International Journal of Research and Development in Engineering Science
ISSN: 2582 - 4201(Online) , http://www.ijrdes.com/
Regular Issue, Vol. 7, Issue.3 (May – June), 2025 , Pages: 1 - 7
Received: 20 August 2024 ; *Accepted:* 25 January 2025 ; *Published:* 30 March 2025
https://doi.org/10.63328/IJRDES-V7RI3P1
Original Paper : Policy Research – Editorial Paper

Machine Learning-Based Student Placement Prediction Analysis: A Data-Driven Approach To Enhance Employability

S Syed Abuthahir [1] , P Likhitha [2], V C Bharathi [3], K Manogna [4], V Harshavardhan Reddy [5]

[1,2,4,5] Department of Computer Science & Engineering, Madanapalle Institute of Technology & Science, Madanapalle, Andhra Pradesh, India; [1] syedabuthahirs@mits.ac.in , [2] pothullalikhitha2002@gmail.com , [4] kamanogna@gmail.com , [5] vobulapuharshavardhanreddy@gmail.com

[3] Department of School of Computer Science and Engineering, VIT-AP University, Amaravati, Andhra Pradesh, India; bharathi.vc@vitap.ac.in

* *Corresponding Author:* S Syed Abuthahir, syedabuthahirs@mits.ac.in

Abstract: Student placement prediction is a crucial task for educational institutions and recruiters to optimize campus hiring processes. This study employs a data-driven machine learning approach to predict student placement outcomes based on academic performance, extracurricular activities, certifications, aptitude scores, and soft skills ratings. A dataset comprising 10,000 student records was analyzed, and multiple machine learning models were trained, including LR, SVM, DT, RF, KNN, and GNB. To address data imbalance, the SMOTE was used to ensure robust model performance. Feature selection identified CGPA, aptitude test scores, and placement training as the most influential factors. Among all models, RF achieved the highest accuracy of 79.72%, outperforming traditional statistical methods. Model performance was evaluated metrics and execution time analysis. The findings provide valuable insights for students, helping them understand the key factors influencing placement success, and assist institutions in refining training programs. This study demonstrates the effectiveness of machine learning in enhancing placement prediction accuracy and suggests potential future improvements using deep learning techniques for more precise outcomes.

Keywords: Student Placement Prediction, ML, Campus Recruitment, Data-Driven Analysis, SMOTE, Random Forest.

1. Introduction

Campus placement plays a crucial role in shaping students' careers and bridging the gap between academic learning and industry requirements. Educational institutions and recruiters seek data-driven approaches to streamline the hiring process and improve student employability. Traditional placement prediction methods primarily rely on academic scores and basic eligibility skills and competencies required by employers. With the increasing availability of student performance data, ML has emerged as a powerful tool for predicting placement outcomes with higher accuracy and efficiency. By leveraging ML techniques, institutions can gain insights into the key factors influencing student placements, enabling them to enhance their training programs accordingly. This study proposes a ML-based approach to predict student placement outcomes using various academic and non-academic features. The dataset consists of 10,000 student records, including attributes such as CGPA,internships,projects,workshops/certificationsaptitud e test scores, soft skills rating, extracurricular activities, placement training, SSC marks, and HSC marks. Six different ML models—LR, SVM, DT, RF, KNN, and GNB—are applied to classify students as "placed" or "not placed." Additionally, SMOTE is used to handle data imbalance and ensure fair model evaluation.

The key objectives of this study include:

- Evaluating the performance of different ML algorithms, identifying the most influential features affecting student placements, and providing actionable insights for students and academic institutions.
- Using Random Forest model achieved the highest accuracy of 79.72%, outperforming other models.
- This research contributes to improving placement prediction accuracy, allowing institutions to refine their training programs and guiding students toward skill development strategies that enhance their employability.

Future work can explore deep learning-based models and real-time predictive analytics to further optimize placement prediction frameworks.

