

¹Anuj Gupta²Sunny Gupta³Pawan Kumar
Mall⁴Swapnita
Srivastava⁵Aman Singh
Saluja⁶Neeraj Yadav⁷Vipul Narayan⁸Dr. Mandhir K
Verma⁹Srinivasan
Sriramulu

ML-CPC: A Pathway for Machine Learning Based Campus Placement Classification



Abstract: - The intense competition among students for a limited number of job opportunities poses a significant challenge to campus placements. There are various strategies that organizations can employ to tackle this issue. Primarily, it is essential to provide high-quality educational programs and opportunities for professional development that align with current market needs. This involves regularly updating the curriculum, integrating sector-relevant projects, and facilitating hands-on training experiences. Campus placements play a crucial role in evaluating an institution's caliber and ensuring the employability of its students. Institutions can enhance their placement records by implementing innovative solutions to challenges encountered in placements, such as intense competition and economic fluctuations. This requires a proactive strategy, collaboration with businesses, a focus on skill enhancement, and support for students' soft skills and professional development. By implementing these corrective measures, institutions can contribute to students' future success by better preparing them for the workforce. The primary objective of this paper is to conduct an exploratory analysis of the recruitment dataset. The application of supervised machine learning is employed to predict whether a student was placed, utilizing classification models. The proposed approaches and methods surpass all other machine learning models, achieving a recall value of 1, accuracy of 0.9524, precision

¹Assistant Professor, G.L. Bajaj Institute of Technology and Management
er.anujgupta013@gmail.com

²Assistant Professor, G.L. Bajaj Institute of Technology and Management
gupta08aug@gmail.com

³Assistant Professor, G.L. Bajaj Institute of Technology and Management
pawankumar.mall@gmail.com

⁴Assistant Professor, G.L. Bajaj Institute of Technology and Management
swapnitasrivastava@gmail.com

⁵Assistant Professor, SR Group of Institutions, Jhansi
Amansaluja@srgi.ac.in

⁶Assistant professor, SR group of institutions jhansi
neerajyadavcse09@gmail.com

⁷Assistant Professor, Galgotias University, Greater Noida
vipulupsainian2470@gmail.com

⁸Associate Professor, ECE Department GL Bajaj Group of Institutions, Mathura UP

⁹Professor School of Computing Science and Engineering GALGOTIAS UNIVERSITY Greater Noida
s.srinivasan@galgotiasuniversity.edu.in

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of 0.8667, and an F1 score value of 0.9286 to address the ensemble architectural.

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I. INTRODUCTION:

Campus placement has received a great deal of attention recently. It is a scheme run within educational institutions or in a public setting to give jobs to students who are enrolled in or nearing completion of the degree. Pre-placement talks, online assessments, group discussions, technical interviews, Human Resources (HR) interviews, and post-placement speeches are the procedures that are often taken in university hiring. Businesses visit universities to choose students based on their aptitude for the job, capacity, concentration, and goal. Engagement with business is another effective approach. The institution can work with companies to establish collaborations, invite visiting lecturers and subject-matter experts for seminars, and set up internships and business trips. Students are exposed to real-world scenarios, business practices, and networking opportunities in these curricula, which increases their employability.

Every institution's goal is to increase the number of placements. It not only helps students by giving them greater employment possibilities, but it also has a big impact on the school's standing, admissions, reputation, and financial stability. In order to improve their placement results and live up to the expectations of students, parents, and management, institutions use a variety of tactics, such as working with recruiters, skill development programmes, and effective placement cells. It is true that the placement process has a significant impact on both students and organisations. As the start of their professional lives, placements are highly anticipated by students. On the other side, universities are eager to boost placement rates since they influence future admissions and reflect the calibre of education delivered. Since placements signal the start of their professional lives, students excitedly get ready for them. On the other side, colleges are motivated to increase the number of placements since it not only reflects the quality of education delivered but also influences future admissions.

There is a worrying trend in the National Association of Software and Services Companies (NASSCOM) predictions for recruiting in the IT sector. Key companies including TCS, Wipro, Accenture, Tech Mahindra, Mercedes Benz, Robert Bosch, and Infosys are focusing on automation, which points to a change in their hiring strategy that may lead to fewer hires in the near future. NASSCOM surveys, analysis, and observations indicate that a 20% decrease in hiring is anticipated in the IT sector. This forecast is in line with the decrease in hiring plans made by NASSCOM for the domestic software industry. 2.3 lakh recent graduates were projected to be hired in the 2016–17 fiscal year, down from 2.95 million the previous year.

The demand for more efficiency, cost savings, and technical improvements are what are driving the focus on automation in the IT industry. While automation may result in a decline in some work functions, it also opens up new career options for qualified experts in cutting-edge fields. Given these predictions, it becomes imperative for educational institutions and students to adjust and match their education and skill sets to the shifting needs of the market. To increase their employability in the changing employment market, students should concentrate on gaining knowledge in fields like artificial intelligence, machine learning, data analytics, cybersecurity, and other new technologies.

