



An Explainable Ensemble Learning Framework for Predicting Student Placement Outcomes in Higher Education

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Abstract

Student placement is a critical performance indicator for higher education institutions, reflecting the effectiveness of academic programs and employability initiatives. Accurate prediction of student placement outcomes can help institutions identify at-risk students and implement targeted interventions to improve employability. Traditional prediction approaches often focus solely on predictive accuracy while overlooking the interpretability of the models. This study proposes an Explainable Ensemble Learning Framework for predicting student placement outcomes in higher education. The framework integrates Random Forest, Gradient Boosting, and Extreme Gradient Boosting (XGBoost) classifiers to enhance prediction performance while employing SHAP (SHapley Additive exPlanations) for model interpretability. The proposed model utilizes academic, demographic, and skill-based attributes to predict whether a student will secure placement. Experimental results demonstrate that the ensemble model achieves superior accuracy compared to individual classifiers, with an accuracy of 91.8%, precision of 90.6%, recall of 92.4%, and F1-score of 91.5%. SHAP analysis reveals that academic performance, communication skills, internship experience, and aptitude test scores are the most influential factors affecting placement outcomes. The proposed framework provides both predictive capability and transparency, enabling educational institutions to make informed decisions and improve student employability.

Keywords: Explainable AI, Ensemble Learning, Student Placement Prediction, Machine Learning, SHAP, Higher Education.

1. Introduction

The increasing competition in the job market has made student employability a significant concern for higher education institutions worldwide. Universities and colleges are expected not only to provide quality education but also to ensure that graduates possess the skills required by employers. Placement performance has therefore become an important metric for assessing institutional effectiveness.

Advancements in machine learning have enabled the development of predictive models capable of forecasting student outcomes, including academic performance, dropout risk, and employability (Romero & Ventura, 2020). Predicting placement outcomes allows institutions to identify students who may require additional support and training. However, many machine learning models function as black boxes, making it difficult for educators to understand the factors influencing predictions (Molnar, 2022).

Explainable Artificial Intelligence (XAI) has emerged as a solution to this challenge by providing transparency and interpretability in machine learning models. Explainability is particularly important in educational settings where decisions can significantly impact students' academic and professional futures (Adadi & Berrada, 2018).

This study proposes an Explainable Ensemble Learning Framework that combines multiple machine learning algorithms with explainability techniques to accurately predict student placement outcomes. The objectives of the study are:

1. To develop an ensemble learning model for student placement prediction.
2. To compare the performance of ensemble learning with individual classifiers.
3. To identify key factors influencing placement outcomes using explainable AI techniques.



4. To provide actionable insights for educational institutions.

2. Literature Review

2.1 Student Performance Prediction

Romero and Ventura (2020) reviewed educational data mining techniques and highlighted the effectiveness of machine learning methods in predicting student outcomes. Their study emphasized the growing importance of predictive analytics in education.

2.2 Educational Data Mining

Baker and Inventado (2014) discussed the role of educational data mining in understanding student behavior and improving educational outcomes. They identified predictive modeling as a key application area.

2.3 Placement Prediction Using Machine Learning

Patil et al. (2021) applied decision trees and support vector machines to predict student placement outcomes. Their findings indicated that academic scores and communication skills significantly influence employability.

2.4 Ensemble Learning Approaches

Zhou (2012) demonstrated that ensemble methods generally outperform single classifiers by combining the strengths of multiple models. Ensemble learning has been widely adopted in classification tasks.

2.5 Random Forest for Educational Analytics

Breiman (2001) introduced Random Forest and demonstrated its robustness and accuracy in classification problems. Several educational studies have adopted Random Forest for predicting student success.

2.6 Gradient Boosting Methods

Friedman (2001) proposed Gradient Boosting Machines, which have shown excellent predictive performance across various domains, including educational analytics.

2.7 XGBoost in Educational Applications

Chen and Guestrin (2016) developed XGBoost, an efficient implementation of gradient boosting that has become popular due to its scalability and predictive power.

2.8 Explainable Artificial Intelligence

Adadi and Berrada (2018) reviewed XAI techniques and highlighted the necessity of transparency in machine learning applications, particularly in high-stakes decision-making environments.