ISSN: 2582 - 4201(Online) , http://www.ijrdes.com/ , IJRDES, Vol. 7, Issue 3, 2025 , https://doi.org/10.63328/IJRDES-V7RI3P1

2. Literature Survey

Shahane (2022) explored campus placements prediction and analysis using machine learning techniques in the International Conference on Emerging Smart Computing and Informatics (ESCI). The study analyzed historical campus recruitment data to identify key factors influencing student placements. Various classification models were employed to predict hiring trends, with a focus on improving recruitment efficiency for both students and companies. The research demonstrated that machine learning models can effectively support decision-making in campus hiring processes[1].

Nichat and Raut investigated student performance prediction using Decision Tree-based approaches. Their study emphasized the role of academic performance metrics and skill-based attributes in influencing placement outcomes. Decision Trees were utilized to classify students based on their likelihood of getting placed, highlighting the interpretability and effectiveness of rule-based machine learning models for placement analysis[2]Singh et al. (2022) introduced a novel approach to placement analysis, aiming to simplify recruitment processes. The study, published in Lecture Notes in Electrical Engineering, suggested that predictive models could streamline the hiring pipeline by identifying students who best match company expectations, thus improving recruitment efficiency[3].

Raya and S.K.V. analyzed campus recruitment parameters specific to the Indian education system in the Mediterranean Journal of Social Sciences. Their study provided insights into how different educational backgrounds, training programs, and extracurricular activities impact placement rates. Their findings were instrumental in understanding region-specific challenges in campus hiring[4]. Nesamanikandan and Kannan (2016) explored placement analysis using data mining, where clustering and classification algorithms were applied to student datasets to derive patterns affecting employability. Their study demonstrated the advantages of data-driven methods in optimizing placement strategies[5].

Zhang et al. (2019) investigated the effectiveness of campus recruitment using Big Data analytics. Presented at the 2019 International Conference on Smart Grid and Electrical Automation (ICSGEA), the study explored how large-scale data processing techniques can improve talent acquisition strategies. The research highlighted the importance of leveraging advanced computational models to enhance recruitment accuracy, ensuring that companies find the best-fit candidates efficiently[6].

These studies collectively underscore the growing importance of machine learning and data-driven approaches in student placement prediction. While prior research has primarily focused on rule-based models, decision trees, and clustering techniques, our study extends the analysis by incorporating multiple machine learning models, feature selection techniques, and data balancing strategies using SMOTE, providing a comprehensive and optimized approach for placement prediction.

Traditional student placement prediction approaches primarily rely on rule-based decision-making and statistical analysis, where academic institutions use historical placement records, CGPA-based cutoffs, and company eligibility criteria to shortlist candidates for recruitment drives. These methods often lack adaptability to evolving industry trends and do not consider non-academic factors influencing employability.

Several studies have attempted to improve placement prediction using machine learning and data mining techniques. Research by Nichat & Raut and Nesamanikandan & Kannan applied Decision Trees and data mining methods to classify students based on academic performance and extracurricular activities. Similarly, studies by Shahane (2022) and Singh et al. (2022) employed Decision Trees, Naïve Bayes, and simple regression models for predicting placement outcomes. However, these traditional models have several limitations that impact their effectiveness:

Limited Feature Consideration: Most conventional models focus primarily on CGPA, SSC, and HSC marks while neglecting essential factors such as internships, certifications, soft skills, and placement training, which significantly influence hiring decisions.

Imbalanced Data Handling: Many existing studies fail to address the issue of class imbalance between placed and non-placed students, leading to biased models that favour the majority class.

Model Performance Constraints: Prior research often relies on single-algorithm approaches, such as Decision Trees or Naïve Bayes, without comparing multiple models to determine the best-performing classification technique.

Lack of Scalability: Traditional rule-based and static models struggle to adapt to changing recruitment trends, evolving job requirements, and industry-specific hiring practices, making them less effective in dynamic placement environments.

