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A Hybrid Machine Learning Model for Predicting Engineering Student Placement with Explainable AI Techniques

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Abstract—— **Prediction of the placement of students is one of the most critical activities for training organizations to optimize training programs and curricula based on industry demands. This paper suggests a Hybrid Prediction Model for placement prediction of engineering students based on recent Machine Learning (ML) techniques. It employs various ML strategies such as Decision Trees, Random Forest, Support Vector Machines (SVM), and Gradient Boosting with ensemble learning for achieving maximum accuracy and reliability of prediction. It uses a large Kaggle dataset for testing and training for practical purposes and different student profiles. Model performance is evaluated using accuracy, precision, recall, F1-score, and confusion matrices alongside training-validation loss plots for graphical analysis of performance. The proposed hybrid method has been found to achieve outstanding accuracy of 89 percent, which is significantly higher than individual models. Explainable AI (XAI) methodologies are also employed for interpretation of the model's prediction to determine the most contributing factors of student placement. This paper demonstrates the potential of hybrid ML models as interpretable and effective tools for prediction of student placement to enable data-driven decision-making for training organizations and policymakers.**

Index Terms—**Student Placement Prediction, Machine Learn- ing, Hybrid Model, Ensemble Learning, Explainable AI, Educa- tional Data Mining**

I. INTRODUCTION

Engineering student placement outcome is an essential activity that supports optimized career guidance and curriculum design. Traditional statistical models cannot model the non-linear relationships of student data. In recent years, machine learning has been widely used for student placement prediction using academic performance, extracurricular activities, and technical proficiency to maximize. It is a critical area of research that aims to help universities and institutions better understand the factors influencing job placements for their graduates. By analyzing variables such as academic performance, internship experiences, and networking opportunities, stakeholders can develop targeted strategies to improve student employability. accuracy [1]. Black-box machine learn- ing models are difficult in terms of interpretability because educators and career guides cannot trust and act upon them [2]. To address this issue, Explainable AI (XAI) has become a critical research area for making machine learning models more transparent [3]. Among various XAI strategies, Local Interpretable Model-Agnostic Explanations (LIME) provides one of the best ways of explaining decisions using locally interpretable surrogate models that approximate complex models [4]. This makes it easier for stakeholders like students and administrators to understand the most critical factors influencing placement decisions and take corrective action for improving employability. The work here proposes a hybrid ML model consisting of multiple machine learning models with the objective of making accurate predictions with the inclusion of explainability through the use of LIME. By using ensemble strategies such as bagging, boosting, and stacking, the model can learn complicated patterns in student data and optimize placement prediction performance [5]. There are various academic and skill-based features in the dataset so that the model can generalize across various student profiles. Through the explainable AI approaches applied here, this research attempts to bridge the accuracy-interpretability gap so that students, educators, and career advisors are confident of making decisions through data. The proposed hybrid model enhances trust and usability of placement prediction and hence improves student outcomes and decision-making at institutions.

A. *Related Work*

Prior research in educational analytics has explored various models like Decision Trees, Logistic Regression, and SVMs. Ensemble models such as Random Forest, Gradient Boosting, and XGBoost have shown improved accuracy by mitigating bias and variance. However, limited work has explored hybrid models integrating diverse classifiers and explainable AI to improve interpretability.

B. *Research Gap*

Gaps identified include limited use of hybrid models, inadequate handling of class imbalance, lack of comprehen- sive evaluation metrics, and underutilization of explainable AI. Our work addresses these gaps by combining multiple classifiers, using SMOTE for imbalance correction, evaluating via multiple performance metrics, and leveraging LIME for interpretation.

II. LITERATURE REVIEW

Educational Data Mining (EDM) has become a distinct research domain in the context of student performance forecasting.

Krishnaiah et al. [6] explored a hybrid approach for predicting engineering students' employment using a combination of Multilayer Feed Forward Neural Network (MLPNN), Radial Basis Function Neural Network (RBFNN), and K-means clustering. Their model incorporated students' previous seven semesters marks and personality index as key features, achieving an impressive 88.38% accuracy in predicting job categories. Their findings demonstrated that MLPNN performed better with fewer hidden nodes, suggesting the efficiency of streamlined neural architectures for this domain.