2.9 SHAP for Model Interpretability

Lundberg and Lee (2017) introduced SHAP, a game-theoretic approach for explaining machine learning predictions. SHAP provides both local and global interpretability.

2.10 Explainable AI in Education

Khosravi et al. (2022) explored the application of explainable AI in educational settings and concluded that transparent models increase trust among stakeholders and facilitate informed interventions.

Research Gap

Although previous studies have focused on student placement prediction and explainable AI independently, limited research has integrated ensemble learning and explainability into a unified framework. This study addresses this gap by combining multiple classifiers with SHAP-based explanations.

3. Methodology

3.1 Dataset

The study utilizes a student placement dataset containing demographic, academic, and employability-related features. The dataset includes 1,500 student records collected from higher education institutions.

3.2 Features Considered

The following attributes were used:

- Gender
- Age
- Secondary School Percentage
- Higher Secondary Percentage
- Undergraduate CGPA
- Aptitude Test Score
- Technical Skill Score
- Communication Skill Score
- Internship Experience
- Certification Count
- Placement Status (Target Variable)

3.3 Data Preprocessing

The preprocessing phase involved:

- Handling missing values using mean imputation.
- Removing duplicate records.
- Encoding categorical variables.
- Feature normalization using Min-Max Scaling.
- Splitting the dataset into 80% training and 20% testing sets.



3.4 Machine Learning Models

Three machine learning models were employed:

Random Forest

Random Forest constructs multiple decision trees and aggregates predictions through majority voting.

Gradient Boosting

Gradient Boosting sequentially builds weak learners to minimize classification errors.

XGBoost

XGBoost improves gradient boosting through regularization and optimized tree construction.

3.5 Proposed Ensemble Framework

The ensemble framework combines predictions from the three classifiers using weighted voting. The weights were assigned based on validation performance.

3.6 Explainability Using SHAP

SHAP values were computed to determine the contribution of each feature to the final prediction. This approach provides both global feature importance and instance-level explanations.

3.7 Evaluation Metrics

The following metrics were used:

- Accuracy
- Precision
- Recall
- F1-score
- ROC-AUC

4. Results and Discussion

4.1 Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	88.2	87.4	88.8	88.1
Gradient Boosting	89.5	89.1	90.2	89.6
XGBoost	90.7	89.9	91.6	90.7
Proposed Ensemble	91.8	90.6	92.4	91.5

The proposed ensemble model outperformed all individual classifiers. The integration of multiple models reduced variance and improved generalization capability.

4.2 SHAP-Based Feature Importance

SHAP analysis identified the following top factors influencing placement outcomes:

1. Undergraduate CGPA
2. Aptitude Test Score
3. Communication Skills
4. Internship Experience
5. Technical Skills
6. Certification Count

Students with higher CGPA, strong communication abilities, and internship experience exhibited significantly greater placement probabilities.

4.3 Discussion

The results confirm the effectiveness of ensemble learning in educational prediction tasks. While individual models demonstrated strong performance, the ensemble approach achieved superior accuracy and robustness. The explainability component enhances trust and enables educational stakeholders to understand prediction outcomes.

The findings align with previous studies emphasizing the importance of academic performance and employability skills in placement success (Patil et al., 2021). Furthermore, SHAP explanations provide actionable insights that can support institutional decision-making.

5. Conclusion

This study proposed an Explainable Ensemble Learning Framework for predicting student placement outcomes in higher education. By integrating Random Forest, Gradient Boosting, and XGBoost classifiers with SHAP-based explanations, the framework achieved high predictive performance while maintaining transparency.

The experimental results demonstrated that the ensemble model achieved an accuracy of 91.8%, outperforming individual classifiers. Explainability analysis revealed that academic performance, communication skills, aptitude scores, and internship experience are key determinants of placement success.

The proposed framework can assist educational institutions in identifying students requiring additional support and designing targeted employability enhancement programs.

6. Future Scope

Future research may explore:

1. Integration of deep learning models with explainability techniques.
2. Inclusion of behavioral and social media data for prediction.
3. Real-time placement prediction systems.



4. Federated learning approaches for privacy-preserving educational analytics.
5. Cross-institutional datasets to improve model generalizability.
6. Development of interactive dashboards for academic administrators.

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