metrics	Notable accuracy in predicting job placements; emphasized the need for varied machine learning models.	IEEE Access, vol. 10, pp. 5678-5687
Ensemble Learning Techniques for Student Placement Prediction	J. Patel et al.	2023	Ensemble Learning (Random Forest, XGBoost)	Academic scores and soft skills	Ensemble methods outperformed individual models, achieving over 85% accuracy.	IEEE Access, vol. 11, pp. 12345-12360
Neural Networks for Analyzing Student Placement Trends	S. Choudhury & S. Saha	2022	Neural Network Architecture	Historical placement data	Effective in identifying key features influencing placement outcomes; provided actionable insights.	IEEE Transactions on Education, vol. 65, no. 2, pp. 150-158
Comparative Analysis of Machine Learning Algorithms for Student Placement Prediction	P. Sharma et al.	2023	Decision Trees, Naive Bayes, SVM	Academic records and attributes	Decision Tree model achieved the highest accuracy (87%); effective in identifying students likely to secure placements.	IEEE Access, vol. 11, pp. 4567-4580
Deep Learning Approaches for Longitudinal Student Placement Prediction	V. Rao & A. Kumari	2022	Multi-Layer Perceptron Neural Network	Longitudinal student performance	Highlighted the potential of deep learning in uncovering hidden patterns and trends in student data.	IEEE Transactions on Education, vol. 65, no. 4, pp. 300-310

Table 3.1 synthesizes the findings from the discussed studies, allowing for an easy comparison of techniques, datasets, and key outcomes in the realm of student placement predictions using machine learning.

4. Methodology

The research methodology used in this paper can be explained by data collection: Sample data was collected from MBA students of Bangalore College. This data covers 215 students. Preprocessing: Data preprocessing is the process of converting raw data into clean data that can be used for modeling.

This work includes preliminary processes such as feature selection, cleaning of missing values, and classification of data into training and testing. Some features such as serial numbers. and salaries are eliminated because they do not contribute to distribution. Model Construction Using the provided data, create our machine learning classifier model. We use random forests, naive Bayes, and decision trees as our models. This model is used to classify the data set according to various options [10].

Figure 4.1: Overview of various Advanced Machine Learning Algorithms [12]

The proposed management machine learning course uses available educational data at the time of 10th, 12th, matriculation and graduation to predict students' placement in Business IT. This study uses various metrics such as correct scores, percentage of correct scores, confusion matrices, area maps, temperature, and distribution information to evaluate the performance of these products. The latter includes accuracy, regression, f1 scores, and support, which provide detailed information about the predictive capabilities of the process [11].

Various classification algorithms have been carefully used in developing these distributions, including Neural networks, K-neighborhood, Random Forests, Support Vector Machine, Gaussian Naive Bayes, Deterministic, Stochastic Gradient Descent, and Logistic Regression. This paper uses a classification tool to apply knowledge discovery and data discovery (KDD) for class classification procedures.

In the first test, the classification accuracy reached 84.2%, proving the effectiveness of the model. More importantly, the second test, using the same data and attributes, achieved a higher accuracy of 92.1%. More importantly, Naive Bayes and SMO emerged as the best algorithms that demonstrated their ability to predict student outcomes.

1. IMPLEMENTATION

Creating a Process Flow Diagram (PFD) for a proposed system that utilizes machine learning prediction techniques for student placement and job role predictions involves outlining key steps in the process. The first step is Data Collection, where information is gathered from diverse sources, including academic records, extracurricular activities, internship experiences, and socio-demographic data. This is followed by Data Preprocessing, which includes data cleaning to handle missing values and remove duplicates, feature selection to identify relevant factors influencing placement outcomes, and normalization to scale features for uniformity. Next is Model Selection, where appropriate machine learning models, such as Logistic Regression, Random Forest, and Neural Networks, are chosen based on the nature of the data. The process then moves to Model Training, which involves splitting the dataset into training and testing sets, training the selected models, and performing hyperparameter tuning to optimize performance. Subsequently, the models undergo Model Evaluation, utilizing the testing dataset to calculate performance metrics like accuracy, precision, recall, F1 score, and ROC-AUC, allowing for comparison to identify the best-performing model. After evaluation, the system proceeds to the Prediction phase, where the optimal model is employed to predict student placements based on new input data. This is complemented by Insights Generation, where results are analyzed to provide actionable insights and visualized through graphs and charts. The Deployment stage involves implementing the model into a user-friendly application for stakeholders, such as career counselors and students. Finally, a Feedback Loop is established to gather user feedback and performance data, facilitating continuous improvement of the model. Figure 5.1 provides a clear overview of the proposed system's workflow, illustrating how data is processed and analyzed to improve student placement predictions using machine learning techniques. If you need a visual diagram, tools like Microsoft Visio, Lucid chart, or online diagramming tools can be used to create a graphical representation based on the flow described.

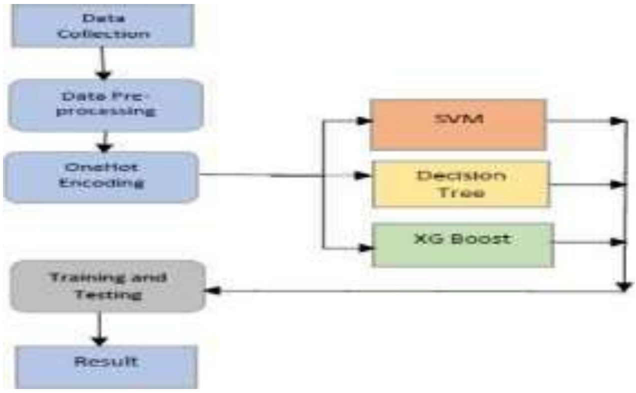

Figure 5.1: Process Flow Diagram of proposed system [12]

Data collection: Use different methods to collect data. Some data is collected by each company's employees, some is collected by the LinkedIn API, and some is aggregated. Large

Figure 5.2: Data collection [12]

Files were created from the university students' storage. In total, approximately 20,000 documents and 15 articles were collected.