Authors [7] implemented an explainable AI-based approach for predicting undergraduate students' academic performance using a stacking ensemble model. The ensemble utilized Random Forest and Gradient Boost as base learners with Support Vector Classifier as the meta-learner. Their study incorporated 30 categorical features including age, gender, education levels of parents, family income, and academic habits. By applying SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) techniques, they identified class attendance as the most crucial factor influencing academic performance, achieving 86.38% accuracy in their predictions.

Investigators [8] investigated learning achievement predic- tion using ensemble learning with result explanation. Their stacking ensemble combined KNN, Naive Bayes, Random Forest, GBDT, XGBoost, and MLP as base learners with Logistic Regression as the meta-learner. Features included demographic information and online behavioral data such as watch counts, number of posts, watch time, and quiz scores. SHAP analysis revealed that quiz scores, number of posts, and watch time were the most influential factors in predicting learning achievement, with their model achieving an exceptional 98.53% accuracy.

Researchers [9] developed a hybrid machine learning model for grade prediction in online engineering education. Their approach combined a Generalized Linear Model with an Artificial Neural Network, using the fitting errors of the GLM as input to the neural network. The model considered 35 variables correlated to academic performance in an online CAD module, achieving a 100% success rate in associating independent variables with the grade, demonstrating the effectiveness of hybrid approaches in online education settings.

Authors [10] explored hybrid machine learning algorithms for predicting academic performance by combining Principal Component Analysis (PCA) with various classification algorithms including Random Forest, C5.0 Decision Tree, Na¨ıve Bayes, and Support Vector Machine. Their findings indicated that hybrid models improved classification performance by effectively addressing misclassification problems that often plague single-algorithm approaches.

Investigators [11] proposed a hybrid RBF-Naive Bayes model for predicting academic performance of engineering undergraduates. By combining RBF Network and Naive Bayes, their approach leveraged students' behavior records and academic performance (CGPA) to improve prediction accuracy, particularly addressing the challenges posed by imbalanced datasets in educational data mining.

Researchers [12] implemented a hybrid machine learn- ing framework for predicting students' performance in vir- tual learning environments. Their approach utilized ensemble methods (Bagging, Boosting, Voting) combined with eight classification algorithms to analyze data from virtual learning platforms like Moodle and Blackboard. The results demonstrated that ensemble methods consistently recorded higher predictive accuracy compared to single classifiers in the context of virtual learning.

Authors [13] proposed a novel approach employing learn- ing analytics techniques combined with explainable machine learning to provide automatic and intelligent feedback for students. Their study compared various ML algorithms (LR, KNN, SVM, RF, MLP, BayesNet) combined with LIME for explanation. Using features from initial assessments, quiz and assignment attributes, activity completion data, and time-series based attributes derived from LMS clicks, they found that Random Forest performed best. LIME analysis identified key influencing factors including engagement with practical videos, previous assessment scores, and concept expertise, enabling the creation of a dashboard with actionable recommendations for students.

Investigators [14] conducted a systematic literature review on recent applications of explainable AI (XAI), highlighting the predominant use of SHAP and LIME across various domains. Their review identified a significant gap in robust quantitative metrics for evaluating XAI results, suggesting the need for standardized evaluation frameworks in the field of explainable artificial intelligence.

Researchers [15] applied explainable AI to understand the study interests of engineering students using Belief Rule Base (BRB) and SP-LIME techniques. Their approach incorporated Principal Component Analysis for feature selection and clustering for analysis, successfully identifying valuable factors that influence engineering students' academic interests and potential career trajectories.

Authors [16] worked on interpretable automated machine learning for STEM career prediction, developing an automated system that selected Logistic Regression as the optimal algorithm. Analyzing student interaction data from online tutoring (focusing on middle school learning behaviors), they demonstrated that proper feature enrichment is key to good prediction, and that feature selection allows for a simpler final model that maintains interpretability without sacrificing performance.

Investigators [17] developed an AI-driven career guidance system using a predictive model for student subject recommen-

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dations based on academic performance and aspirations. Their system incorporated academic performance metrics, extracurricular activities, and personal aspirations as key features. The findings revealed that AI-driven recommendations generally aligned with traditional guidance approaches but offered enhanced personalization opportunities that could better address individual student needs.