II. PLACEMENT CHALLENGES:

Campus placement processes can come with various challenges for both students and institutions. Some common challenges include:

- **Competition:** Campus placements often attract a large number of students vying for a limited number of job opportunities. The high level of competition can make it challenging for students to stand out and secure their desired job placements [10].
- **Industry Requirements:** Matching the skills and qualifications of students with the specific requirements of the industry can be a challenge. Sometimes, the curriculum and training provided by institutions may not align perfectly with the dynamic needs of employers, making it harder for students to meet the desired criteria[11].
- **Economic Fluctuations:** Economic conditions and business cycles can significantly impact job opportunities. During economic downturns or recessions, companies may reduce their hiring or freeze their recruitment processes, leading to fewer placement opportunities for students [12].

- **Lack of Soft Skills:** While technical knowledge is important, employers also value soft skills such as communication, teamwork, problem-solving, and adaptability. Students who lack strong soft skills may face challenges in interviews and interacting with potential employers [13].
- **Limited Company Participation:** Some institutions may face challenges in attracting a diverse range of companies for campus placements. Limited participation from companies, especially from sectors that are highly sought after by students, can restrict the variety of job opportunities available [14].
- **Mismatched Expectations:** Students may have certain expectations regarding salary, job roles, or company reputation, which may not always align with the opportunities available during campus placements. Managing these expectations and finding the right fit can be a challenge for both students and placement coordinators [15].
- **Lack of Guidance and Preparation:** Students may face challenges in understanding the placement process, writing effective resumes, preparing for interviews, and showcasing their skills and achievements. Inadequate guidance and preparation support from institutions can hinder students' ability to perform well during placements [16].
- **Gender Bias and Diversity:** In some cases, gender bias and lack of diversity in certain industries or companies may pose challenges for students from underrepresented groups in securing placements [17].

Addressing these challenges requires a multi-faceted approach involving students, institutions, and recruiters. Institutions can focus on providing holistic education, incorporating skill development programs, strengthening career development and placement cells, and fostering industry collaborations. Students can proactively enhance their technical and soft skills, seek mentorship, and leverage networking opportunities to increase their chances of placement success. Recruiters can contribute by considering diverse talent pools and providing equal opportunities to students from different backgrounds. By recognizing and addressing these challenges, institutions can work towards improving the campus placement experience and enhancing students' employability in a competitive job market [18].

III. RELATED WORK:

In [1], authors have proposed the LMT prediction model using real data from the University of Peshawar that is based on academic demographic and socioeconomic futures factors for option selection for more investigations. In comparison to the LMT model, J48 and Random Forest are used. 83.1% accuracy was attained using the suggested LMT model. In [2], authors have proposed ML based model to forecast student performance using real student data from VNU University of Science as well as three educational data sets acquired from KDD data sets, authors have suggested MANFIS with RS. Compared to previous fuzzy and tree-based models, the experimental validation produced high accuracy. In [3], authors have proposed ML based model to forecast placement in the present student data set using the previous student data set, writers have recommended using Naive Bayes and KNN ML models. The suggested ML models' training data set is a set of passed-out student data with placement status. In [4], authors have proposed convolutional neural network (CNN) model to predict student performance using historical data set. The accuracy of the CNN-based deep learning model, which generated 97.5%, is higher than that of other models. The placement forecast process has been investigated by authors in [5] using SVM, LR, KNN, and Random Forest, and the accuracy and performance metrics have been compared. The characteristics utilised for the placement training include the scores in the areas of verbal, technical programming, reasoning, numeric aptitude, and academic CGPA, as well as backlogs and certification information. In [6], authors proposed hybrid model to study student placement data using the AdaBoost classifier together with the Decision Stump, NB Tree, and Random Forest classifiers. They found that the AdaBoost + Random Forest classifier combination achieved higher accuracy (87.09%) than the Decision Stump and NB Tree classifiers. The Random Forest performs better with the assistance of AdaBoost. Only 79.85% accuracy was obtained by Random forest without AdaBoost. In [7], authors have proposed using J48 to categorise student academic data and forecast academic performance during the era of the covid epidemic. The categorization and end-of-semester test performance prediction method in this model uses a real-time student academic data set with 96.42% accuracy. In [8], authors have proposed that J48 be used to predict the likelihood of student placement with 87% accuracy across the whole data set. This forecast makes use of a data collection of students who have graduated. In [9], authors have proposed ML models NB, SVM, DT, KNN, and Neural network to examine and provide prediction techniques for learning outcomes. For this method, a data set was derived from internal marks and student CGPA.

IV. METHODOLOGY

There are several steps involved in experiment process. This includes data pre-processing, feature selection, proposed methodology implementation, model training, model evaluation.

4.1 Dataset: This dataset contains of Placement record of Indian Institute of Management, Bangalore students shared by Dr. Dhimant ganatara on kaggle platform. It includes percentage details of secondary and higher secondary school including specialization. It also provide additional details like degree specialization, experience and salary offers to students during placement. In total we have 215 records. Table 1 contains top five rows from dataset.