3. Methods and materials

The proposed system for student placement prediction integrates multiple machine learning algorithms to analyze

ISSN: 2582 - 4201(Online) , http://www.ijrdes.com/ , IJRDES, Vol. 7, Issue 3, 2025 , https://doi.org/10.63328/IJRDES-V7RI3P1

both academic and non-academic factors influencing employability. Unlike traditional methods that primarily focus on CGPA and academic scores, this system incorporates additional attributes such as internships, projects, certifications, aptitude scores, soft skills, and extracurricular activities. By considering a holistic set of features, the system provides a more accurate and realistic placement prediction model.

The system applies six machine learning algorithms— LR, SVM, DT, RF, KNN, and GNB —to classify students as "placed" or "not placed." Each model is evaluated based on metrics to determine the best-performing approach. To address data imbalance, the SMOTE is used, ensuring fair classification and unbiased predictions.

Additionally, a feature selection process is implemented to identify the most influential factors affecting student placement. The analysis highlights that CGPA, aptitude test scores, and placement training play a crucial role in recruitment success. Among the models tested, Random Forest achieves the highest accuracy of 79.72%, demonstrating superior predictive capability. This system provides valuable insights for students and institutions, helping them refine training programs and improve placement rates through data-driven decision-making.

4. System Design

System Architecture represents the process of developing a ML/DL model, starting from data loading and preprocessing, followed by feature engineering and model training. After training, the model is tested and evaluated based on accuracy, and if the desired accuracy is not achieved, it is retrained through iterations. Once satisfactory performance is attained, the results are displayed, completing the workflow.

4.1. Datasets

The dataset used in this study consists of 10,000 student records, providing a comprehensive view of various factors affecting placement outcomes. It includes a combination of academic, skill-based, and behavioral attributes to enhance the predictive capabilities of machine learning models. The key attributes in the dataset are:

Academic Performance: CGPA, SSC Marks, HSC Marks.
Skill-Based Attributes: Number of internships, projects, workshops, and certifications completed.
Aptitude and Soft Skills: Aptitude test score and soft skills rating.

Extracurricular Activities: Participation in clubs, sports, and student organizations.

Placement Training: Whether the student attended formal placement preparation programs.

Placement Status: The target variable indicating whether a student is placed (1) or not placed (0).

The dataset allows for a detailed analysis of the factors influencing placement trends and provides a strong foundation for machine learning-based predictive modelling.

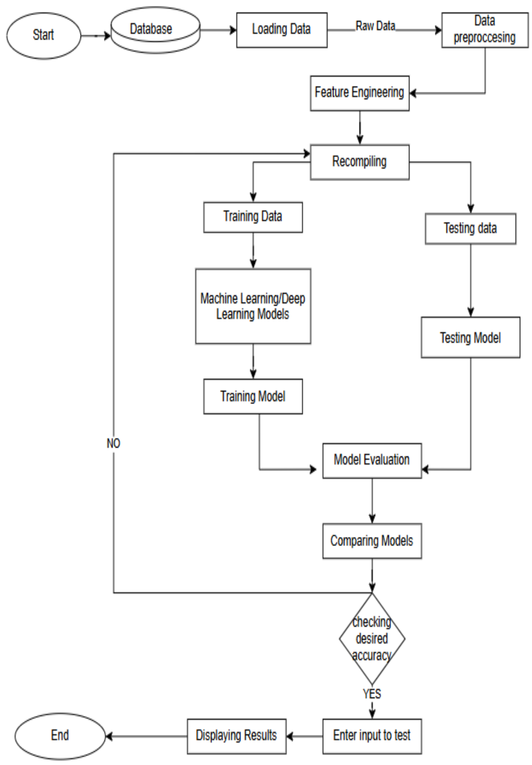

Fig.1 System Architecture

4.2. Data Preprocessing

Data preprocessing is a crucial step in ensuring data quality before training machine learning models. The following preprocessing techniques were applied:

Handling Missing Values: The dataset was examined for missing values, and no missing entries were detected. If missing values were present in real-world applications, they would be handled using techniques such as mean imputation for numerical attributes or categorical encoding for categorical variables.

