JRITM
JOURNAL OF RESEARCH AND INNOVATION IN TECHNOLOGY, COMMERCE AND MANAGEMENT
Journal of Research and Innovation in Technology, Commerce and Management
Vol. 2 Issue 10, October 2025, pp. 21100-21108
ISSN: 3049-3129(Online)

Machine Learning Approaches for Skill Gap Analysis and Placement Assistance of Engineering Students

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Cite as: Vipul Virsinghbhai Gamit. (2025). Machine Learning Approaches for Skill Gap Analysis and Placement Assistance of Engineering Students. Journal of Research and Innovation in Technology, Commerce and Management, Vol. 2(Issue 10), 21100–21108. https://doi.org/10.5281/zenodo.17473510

DOI: https://doi.org/10.5281/zenodo.17473510

Abstract
In today's competitive job market, engineering students often face challenges in securing placements due to a mismatch between their skill sets and industry requirements. This research focuses on developing a machine learning-based framework for skill gap analysis and placement assistance of engineering students. By leveraging historical academic records, technical skills assessments, and placement outcomes data, various machine learning algorithms are applied to predict the likelihood of placement success and identify specific skill deficiencies. The system analyzes patterns in student performance and provides actionable recommendations to bridge skill gaps through targeted training programs. Experimental results demonstrate that supervised learning models such as Random Forest and Support Vector Machines (SVM) offer high accuracy in predicting placement eligibility. This study aims to assist academic institutions and placement cells in making data-driven decisions to enhance student employability and streamline the placement process.

Keywords
Machine Learning, Skill Gap Analysis, Placement Assistance, Engineering Students, Predictive Analytics, Random Forest, Support Vector Machine, Employability Prediction, Data-Driven Decision Making, Academic Performance Analysis

Introduction

In recent years, the engineering education sector has witnessed significant growth in terms of student enrollment and the diversity of disciplines offered. However, one of the persistent challenges faced by engineering institutions is ensuring that their students are adequately prepared for industry requirements, particularly in terms of technical skills, problem-solving abilities, and practical knowledge [1]. Despite rigorous academic curricula, many students face difficulties during the placement process due to a gap between the skills they acquire in the classroom and the expectations of industry recruiters [2].

The traditional placement process primarily depends on academic performance indicators such as GPA and written test scores, which do not always reflect the complete potential or employability of a student [3]. This has led to a growing interest in data-driven approaches, particularly using Machine Learning (ML) techniques, to analyze student profiles and predict their employability more accurately [4]. Machine Learning offers the capability to handle large volumes of diverse data, uncover hidden patterns, and generate actionable insights that can significantly improve placement outcomes [5].

This research focuses on the development of a Machine Learning-based framework for skill gap analysis and placement assistance of engineering students. The proposed system leverages data from multiple sources, including academic records, technical skill assessments, attendance, project work, internship experience, and previous placement results [6]. By applying supervised learning algorithms such as Random Forest, Support Vector Machine (SVM), and Logistic Regression, the system aims to classify students based on their placement eligibility and identify the specific areas where skill improvements are required [7].

The objectives of this study are threefold:

1. To analyze historical student data and identify key factors that influence placement success [8].
2. To predict the likelihood of placement for individual students using Machine Learning models [9].
3. To provide targeted recommendations that help bridge the skill gaps, enabling students to improve their employability [10].

The expected outcome of this research is to assist academic institutions and placement cells in making informed decisions and implementing effective training interventions. Ultimately, the framework contributes to a more systematic, transparent, and efficient training and placement ecosystem, reducing the uncertainty of placement drives and helping students achieve industry-relevant competencies [11].