Table 1: Top five rows of the dataset

Index	gender	ssc_p	ssc_b	hsc_p	hsc_b	hsc_s	degree_p	degree_t	Workex	etest_p	Specialisation	mba_p	salary	status
0	M	67	Others	91	Others	Commerce	58	Sci&Tech	No	55	Mkt&HR	58.8	270000	Placed
1	M	79.33	Central	78.33	Others	Science	77.48	Sci&Tech	Yes	86.5	Mkt&Fin	66.28	200000	Placed
2	M	65	Central	68	Central	Arts	64	Comm&Mgmt	No	75	Mkt&Fin	57.8	250000	Placed
3	M	56	Central	52	Central	Science	52	Sci&Tech	No	66	Mkt&HR	59.43	NaN	Not Placed
4	M	85.8	Central	73.6	Central	Commerce	73.3	Comm&Mgmt	No	96.8	Mkt&Fin	55.5	425000	Placed

4.2 Data Pre-processing:

This involves handling missing values we found that salary feature is having 67 records missing, encoding categorical variables, duplicate records and splitting the dataset into training and testing sets. To handle the missing values in the salary feature, there are several options you can consider:[19][20].

- Dropping missing values: If the number of missing values is relatively small compared to the overall dataset, you can choose to drop those records. However, this approach should be used with caution as it may result in a loss of valuable data.
- Imputation: Imputation involves replacing missing values with estimated values based on the available data. There are different techniques for imputation, such as mean imputation (replacing missing values with the mean of the available data), median imputation, mode imputation, or using more advanced imputation methods like regression imputation or multiple imputation.

The missing values in the salary feature are as no data was available. Table 2 provides detail description of the dataset. We have use mean value use in our approach approaches.

Table 2: Details description of the dataset

Index	ssc_p	hsc_p	degree_p	etest_p	mba_p	salary
Count	215	215	215	215	215	148
Mean	67.3034	66.33316	66.37019	72.10056	62.27819	288655.4
Std	10.82721	10.89751	7.358743	13.27596	5.833385	93457.45
Min	40.89	37	50	50	51.21	200000
25%	60.6	60.9	61	60	57.945	240000
50%	67	65	66	71	62	265000
75%	75.7	73	72	83.5	66.255	300000
Max	89.4	97.7	91	98	77.89	940000

Use the Python pandas package to detect and manage duplicate records. Duplicate rows may be found using the duplicated() function, and they can be eliminated from the dataset using the drop_duplicates() function. Detecting null values: The isnull() method in pandas may be used to detect null values in the dataset. A Boolean mask specifying the locations of null values to be returned. After that, you may find the columns or rows containing null values by using procedures like sum() or any(). Many machine learning algorithms can only analyse categorical variables when they are numerically represented. For each category within a categorical variable, we have used the One-Hot Encoding approach to construct binary columns. The binary values (0 or 1) for each category are shown in distinct columns.

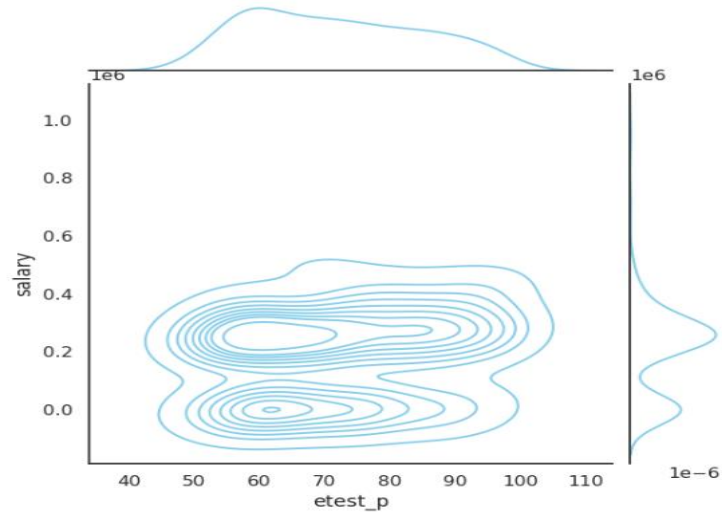


Figure 1: candidates score vs package

In figure 1 indicates that most of students having 60% marks have got the decent package of 3 lakhs annual, very few students have package above or around 4 lakhs and lower part of the graph indicates most of the student were not placed.