Removing Duplicates: To maintain data integrity, duplicate entries were identified and removed to ensure that each student record was unique.

Encoding Categorical Values: Categorical variables were converted into numerical representations for effective processing by machine learning models. The attributes Extracurricular Activities and

ISSN: 2582 - 4201(Online) , http://www.ijrdes.com/ , IJRDES, Vol. 7, Issue 3, 2025 , https://doi.org/10.63328/IJRDES-V7RI3P1

Placement Training were assigned binary values (Yes = 1, No = 0), and Placement Status was labelled as (Placed = 1, Not Placed = 0).

Feature Scaling: Since the dataset contains continuous variables such as CGPA, aptitude test scores, soft skills rating, SSC marks, and HSC marks, feature scaling was applied to normalize the range of numerical values. This ensures that no single feature dominates the machine learning models, improving predictive performance.

Handling Data Imbalance: The dataset exhibited an imbalance between placed and non-placed students, which could lead to biased predictions. To address this, SMOTE was applied to balance the dataset, ensuring an equitable distribution of placed and non-placed students. This technique prevents the model from favouring the majority class and enhances classification accuracy.

4.3. Feature Selection

Feature selection was conducted to identify the most relevant factors influencing student placement. The Select Best (ANOVA F-test) method was employed to rank the significance of features based on their statistical correlation with the placement outcome. The five most significant attributes identified were:

- *CGPA* – A strong determinant of placement success.
- *Aptitude Test Score* – Higher scores were correlated with increased placement probability.
- *Placement Training* – Students who participated in formal training were more likely to be placed.
- *Internships & Certifications* – Industry exposure and additional qualifications significantly influenced placement success.
- *Soft Skills Rating* – Higher soft skills ratings were associated with better interview performance and job offers.

4.4. Feature Importance Analysis

A detailed analysis of feature importance was conducted using visualization techniques.

- CGPA vs Placement Status: Higher CGPA showed a strong positive correlation with placement success.
- Internships vs Placement Status: A higher number of internships increased placement chances.
- Projects vs Placement Status: Completing multiple projects was linked to better placement outcomes.
- Extracurricular Activities vs Placement Status: Participation in extracurricular activities improved placement opportunities.

By selecting the most significant features, unnecessary attributes were removed, reducing overfitting and improving model generalization.

4.5. Building Training and Testing Sets

Ensuring balanced representation of placed and non-placed students. Various split ratios such as 80:20, 70:30, and 60:40 were analyzed, and the 80:20 split was found to be optimal for model performance.

4.6. Machine Learning Algorithms

The Student Placement Prediction System utilizes six machine learning algorithms to classify students as placed (1) or not placed (0). These models process historical placement data, analyze key features, and generate predictions based on academic, skill-based, and behavioral attributes. Each algorithm follows a structured computational process, including data preprocessing, model training, classification, and evaluation. The models implemented in this study are LR, SVM, DT, RF, KNN, and GNB.

Logistic Regression in this probability ≥ 0.5, the student is classified as placed (1); otherwise, they are not placed (0). Logistic Regression is computationally efficient and interpretable, making it useful for linear classification problems. However, it struggles with non-linearly separable data, limiting its applicability in complex datasets. The Support Vector Machine (SVM) model, on the other hand, constructs an optimal to map non-linear relationships. SVM performs well in high-dimensional spaces but requires proper hyperparameter tuning and is computationally expensive for large datasets.