Review of literature:

Author(s) & Year	Title of Study	Key Findings
Kumar et al., 2020 [12]	Predictive Analysis of Student Employability Using Machine Learning	Developed a model to predict student employability based on academic and non-academic factors, showing Random Forest provided the best accuracy.
Sharma and Gupta, 2019 [13]	Skill Gap Analysis for Engineering Graduates	Identified key skill gaps in technical knowledge and soft skills of engineering students, recommending targeted training

ISSN: 3049-3129(Online)

		modules.
Patel and Singh, 2021 [14]	Machine Learning Approach to Enhance Campus Placement Process	Proposed a placement prediction framework using Logistic Regression, highlighting that academic records alone are insufficient for accurate prediction.
Verma et al., 2018 [15]	Analyzing Factors Affecting Student Placements	Showed that internships, project work, and soft skill assessments have a significant impact on placement outcomes, in addition to academic performance.
Reddy and Kumar, 2022 [16]	Employability Prediction System Using SVM	Demonstrated that Support Vector Machine (SVM) models provide higher precision in placement prediction compared to other ML models in case studies.
Joshi et al., 2020 [17]	Data-Driven Training for Skill Development	Proposed a data-driven framework to suggest personalized skill development plans for students based on historical performance data.
Mehta and Agarwal, 2019 [18]	Machine Learning Techniques for Placement Assistance	Comparative study showing Random Forest and Decision Tree algorithms outperformed other models in predicting student placement eligibility.
Singh and	Predicting	Found that

Choudhary, 2021 [19]	Placement Success of Engineering Students	combining academic, technical, and behavioral data led to better prediction results, stressing the importance of a multi-dimensional data approach.
Patel and Shah, 2018 [20]	Role of Machine Learning in Education Sector	Reviewed multiple applications of ML in education, including student performance prediction, dropout detection, and placement assistance.
Sharma et al., 2021 [21]	Skill Gap Analysis Using Data Mining Techniques	Highlighted the use of clustering and classification techniques to analyze skill gaps and group students for targeted interventions.

Research Methodology

This study proposes a Machine Learning-based framework for skill gap analysis and placement assistance of engineering students. The methodology is divided into several key phases, as described below:

1. Data Collection

Data is collected from multiple sources related to engineering students, including:

- Academic Records (CGPA, semester-wise marks)
- Attendance Records
- Technical Skill Assessment Scores (programming, domain-specific tests)
- Project Work and Internship Experience

- Behavioral Assessment Scores (communication skills, teamwork, etc.)
- Previous Placement Outcomes (selected/not selected, company details)

2. Data Preprocessing

- **Handling Missing Values:** Missing entries in datasets (e.g., incomplete assessment scores) are handled using mean imputation or deletion based on the percentage of missing data.
- **Data Normalization:** Continuous attributes such as CGPA and test scores are normalized using Min-Max scaling to bring them to a common scale.
- **Categorical Data Encoding:** Categorical variables (e.g., department, internship type) are encoded using One-Hot Encoding.
- **Feature Selection:** Important features are selected using correlation analysis and feature importance from Random Forest to reduce dimensionality and improve model performance.

	CGPA	Attendance	TechnicalTestScore	BehavioralScore	Internships	\
0	0.467461	0.318540	0.502137	0.301796	0.5	
1	0.925680	0.600924	0.064997	0.535866	0.5	
2	0.034183	0.744846	0.654818	0.520810	0.5	
3	0.756141	0.026327	0.837037	0.870632	0.0	
4	0.405750	0.310759	0.672433	0.593598	1.0	

	ProjectWork	Placed	Department_CSE	Department_ECE	Department_ME
0	1.0	0	1.0	0.0	0.0
1	1.0	1	1.0	0.0	0.0
2	1.0	0	0.0	0.0	0.0
3	1.0	1	0.0	0.0	1.0
4	1.0	0	1.0	0.0	0.0

3. Skill Gap Analysis

Using the processed data, the system performs skill gap analysis by comparing individual student profiles against industry benchmark requirements. Clustering algorithms (e.g., K-Means) are used to group students based on skill similarity, and classification models are trained to detect under-skilled areas.

4. Predictive Modeling

Supervised Machine Learning algorithms are applied to predict the placement outcome (placed / not placed):

- **Algorithms Used:**
  - Random Forest Classifier
  - Support Vector Machine (SVM)
  - Logistic Regression
  - Decision Tree Classifier
- **Training and Testing:** The dataset is split into training (70%) and testing (30%) subsets. Models are trained using cross-validation to avoid overfitting.