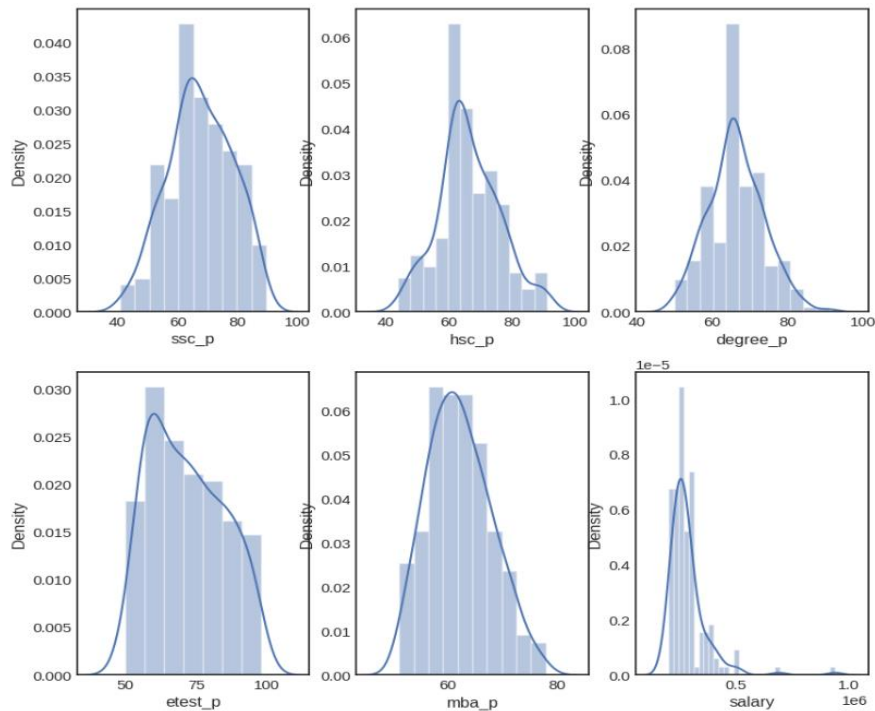


Figure 2: Student educational performance vs except salary distribution

Figure 2 indicates most of the student performance is range of 60 to 80 percentage. The distribution suggest all the distribution are normal except one feature that is salary. This feature has outliers as few student got salary in range 7 lakhs to 10 lakhs per annum.

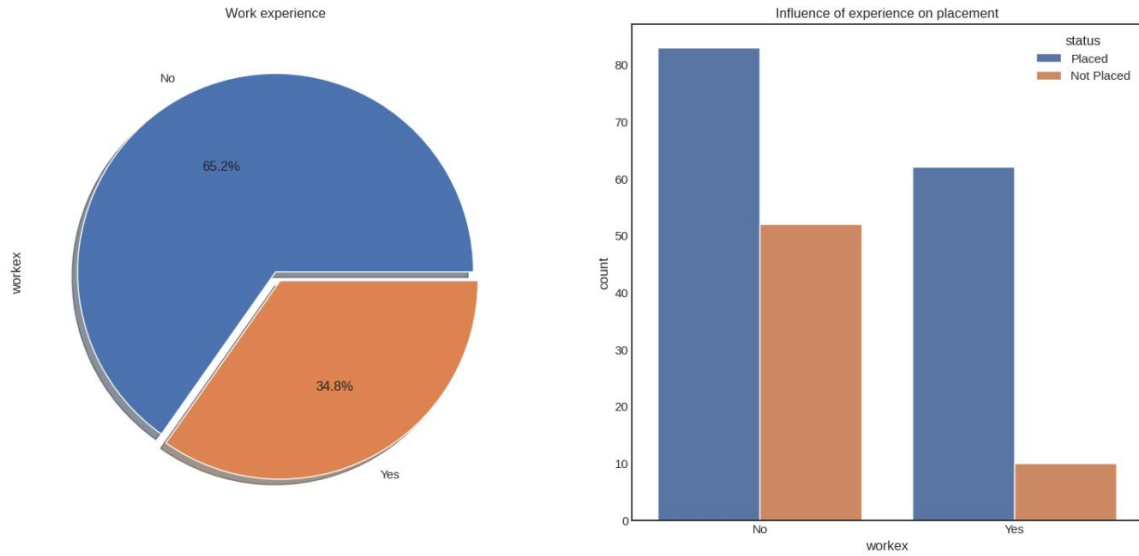


Figure 3: Placement Status Vs Work experience

Figure 3 indicates 66.2 percentage of student, who does not have any kind of work experience but statics shows that most of the student got placed who were having zero experience or they were just fresher's. We can conclude that most of work experiences does not influence the placement drives.