Decision Tree is a rule-based model that classifies students by splitting data into hierarchical decision paths. The tree is built using conditions on feature values (e.g., "If CGPA > 8, then placed; otherwise, check internships"). The model calculates the Gini Index or Entropy to determine the best split at each node, ensuring an optimal classification path. While Decision Trees are interpretable and handle mixed data types, they are prone to overfitting and often require pruning techniques to generalize well. Random Forest, an ensemble learning method, overcomes this issue by combining multiple Decision Trees, each trained on random subsets of the dataset.

The final classification is determined through majority voting, reducing overfitting and increasing accuracy. Random Forest achieved the highest accuracy (79.72%), making it the best-performing model for placement prediction. However, it requires higher computational power and hyperparameter tuning to optimize performance.

K-Nearest Neighbours (KNN) classifies students based on the placement status of their closest K data points. The model calculates the Euclidean distance between the new

ISSN: 2582 - 4201(Online) , http://www.ijrdes.com/ , IJRDES, Vol. 7, Issue 3, 2025 , https://doi.org/10.63328/IJRDES-V7RI3P1

student's attributes and the training dataset, selecting the K-nearest neighbors to determine the majority class. KNN is simple and requires no training phase, making it efficient for small datasets. However, choosing an optimal K value and handling large datasets can be computationally expensive. GNB applies Bayes' Theorem to calculate the probability of placement based on independent feature distributions. It assumes a Gaussian (normal) distribution for numerical features and calculates the likelihood of a student being placed given their academic and skill-based attributes. GNB is computationally fast and effective for small datasets but assumes feature independence, which is unrealistic in complex placement data. Overall, while each model has strengths and weaknesses, Random Forest demonstrated the best classification performance, making it the most reliable predictor of student placements.

4.7. Placement Prediction Testing System

A real-time placement prediction system was developed, enabling students to input their academic and skill-related details to receive an automated prediction of their placement probability. This system provides valuable insights to students, allowing them to assess their employability and improve weak areas before participating in recruitment processes.

5. Results

The process of predicting a student's placement outcome involves several computational steps to ensure accuracy and reliability. The model receives student details, processes the input data using machine learning algorithms, and predicts the likelihood of the student securing a placement.

Fig.1 Placement training vs PS

Figure-1 describes the bar chart shows that students who underwent placement training had a higher chance of securing placement. Those without training had significantly fewer placements.The outcome is expressed in binary form, where 1 represents a placed student and 0 represents a non-placed student. This result provides valuable insights for students and institutions regarding factors that contribute to employability. The accuracy and robustness of the predictions depend on the quality of the dataset, feature selection, and the effectiveness of the applied machine learning models.

To evaluate the performance of different machine learning algorithms, six classifiers were implemented: LR, SVM, DT, RF, KNN, and GNB Each model was tested using accuracy, precision, recall, and F1-score to assess its predictive capability. Among all models, Random Forest achieved the highest accuracy of 79.72%, demonstrating its effectiveness in placement prediction. This model outperformed others due to its ability to handle complex datasets by combining multiple decision trees, reducing overfitting, and improving prediction stability. Other models, such as Logistic Regression and SVM, also showed competitive performance, while Decision Tree and KNN had moderate accuracy.

Gaussian Naïve Bayes performed the worst, likely due to its assumption of feature independence, which is rarely applicable in real-world placement datasets.Apart from model evaluation, this study also focused on identifying the most influential factors affecting student placements. Feature selection using Select KBest (ANOVA F-test) revealed that the top five contributing factors were CGPA, aptitude test scores, placement training, internships & certifications, and soft skills rating. These results indicate that academic performance alone is not sufficient for securing placements; a combination of technical skills, aptitude, industry exposure, and communication skills significantly enhances employability. This insight is crucial for students, as it helps them understand the areas they need to focus on to increase their chances of securing a job. Similarly, institutions can optimize their training programs by incorporating industry-specific certifications, mock interviews, and soft skills development programs to better prepare students for campus recruitment.