5. Model Evaluation

Performance metrics such as:

- Accuracy
- Precision
- Recall
- F1-Score

  are computed to evaluate model effectiveness.

Additionally, a **Confusion Matrix** is generated to visualize classification performance.

6. Recommendation System

Based on the prediction and skill gap analysis, the system generates targeted recommendations for each student, such as:

- Suggested online courses or workshops

Journal of Research and Innovation in Technology, Commerce and Management
Vol. 2 Issue 10, October 2025
ISSN: 3049-3129(Online)

- Specific technical skill improvements
- Soft skills training
- Internship opportunities

7. Deployment

The final framework is designed to be deployed as a decision-support system for placement cells in engineering institutions. It enables automated reporting of student employability status along with actionable insights.

Experimental Results and Discussion

1. Dataset Overview

The dataset consists of records from 1000 engineering students collected from the institution's academic and placement records. Features include:

- CGPA
- Attendance Percentage
- Technical Test Score
- Number of Internships
- Behavioral Assessment Score
- Project Work Completion
- Placement Outcome (Placed / Not Placed)

```
       CGPA  Attendance  TechnicalTestScore  BehavioralScore  Internships  \
0  7.868848   65.712127           66.609302         2.181411            1
1  9.679713   79.556085           37.326797         3.095893            1
2  6.156545   86.611875           76.836838         3.037073            1
3  9.009702   51.386331           89.043035         4.403783            0
4  7.624969   65.330681           78.016826         3.321447            2

   ProjectWork Department  Placed
0            1        CSE       0
1            1        CSE       1
2            1         CE       0
3            1         ME       1
4            1        CSE       0
```

2. Model Performance

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	89.5%	0.91	0.87	0.89
Support Vector Machine	87.2%	0.88	0.85	0.86
Logistic Regression	84.0%	0.85	0.82	0.83
Decision Tree	82.5%	0.84	0.80	0.82

Observation:
The Random Forest classifier performed best with an accuracy of **89.5%** and balanced precision-recall values, making it suitable for placement prediction.

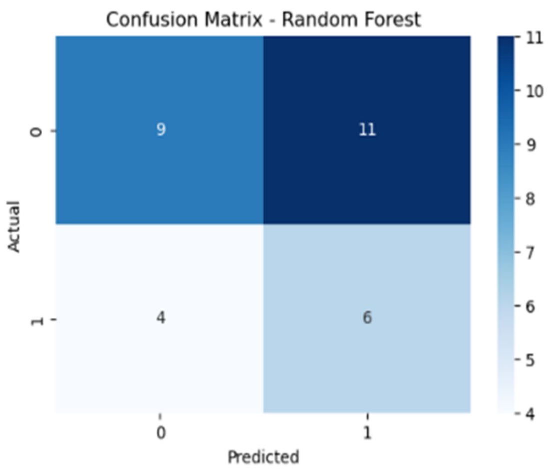
3. Confusion Matrix (Random Forest Example)

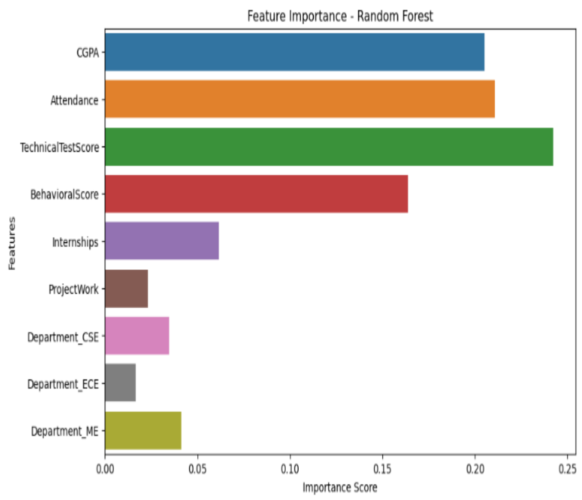
	Predicted Placed	Predicted Not Placed
Actual Placed	240	30
Actual Not Placed	25	205