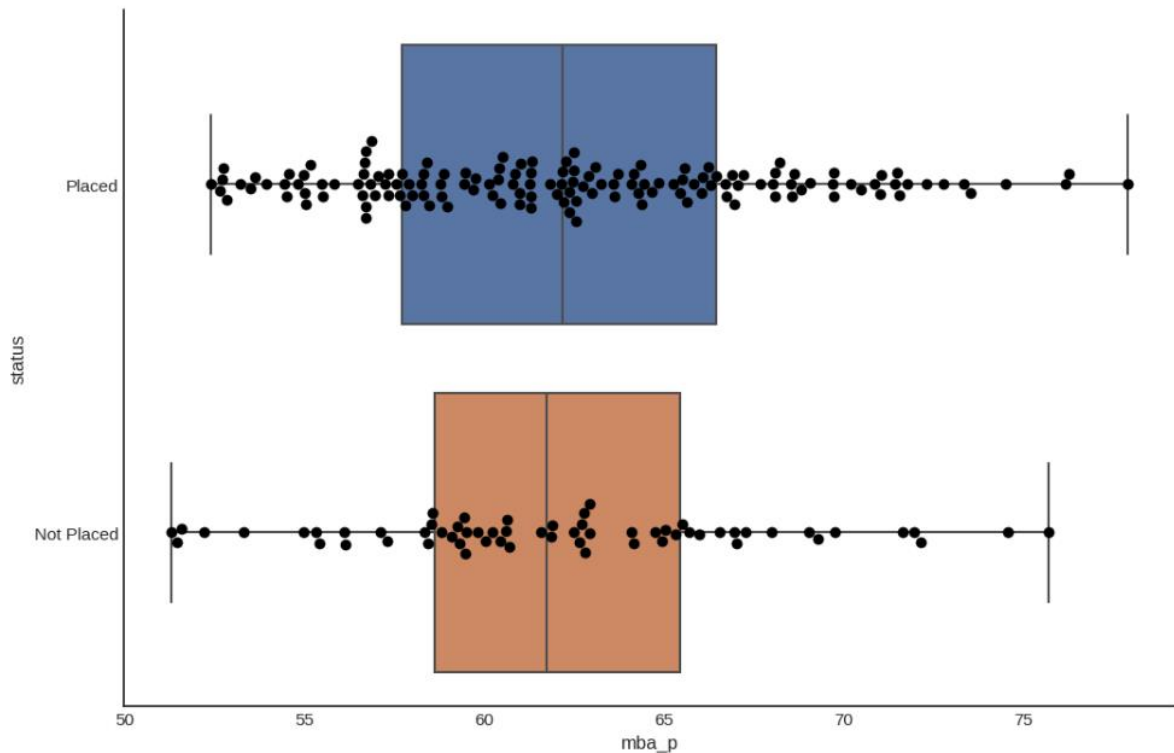


Figure 4: comparative analysis between students score and placed groups

Figure 4, Comparatively, the percentage scores between the two groups fluctuate little, but as we observe in the swarm together, the applicants who were placed still have the advantage in terms of numbers. Therefore, according to the plot, percentages do affect the placement status.

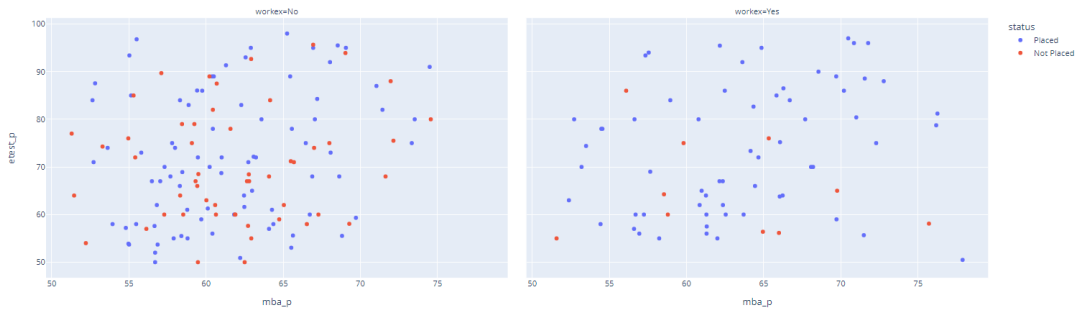


Figure 5: employability test VS mba percentage

The employability exam and mba percentage have no relationship. Since they lack job experience, many applicants have not been hired. The majority of students who scored well on both examinations were placed.

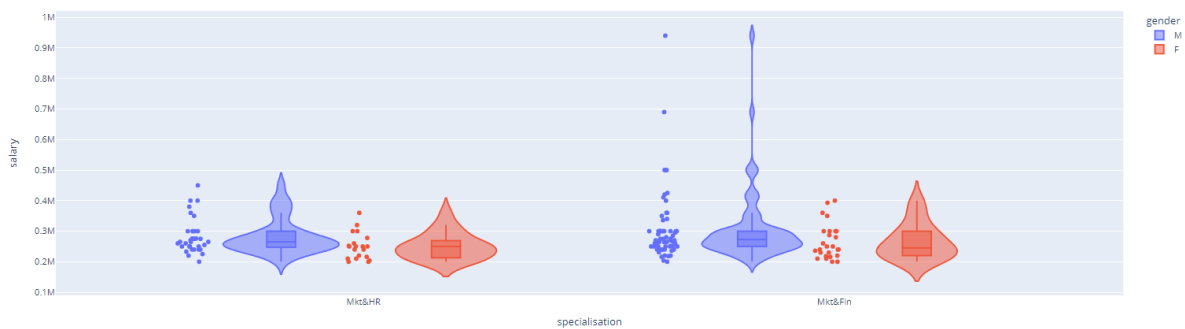


Figure 6: Comparative analysis of student based on gender of students

The figure 6 provides a comparative analysis of students depending on their gender. The highest incomes were obtained by male. Additionally, male received average salaries that were greater. Compared to female candidates, more male candidates were hired.