5.1. Experimentation Analysis

Table-1 summarizes the presents the accuracy of different machine learning algorithms used for placement prediction. The highest accuracy was achieved by the Random Forest model (79.72%), while the Decision Tree performed the lowest at 73.42%.

Table.1 Our Accuracy scores

Algorithm	Accuracy (%)
LR	79.06
SVM	78.46
DT	73.42
RF	79.72
KNN	76.96
GNB	78.04

ISSN: 2582 - 4201(Online) , http://www.ijrdes.com/ , IJRDES, Vol. 7, Issue 3, 2025 , https://doi.org/10.63328/IJRDES-V7RI3P1

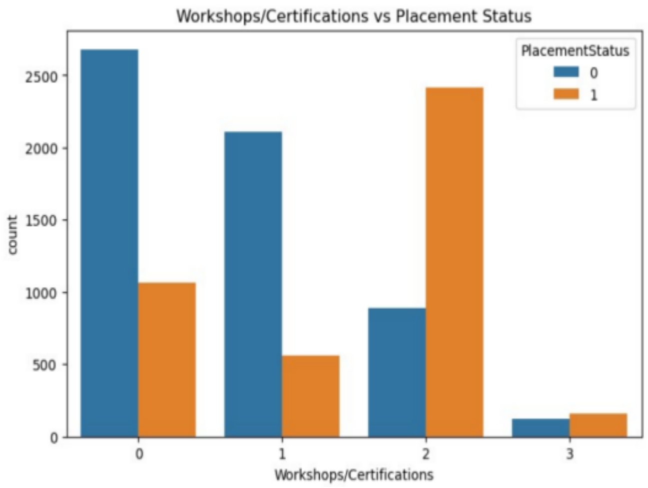

Fig.2 workshops vs PS

Figure-2 describes the plot indicates that students who participated in more workshops and certifications had a higher placement rate. The highest placements were observed in students with two certifications.

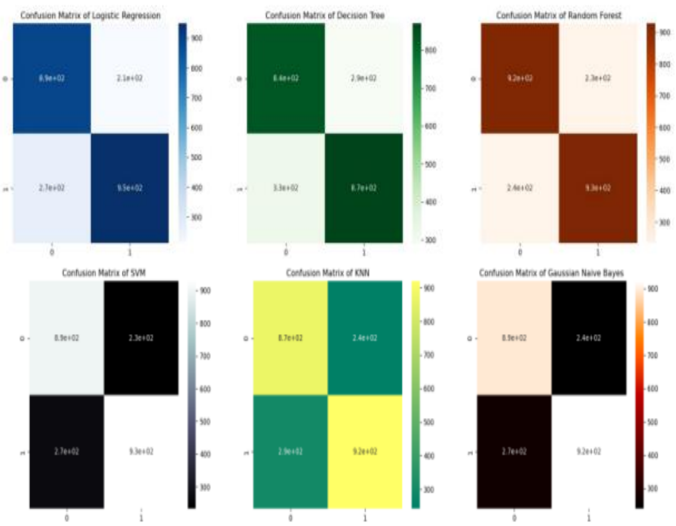

Fig.3 Confusion matrix

Figure-3 describes the confusion matrices illustrate the classification performance of LR, DT, and RF models. Random Forest achieved the highest correct classifications.

Figure-4 describes the line graph visually compares the accuracy of different machine learning models. Random Forest had the highest accuracy, while Decision Tree had the lowest.

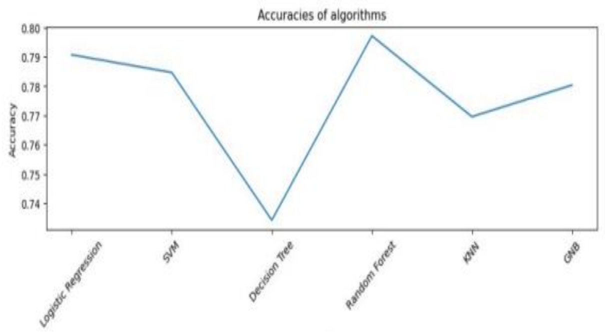

Fig.4 Accuracy graph

Table-2 summarizes the precision, recall, and F1-score of various classification models. Random Forest demonstrated the best performance across all metrics, closely followed by Logistic Regression.