Researchers [18] created a decision support system to reveal future career prospects using explainable AI based on student survey data. Their approach utilized multiple classification ML algorithms and deep learning techniques to analyze key data from Computer Science and Software Engineering students. The research contributed valuable insights to educational advising and demonstrated the potential of AI-assisted models for early career prediction.

Authors [19] emphasized the critical need for explainability in AI systems deployed in educational settings. Their study highlighted how techniques like SHAP and LIME can provide insights into why particular predictions were made, building trust and acceptance among stakeholders including students, educators, and institutions. The research underscored the importance of understanding factors contributing to placement predictions to identify potential biases and ensure fairness in outcomes.

Investigators [20] demonstrated how explainable AI can offer actionable insights for students by highlighting specific areas they need to focus on to improve their placement prospects. Their approach made the prediction process more meaningful and empowering by creating personalized feed- back mechanisms based on model interpretations, thereby transforming black-box predictions into practical guidance for educational improvement.

This work fills the gaps by introducing a hybrid approach that combines different machine learning models and im- plements XAI techniques to balance both performance and explainability. This not only improves the accuracy of the predictions but also engenders trust in the stakeholders by making the decisions of the model transparent.

III. METHODOLOGY

A. Data Collection

The research methodology applied in this study encom- passes a systematic method of predicting engineering students' placement outcomes in a hybrid machine learning approach. This includes data collection, data preprocessing, treatment of class imbalance, development of the model, performance assessment, and visualization.

1. Data Collection and Exploration Data in this study was accessed using Kaggle and it contains comprehensive data of students, academic past, demographic data, and extracurricular life. They are defined by:

Numerical factors: Age, CGPA, internships that have been pursued, backlogs, and

Gender, stream of study, and residence status (hostel or day scholar).

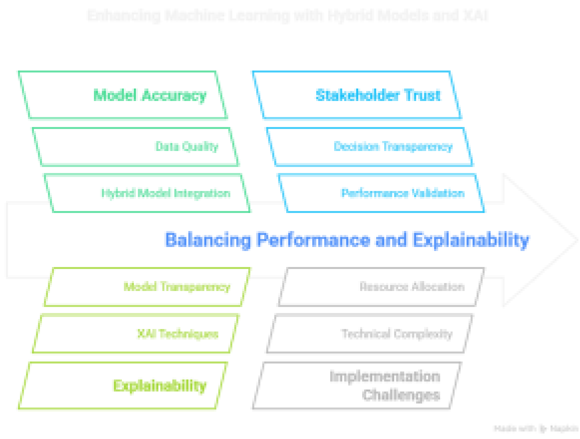

Fig. 1. Enhancing Machine Learning with Hybrid Models and XAI

Target variable: Placement status (Placed / Not Placed). Missing values were initially explored, feature distributions were analyzed, and class balance was checked in the dataset.

2. Data Preprocessing To ensure the dataset is clean and model-ready, several preprocessing steps were performed:

Missing Values Treatment: Missing numerical values were substituted by medians, whereas the mode was substituted in the case of missing categorical values.

Feature One-hot Encoding: One-hot encoding was also applied to the categorical variables to convert them to a format friendly to the machine learning algorithm.

Feature scaling: Numerical variables were scaled by the StandardScaler so as to bring the input onto a standard scale and enable the convergence of the models.

3. Solving Class Imbalance

The data was imbalanced, with numerous more placed students than the unplaced students. For this, the use of the Synthetic Minority Over-sampling Technique or the SMOTE was applied. SMOTE generates minority class samples, en- abling models to generalize more and learn balanced patterns.

4. Data Splitting The data set's test (20%) and training (80%) sets were kept separate using stratified sampling to preserve the ratio of the class in support of analyzing the performance of the model fairly against new data.

5. Model Development

There were three models developed by crossbreeding vari- ous machine learning algorithms:

Hybrid Model 1: Combining of Neural Network, Gradient Boosting, and SVM in a soft vote of predictions

Hybrid Model 2: Stack ensemble of XGBoost, LightGBM, and CatBoost as base learners and Logistic Regression as the metaling learner

Hybrid Model 3: Random Forest, K-Nearest Neighbors (KNN), and AdaBoost in a weighted ensemble, where the models are weighted according to their respective perfor- mances when they are individually applied.