4.3 Feature Selection: Analysis the dataset to identify relevant features that may impact the placement outcome. This step can involve removing irrelevant features or creating new features based on domain knowledge. We have computed the correlation to find most correlated features from the dataset. The f figure 7 indicate that ssc percentage, degree percentage, etest percentage, mba percentage features are the important features.

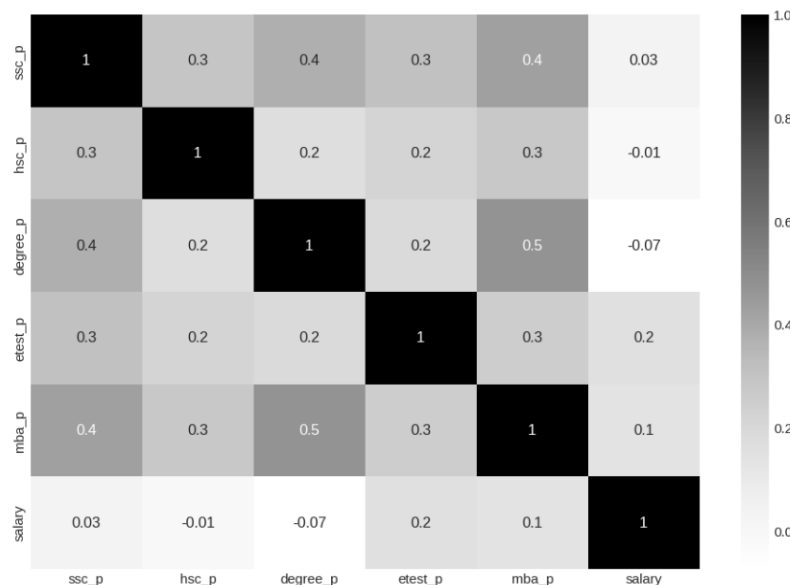


Figure 7: Correlation between the features

Standard Machine learning Models: an appropriate classification model from the pool of machine learning models such as Logistic Regression, Decision Trees, Random Forest, or Support Vector Machines (SVM). The choice of model depends on the dataset size, complexity, and performance requirements. We have proposed an ensemble learning based approach on voting pattern.

XGBoost:

Extreme Gradient Boosting, often known as XGBoost, is a potent machine learning algorithm that is a member of the ensemble learning family. It is frequently used for supervised learning tasks like classification and regression and makes use of a gradient boosting architecture. One of the most well-liked methods for structured/tabular data issues is XGBoost, which combines the benefits of gradient boosting techniques while addressing some of its drawbacks. It is renowned for its top-notch efficiency, scalability, and capacity for managing intricate relationships and feature interactions.

KNN:

A straightforward and understandable machine learning technique known as KNN, or k-nearest neighbours, is utilised for both classification and regression problems. It is a non-parametric technique that operates on the tenet that comparable data points frequently coexist in the feature space in close proximity to one another. A new data point is assigned by KNN to the class or value of its closest neighbours, where "k" is the number of neighbours taken into account. KNN is simple to use and understand, but it can be costly to compute for big datasets.

Random Forest:

An ensemble learning system called Random Forest mixes many decision trees to provide predictions. It is an effective technique that is frequently used for both classification and regression problems. By training each tree on a randomly chosen portion of the training data and employing a randomly selected subset of features at each split, Random Forest creates an ensemble of decision trees. Then, the combined forecasts of all the different trees are used to create the final prediction. The strengths of Random Forest include resilience, handling of high-dimensional data, and resistance to overfitting.

Decision Tree:

An efficient machine learning approach known as a decision tree is frequently used for classification and regression problems. On the basis of a variety of input features, it constructs a model resembling a tree of decisions and potential outcomes. Recursively dividing the data into the features that best distinguish between classes or reduce variation in the target variable results in the construction of the tree. Decision trees can handle both numerical and categorical data and are simple to comprehend. However, they are not appropriate for complicated interactions and can be prone to overfitting.

SVM:

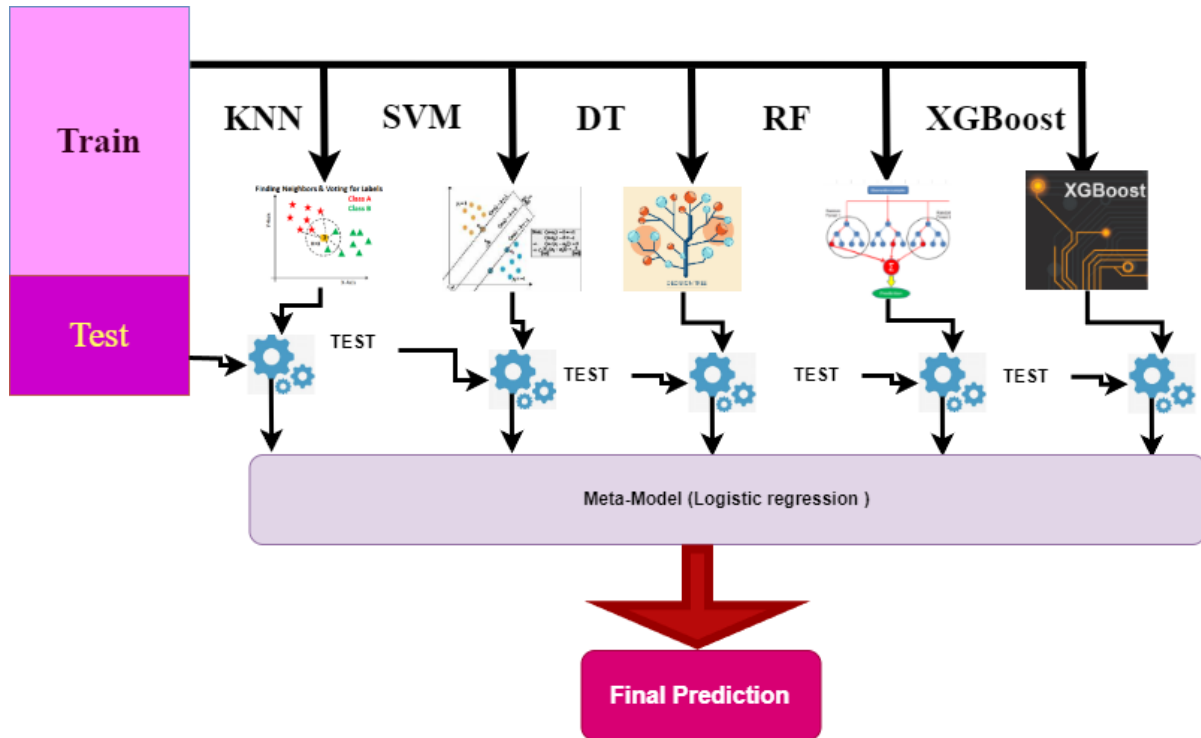
Support vector machines, or SVMs, are effective supervised learning algorithms used for regression and classification applications. The goal of SVM is to identify the ideal hyperplane that divides data points into distinct classes with the greatest possible margin. The input data is transformed into a higher-dimensional feature space, and a decision boundary is built by locating the support vectors, or the data points that are most near the separation hyperplane. High-dimensional data processing, the use of kernel functions to effectively handle non-linear connections, and strong generalisation performance are all strengths of SVM.

Logistic Regression:

For binary classification problems, a common statistical approach is logistic regression. Despite its name, it is a classification-focused linear model as opposed to a regression-focused one. By using the logistic function on a linear combination of the input characteristics, logistic regression calculates the odds that the result variable belongs to each class. Due to its efficiency, readability, and simplicity, it is extensively utilised. Both numerical and categorical features may be handled using logistic regression, which can also be expanded to tackle multi-class classification issues.

1.4 Proposed Methodology:

We have implemented the ensemble learning based on stacking. Combine the predictions of the base models to form the ensemble's output. Figure 8 provide overview of proposed model. Algorithm 1 provides complete details regarding the proposed methodology.



Algorithm 1: Ensemble learning based on stacking

Input:

- Input dataset (D_{Train}) with features (X) and Target labels (y)
- Base models (M_1, M_2, \dots, M_n)
- Meta-model (Meta)

Output:

- Test dataset (D_{test}) prediction result
1. Split the training dataset:
 - Split the training dataset into multiple folds (F_1, F_2, \dots, F_n) for cross-validation.
 2. Initialize the stacked dataset:
 - Create an empty matrix (S) to store the predictions from the base models.

For each fold F_i in F :

Split F_i into a training set (F_{i_train}) and a validation set (F_{i_val}).

3. Generate predictions from base models:

For each base model M_i :

Train M_i on F_{i_train} .

Predict F_{i_val} using M_i .

Append the predictions to S .

4. Train the meta-model on stacked dataset:

➤ Use S as the input features and the corresponding true labels from F_{i_val} as the target variable.

5. Train the meta-model Meta on S .

➤ Generate predictions from meta-model:

For each base model M_i :

Train M_i on the entire training dataset.

Predict the test dataset using M_i .

Append the predictions to a matrix T .

6. Final prediction from the meta-model:
 - Use T as the input features for the meta-model M .
 - Predict the final labels for the test dataset using M .
7. Output:
 - Final predictions for the test dataset (D_{test}).

4.5 Model Training: Train the selected model on the training dataset. This involves fitting the model to the features and the corresponding placement labels. Generating training and test sets from the dataset: To create training and test sets from the dataset, use the `train_test_split()` method in the Python scikit-learn module. In accordance with a defined test size or train size ratio, this function splits the dataset into two groups at random.

4.6 Model Evaluation: Assess the performance of the trained model using evaluation metrics such as accuracy, precision, recall, and F1-score. This step helps determine how well the model predicts the placement outcome.