Table.2 Performance metrics

Algorithm	Acc (%)	Pre (%)	Rec (%)	F1-Score (%)
Logistic Regression	79.06	79.84	76.92	78.36
SVM	78.46	78.62	75.41	77.00
Decision Tree	73.42	74.18	70.39	72.24
Random Forest	79.72	80.25	77.48	78.84
KNN	76.96	77.13	74.29	75.69
GNB	78.04	78.36	74.85	76.55

5.2. Discussion

The study highlights the importance of machine learning in predicting student placement outcomes, providing valuable insights into the key factors influencing recruitment success. The Random Forest model achieved the highest accuracy of 79.72%, outperforming other classification algorithms such as LR, SVM and DT. The feature importance analysis demonstrated that CGPA, aptitude test scores, placement training, internships, and soft skills play a significant role in determining placement success. Additionally, the application of SMOTE for handling data imbalance improved the model's fairness by ensuring equal representation of placed and non-placed students during training.

Despite the promising results, certain challenges and limitations exist. First, while the dataset was diverse, it was limited to specific academic and skill-based parameters, excluding factors such as student projects, extracurricular leadership roles, and external industry certifications. Additionally, the execution time of some models, such as SVM and Random Forest, was relatively high, making them less suitable for real-time applications. Finally, the models primarily relied on historical placement data, and external job market fluctuations were not considered, which may impact generalization.

6. Conclusion and Future Scope

This study successfully implements a machine learning-based approach for predicting student placements by analyzing academic, skill-based, and behavioural attributes. The dataset was pre-processed, and feature selection techniques were applied to identify the most influential factors affecting placement outcomes. A comparison of six classification models demonstrated that Random Forest achieved the highest accuracy of 79.72%, outperforming other classifiers. The findings indicate that CGPA, aptitude test scores, placement training,

ISSN: 2582 - 4201(Online) , http://www.ijrdes.com/ , IJRDES, Vol. 7, Issue 3, 2025 , https://doi.org/10.63328/IJRDES-V7RI3P1

internships, and soft skills play a significant role in determining whether a student secures a placement. Additionally, the application of SMOTE to handle data imbalance ensured fair classification and unbiased predictions across different student categories.

The insights gained from this study can assist students, academic institutions, and recruiters in making data-driven decisions. Educational institutions can utilize these findings to enhance training programs and career counselling initiatives, while students can focus on improving key factors that enhance employability. Future research can explore deep learning models and real-time predictive analytics to further refine placement prediction frameworks. Additionally, integrating industry-specific skill assessments and external job market trends could improve model generalization and practical applicability in real-world hiring processes.

Future research can explore deep learning techniques, such as neural networks and transformer-based models, to improve classification accuracy and enhance feature extraction. Implementing real-time predictive analytics that dynamically updates with new placement data can improve decision-making for students and institutions. Additionally, integrating external job market data, industry hiring trends, and domain-specific skill assessments can refine model generalization and practical applicability.

Another important area for future work is developing an interactive placement prediction system, where students can input their academic performance, skills, and training details to receive a personalized placement prediction along with recommendations for improving employability. Incorporating explainable AI (XAI) techniques can help provide transparent insights into why a particular student is predicted to be placed or not, making the model more interpretable for students and institutions. Finally, expanding the dataset to multiple institutions and industries can help validate the robustness of the model across different educational environments and hiring practices

References

[1] P. Shahane, "Campus Placements Prediction & Analysis using Machine Learning", Internastional Conference on Emerging Smart Computing and Informatics (ESCI), 2022.