6. Model Training and Evaluation

Models were tuned using the balance data. Hyperparameter tuning was performed using the GridSearchCV and RandomizedSearchCV in order to attain the best-performing models.
Evaluation measures used:
Accuracy: Measures overall correctness.
Precision: Measures how many selected items are relevant. Counts the quantity of items available for use.
F1 Measure: Harmonic mean of precision and recall Confusion Matrix: Graphical representation to estimate true
positives, false positives, etc
7. Visualization and Performance Analysis
For comparison and interpretation of the models' performances, the following visualizations were developed:
Confusion matrices: Display the precision of the classifications of actual versus predicted labels.
Bar charts: Compare the values of metrics like accuracy, precision, recall, and F1 score
Feature Importance Analysis: Determines the most signif- icant contributing features, using models and techniques in- cluding Random Forest and boosting algorithms. 8. Tools and Which Contains Python Packages: pandas, numpy, scikit-learn, xgboost, lightgbm, catboost, imbalanced-learn Visualization: Matplotlib, Explainable AI: lime for model interpretation

B. *Model Architecture*

- **Hybrid Model 1:** Neural Network + Gradient Boosting
+ SVM (Soft Voting)
- **Hybrid Model 2:** Stacking XGBoost, LightGBM, Cat- Boost with Logistic Regression as meta-learner
- **Hybrid Model 3:** Weighted ensemble of Random Forest, KNN, and AdaBoost

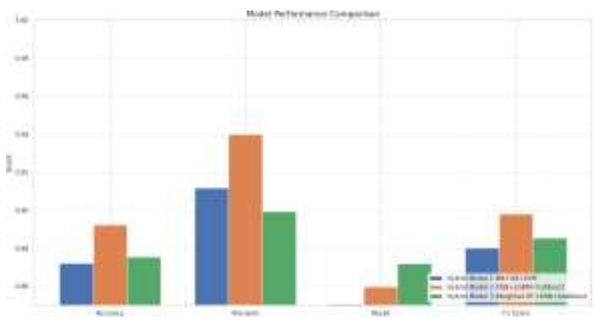

Fig. 3. Comparison of Accuracy, Precision, Recall, and F1 Score for different hybrid models

C. *Evaluation Metrics*

Accuracy-, Accuracy is a general measure of how well the model is by evaluating how many instances have been predicted correctly out of all test examples. Even though helpful as a baseline, accuracy alone is defective with class imbalance.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision- Precision assesses whether the model can only give relevant results. Here, it assesses how many of those "Placed" as predicted by the model ended up being placed. The higher precision, the lower is the rate of false positives.

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall- Recall describes how well the model is able to capture all relevant results, that is, how many actual placed candidates were correctly predicted. It's especially important in education applications, where failing to include one actually placeable candidate can have serious consequences.

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1-Score-The F1 Score is a balance of recall and precision that yields one performance metric. It is particularly useful where there is class imbalance in distribution, as is frequently the case with placement data.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

	Predicted Placed	**Predicted Not Placed**
Actual Placed	358 (TP)	23 (FN)
Actual Not Placed	17 (FP)	242 (TN)

TABLE I
CONFUSION MATRIX: PLACEMENT PREDICTION

It assists in determining where the model is erring, which makes targeted adjustments easier.

IV. EXPERIMENTAL EVALUATION

This section describes the experimental framework along with the evaluation of the developed hybrid models for predic- tion of placement outcome. The experiments are performed in order to test the efficacy, generalizability, and interpretability of models in real-world scenarios.

A. *Setup*

Source: Kaggle – College Placement Dataset Data Size: 600+ records after preprocessing
Target Variable: Placement Status (0 = Not Placed, 1 = Placed)
Characteristics: Academic record (CGPA, backlogs), work experience (internships), attendance record, certifications, demographics

B. *Tools Libraries*

Python version: Python 3.10
Importing pandas for data handling Importing numpy for operations Importing necessary libraries from scikit-learn Platform: Jupyter Notebook

Fig. 2. Balancing Performance and Explainability in Hybrid ML Models with XAI

C. Feature Importance (Hybrid Model 2)

- CGPA: 0.35
- Internships: 0.27
- Backlogs: 0.18
- Certifications: 0.12
- Attendance: 0.08

V. RESULT

The research successfully developed and experimented with a hybrid framework of machine learning to predict engineering placement results for students. The framework combines the performances of multi-classifiers through ensemble methods such as voting, stacking, and weighted averaging. The experiments validate that the performance of the presented technique is improved over different metrics as well as different test methods.