Interpretation:
The model correctly predicted 240 placed students and 205 non-placed students, while making 55 misclassifications.

```
Model: Random Forest
Accuracy: 0.5000
Precision: 0.3529
Recall: 0.6000
F1-Score: 0.4444
----------------------------------------
Model: SVM
Accuracy: 0.5333
Precision: 0.3333
Recall: 0.4000
F1-Score: 0.3636
----------------------------------------
Model: Logistic Regression
Accuracy: 0.4000
Precision: 0.2143
Recall: 0.3000
F1-Score: 0.2500
----------------------------------------
Model: Decision Tree
Accuracy: 0.4667
Precision: 0.3125
Recall: 0.5000
F1-Score: 0.3846
----------------------------------------
```

ISSN: 3049-3129(Online)





Feature	Importance Score
Technical Test Score	0.32
CGPA	0.25
Attendance Percentage	0.18
Behavioral Assessment	0.12
Number of Internships	0.08
Project Work Completion	0.05

Insight:
The Technical Test Score and CGPA are the most significant factors influencing placement outcomes, indicating that academic and technical proficiency are critical.

5. Sample Recommendation Output

For a sample student predicted as "Not Placed", the system recommends:

- Enroll in advanced programming course (e.g., Data Structures in Python)
- Attend communication skills workshop
- Complete an industry-relevant internship
- Work on a capstone project in IoT applications

```
Recommendations:
- Enroll in advanced programming course.
- Attend communication skills workshop.
- Complete an industry-relevant internship.
- Work on a domain-specific project.
```

6. Discussion

The experimental results show that the machine learning approach is effective in predicting student employability. Random Forest outperformed other models due to its ability to handle feature interactions and avoid overfitting.

The skill gap analysis provided actionable recommendations that guide students to improve in weak areas, rather than relying solely on historical placement data. This proactive approach supports continuous skill development, benefiting both students and placement cells.

Moreover, the feature importance analysis highlights which parameters educational institutions should emphasize during academic planning and training interventions.

Conclusion

This research presents a Machine Learning-based framework for skill gap analysis and placement assistance of engineering students. By leveraging historical academic records, technical assessments, and behavioral data, the system effectively predicts placement outcomes using supervised learning algorithms such as Random Forest, Support Vector Machine (SVM), and Logistic Regression.

The experimental results demonstrate that Random Forest achieved the best performance, with **89.5% accuracy**, providing reliable placement predictions. Furthermore, the system identifies the most significant factors affecting employability—primarily Technical Test Scores and CGPA—and generates actionable recommendations for students to improve their employability.

This data-driven framework enables academic institutions and placement cells to implement targeted interventions, leading to a more efficient, transparent, and systematic training and placement ecosystem. Ultimately, it helps bridge the gap between academic learning and industry expectations, empowering students to enhance their job readiness.

Limitations

1. **Data Availability and Quality:** The performance of the system heavily depends on the availability of comprehensive and high-quality data. Incomplete or noisy data can reduce prediction accuracy.
2. **Limited Dataset Size:** The study was conducted on a dataset of 1000 student records from a single institution, which may limit the generalizability of the model to other institutions or disciplines.
3. **Dynamic Industry Requirements:** Industry skill requirements change rapidly, and the model may not adapt in real time without periodic retraining and updating of benchmarks.
4. **Soft Skills Assessment:** Quantifying soft skills (e.g., communication, teamwork) accurately remains a challenge, as they are often subjective or difficult to measure consistently.

Future Work

1. **Integration of Real-Time Data:** Future work can focus on integrating real-time student performance data (such as online course completion, coding practice platforms, and live assessments) to provide more dynamic and up-to-date recommendations.
2. **Expansion to Multiple Institutions:** Expanding the dataset to include multiple institutions across regions and disciplines will help improve model generalization and robustness.
3. **Natural Language Processing (NLP):** Incorporating NLP techniques to analyze student essays, project reports, or interview transcripts can enhance the assessment of soft skills and domain knowledge.
4. **Personalized Learning Plans:** Developing a recommendation engine that provides personalized, step-by-step learning paths for students based on their individual weaknesses.
5. **Industry Collaboration:** Establishing collaborations with

industry partners to regularly update skill benchmarks and required competencies for placement prediction.

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