[2] Nichat, Ankita A and Dr. Anjali B. Raut, "Predicting and Analysis of Student Performance Using Decision Tree Technique", International Journal, 2017.

[3] Singh S, Singh P, Kaur M, "Placement Analysis— A New Approach to Ease the Recruitment Process", Lecture Notes in Electrical Engineering, Springer Science and Business, 2022.

[4] Raya R & S.K.V, "Analysis of Campus Recruitment Parameters in an Indian Context", Mediterranean Journal of Social Sciences.

[5] Nesamanikandan M, Kannan M, "Placement Analysis using Data Mining", International Journal, (6), 194–198.

[6] Y. Zhang, X. Luo, C. Zhong, X. Cai and X. Gao, "Research on The Effectiveness of Campus Recruitment Based on Big Data", 2019 International Conference on Smart Grid and Electrical Automation (ICSGEA), Xiangtan, China, 2019.

[7] Sivaram N, & Ramar K, "Applicability of Clustering and Classification Algorithms for Recruitment Data Mining", International Journal of Computer Applications, 4(5).

[8] Snehal Patil and Pranav Shah, "Campus Recruitment Analysis using Machine Learning Algorithms", International Journal of Advanced Research in Computer Science and Software Engineering, Vol. 9, Issue 1, January 2019.

[9] Suresh Kumar J., Sankar G., and Sathish Kumar V., "Campus Recruitment Prediction using Data Mining Techniques", International Journal of Innovative Technology and Exploring Engineering, Vol. 8, Issue 7, May 2019.

[10] Shruti Sharma, "Predictive Analytics in Campus Recruitment: A Comparative Study", International Journal of Computer Science and Mobile Computing, Vol. 7, Issue 4, April 2018.

[11] S. D. M. L. S, "A Chatbot using NLTK without Human Interaction," *International Journal of Computational Science and Engineering Research*, vol. 1, no. 1, Dec. 2024, doi: 10.63328/ijcser-v1ri1p5.

[12] Chandrakala K. and Divya T., "Campus Recruitment Analysis and Prediction using Machine Learning Techniques", International Journal of Recent Technology and Engineering, Vol. 8, Issue 2, October 2019.

[13] N. Kumar, A. S. Singh, T. K, and E. Rajesh, "Campus Placement Predictive Analysis using Machine Learning", 2020 2nd International Conference on Advances in Computing, Communication Control and Networking (ICACCCN), Greater Noida, India, 2020.

[14] Sachin Bhoite, Anuradha Kanade, Punam Nikam, and Deepali Sonawane, "Predictive Analytics Model of an Engineering and Technology Campus Placement", Proceedings of the International Conference on Computational Science and Applications: ICCSA 2021, Springer Nature Singapore, 2022.

[15] Ms. Sonal Patil, Mr. Mayur Agrawal, Ms. Vijaya R. Baviskar, "Efficient Processing of Decision Tree using ID3 & Improved C4.5 Algorithm", International Journal of Computer Science and Information Technologies.

[16] J. Nagaria and S. V. S, "Utilizing Exploratory Data Analysis for the Prediction of Campus Placement for Educational Institutions", 2020 11th

ISSN: 2582 - 4201(Online) , http://www.ijrdes.com/ , IJRDES, Vol. 7, Issue 3, 2025 , https://doi.org/10.63328/IJRDES-V7RI3P1
International Conference on Computing, Communication and Networking Technologies (ICCCNT), Kharagpur, India, 2020.

[17] R. Ramakrishna V. and B. B. T, "Role of Spirituality in Self-Development : A Conceptual study," *International Journal of Computational Science and Engineering Research*, vol. 2, no. 2, p. 1, Apr. 2025, doi: 10.63328/ijcser-v2i2p1.

[18] S. Bhoite, C. H. Patil, S. Thatte, V. J. Magar, and P. Nikam, "A Data-Driven Probabilistic Machine Learning Study for Placement Prediction", 2023 International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT), Bengaluru, India, 2023.