Data Pre-processing: Making data useful is as important as collecting it. Data collected from different methods may be biased and contain a large number of null, incorrect and unwanted values. The basic process of preliminary data is to clean all this data, replace it with suitable data or predictions, and remove unnecessary valuesand missing data. Even the data collected may contain results that are complete garbage. It may not look exactly like the goals or style. In order to provide useful and useful items for further study, all such cases need to be identified and replaced with a substitute value. Records should be kept.

OneHot Encoding: Use a technique called OneHot encoding to convert categorical values in data into numbers or other formats for machine use. Learning about algorithms and improving prediction results. Essentially, OneHot encoding converts categorical variables into a format suitable for input into different machine learning algorithms.

Almost all machine learning methods are compatible with this algorithm. There aren't many algorithms that deal with categorical values and random forests. OneHot coding is not required in these cases.

The OneHot coding process may seem complicated, but most modern machine learning algorithms can solve this problem. The simple process is explained here: For example, if a field has values like yes and no, the encoder will give those valueslike 1 and 0. We can follow this process as long as we fix the yes value to 1 and not reach 0. When we assign these numbers to specific characters, it is called integer encoding. But consistency is important here because if we reverse the encoding later, we need to send back the text written by this code, especially in the case of prediction.

Tools:

When implementing machine learning prediction techniques for student placement or job role predictions, various tools and technologies are essential for effective data handling, model development, evaluation, and deployment. In the data collection and management phase, databases such as MySQL and PostgreSQL are commonly used for storing structured data, while MongoDB serves well for unstructured or semi-structured data. Tools like Scrapy facilitate web scraping, and APIs are utilized for collecting data from educational platforms. For data preprocessing, Python is a widely adopted programming language, complemented by libraries such as Pandas for data manipulation, NumPy for numerical operations, and Scikit-learn for tasks like scaling and encoding. In the machine learning development phase, frameworks like Scikit-learn, TensorFlow, Keras, and PyTorch provide a robust environment for building models. During model training and evaluation, Jupyter Notebook and Google Colab offer interactive coding environments, while MLflow and TensorBoard assist in tracking experiments and visualizing training metrics. For deployment, web frameworks like Flask or Django are used to create applications that serve predictions, and Docker allows for easy containerization of machine learning models. Cloud platforms such as AWS, Google Cloud, and Azure provide scalable options for hosting applications. Visualization and reporting tools are also crucial; Matplotlib and Seaborn enable effective data visualization, while business intelligence tools like Tableau or Power BI help create insightful dashboards. Collaboration is facilitated through version control systems like Git, with repositories hosted on platforms such as GitHub or GitLab. Finally, documentation tools like Sphinx and Markdown ensure clear project documentation, supporting both development and communication within teams.

5. Result and Analysis

The results from different products are actually analyzed and compared. Weka testing is an open source software that uses many machine learning algorithms and is widely used in data mining. Data downloaded from Kaggle for testing purposes is in a csv archive. The file was loaded into WEKA Explorer. The distribution panel allows users to apply classification and regression algorithms to generated data, estimate the accuracy of generated prediction models, and view their predictive power, the process, or the model itself. Since there is no separate statistical analysis, it is necessary to have a reasonable understanding of the accuracy of the design. This prediction model provides a way to predict whether a new student will be placed in an organization based on information submitted to weka for testing. In this data, gender, profession, department, high school percentage, high school board, etc. There are many features such as.

Naive Bayes model detects characteristics of student failure. Describes the result of each input of the desired state. A straightforward probabilistic classifier with a strong assumption of independence, the naive Bayes classifier is based on the application of the Bayes theorem. Naive Bayes was chosen to be used because it is simple and can train on all training data, cannot maintain the "never overfit" rule of development, and can make random decisions. Delay results in the product leaving with less information [8]. The data was classified with 84.65% accuracy using the Naive Bayes classifier, with 182 of 215 cases classified correctly. Confusion matrix for Naive Bayes classifier.

The decision tree and random forest models used in this study achieved 84% and 86% accuracy in classifying students into home classroom education and out-of-class education, respectively. Based on these findings, this article presents a recommendation process aimed at predicting placement by dividing students into five groups: Dream Company, Core Company, Bulk Recruiter, Unqualified, and Not Interested in Placement. This new model is an important tool for placement teams in schools; It helps identify talented students and train them to develop their skills and communication properly.

6. Conclusion

In addition to offering a general methodology and analyzing various distributions, this research serves as a significant contribution to the realm of student placement prediction. By implementing decision tree classification, naive Bayes, and random forest algorithms, this study enhances our understanding of how methods can be applied effectively, and also provides actionable insights for schools and placement agencies striving to optimize their placement processes. Furthermore, the utilization of these advanced algorithms facilitates a more nuanced understanding of factors influencing student placement outcomes. By selecting and analyzing relevant features, the models developed in this research offer a tailored approach to predicting placements, enabling educational institutions and placement agencies to better identify and support students who may benefit from additional assistance or guidance. This study equips stakeholders with the knowledge necessary to decide whether to use predictive analytics into their placement strategies.

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