- **Accuracy:** Accuracy quantifies how accurately a model's predictions are made in general. It determines the proportion of accurately predicted occurrences to all of the dataset's instances. Although accuracy is a frequently used statistic, it might not be appropriate for datasets with unequal representation of the classes.
- **Precision:** Precision focuses on the percentage of cases that are accurately predicted as positive out of all instances that are projected to be positive. When the model correctly predicts a favourable result, it is an indication of how trustworthy it is. The precision is computed by dividing the total of true positive and false positive predictions by the number of true positive forecasts.
- **Recall (Sensitivity or True Positive Rate):** Recall quantifies the percentage of positive cases that were properly predicted out of all of the actual positive instances in the dataset. It is an indicator of how effectively the model can locate examples of success. The number of accurate positive predictions is divided by the total of accurate positive and accurate negative predictions to determine recall.
- **F1-score:** The F1-score is a balanced statistic that combines recall and accuracy into one number. It offers a harmonic mean of memory and accuracy, giving each metric equal weight. When you wish to take into account both false positives and false negatives, F1-score is helpful. $F1\text{-score} = 2 * (\text{precision} * \text{recall}) / (\text{precision} + \text{recall})$ is the formula used to compute it.

These metrics offer several perspectives on a model's performance and may be used to assess and contrast various classifiers. One measure may be more significant than the others depending on the particular issue at hand and the significance of various sorts of mistakes. It's critical to select an assessment metric that is in line with the objectives and specifications of the current assignment.

V. RESULT:

The performance of models across a range of areas might be enhanced via ensemble learning. It is applicable to several models, including decision trees, neural networks, support vector machines, and more. Ensemble learning can improve generalisation and accuracy by integrating the advantages of many models.

Table 3: Result details different model and proposed

Measure	DT Value	RT Value	KNN Value	KNN Value	SVM Value	XG-Boost Value	Proposed Model Value
Recall	0.8182	0.875	1	0.8182	0.8182	1	1
Precision	0.6	0.4667	0.4667	0.6	0.6	0.0667	0.8667
Accuracy	0.8095	0.7857	0.8095	0.8095	0.8095	0.6667	0.9524
F1 Score	0.6923	0.6087	0.6364	0.6923	0.6923	0.125	0.9286

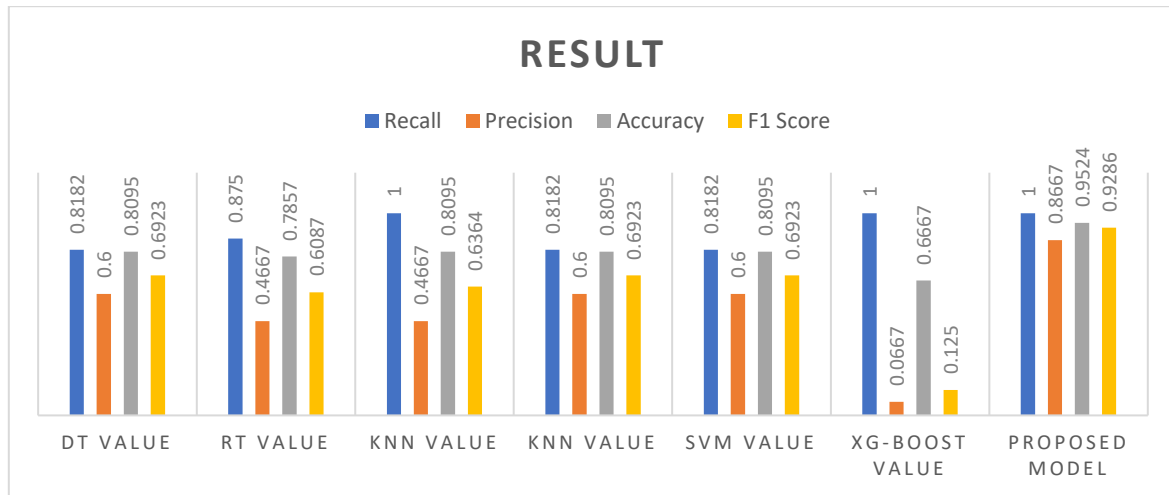


Figure 9: Proposed model result analysis with other models.

The table 3 provides insight into the proposed approaches, the method outperform all other ML models and achieve the recall value 1, accuracy 0.9524, precision of 0.8667 and f1 score value 0.9286 to address the ensemble architectural. Figure 9 demonstrates accuracy, precision, recall, and F1 score. Through the use of different machine learning models, we have presented a method to enhance performance of the model.

VI. CONCLUSION

The outcomes of implementation ensemble learning stacking techniques in practical settings have proven excellent. In this work, we performed, using ensemble machine learning of the XGBoost, SVM, DT, KNN, RF models. The proposed model outperform other models. We may draw this conclusion since students with outstanding grades in upper secondary and undergraduate programmes were placed. Those who performed well in their schools were placed. Comparing the proportion of students that were matched with applicants who scored well on the test and the employability test. The lack of interpretability relative to individual models is one issue with ensemble learning. The development of explanations for ensemble decisions and strategies to improve ensemble models' interpretability might be the focus of future research, making ensemble models more beneficial in crucial fields like finance and healthcare.

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