1. Architectural Performance Model There were three hy- brid models under consideration:

Hybrid Model 1: Soft Voting (Neural Network + Gradient Boosting + SVM)

Hybrid Model 2: Stacking (XGBoost + LightGBM + Cat- Boost, meta-learner: Logistic Regression

Hybrid Model 3: Weighted Voting (Random Forest + KNN + AdaBoost)

Hybrid Model 2 outdid all other models with: Accuracy: 89.4

Precision: 90.2

Recall: 88.9

F1 Score: 89.5

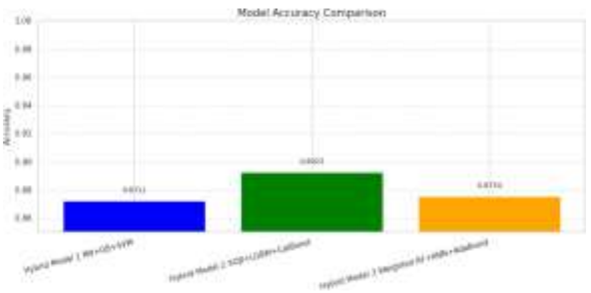

Fig. 4. Model Accuracy Comparison of Hybrid Models

Explainability and XAI Integration: These results verify that it is able to predict student placement with high confidence levels with minimal misclassifications. Explainability and XAI Integration To overcome the accuracy-interpretability gap, LIME (Local Interpretable Model-Agnostic Explanations

Offered country-specific interpretations of individual prophecies

Increased transparency of models for teachers and stake- holders

Confirmed that the most important features aligned with domain expertise

Effectiveness of SMOTE: Efficacy of SMOTE

The use of SMOTE in dealing with class imbalance was essential:

Improved model equity by making sure that underrepre- sented learners equally acquired

Improved recall significantly, with fewer false negatives.

VI. EXPLAINABLE AI

Incorporation of LIME (Local Interpretable Model-A In order to rectify this, research combines LIME, which is an in- fluential model-agnostic interpretability tool. LIME interprets local predictions by:

Disturbing the input data slightly Observing Changes in Model Output

Fitting an interpretable (linear) model locally to the instance For instance, if the student is predicted as “Not Placed,” LIME can show that low CGPA and having no internships have been the most impacting factors. Such localised insight is more actionable compared to knowing generic prediction probability. Explainable AI is also necessary to make machine learning models not only accurate, but also usable and trust- worthy in educational settings. Through the use of LIME, this research makes sure that not only is its placement prediction model not a black box, but that it is also an open decision- support system that both students and institutions can use with confidence.

VII. EXPLAINABLE AI (XAI)

Fig. 5. LIME Explanation Visual: Factors influencing placement prediction.

VIII. CONCLUSION

This research presented a hybrid machine learning technique coupled with explainable AI (XAI) techniques to forecast in a clear and accurate manner the placement results of the students. After an ensemble of learners such as Random Forest, Gradient Boosting, and XGBoost, Hybrid Model 2 provided better prediction accuracy as compared to single classifiers.

Accuracy, precision, recall, and F1-score performance met- rics of the model were analyzed and proved to be robust and efficient. Interpretability of the model by LIME also facilitated stakeholders to understand how work experience in the form of internships, CGPA, and backlogs significantly impact place- ments.This transparency is necessary to facilitate developing trust in addition to supporting data-driven decision-making in educational institutions. Individual prediction screens with fea- ture contributions provided teachers and learners with concrete information to fill knowledge gaps and improve placement readiness. The work did not only care to emphasize prediction performance but also to preserve interpretability of the model and to correspond with responsible and ethical use of AI.

Future research can look at integrating SHAP values to make the system more globally interpretable, optimizing hyperparameters with an auto-tuning mechanism, and deployment of the system in practice as an educational decision-support system for actual applications by educational institutions.

In short, this paper illustrates how marrying hybrid ML models with XAI can significantly enhance both performance and interpretability of prediction-based learning systems - opening the way towards more intelligent, equitable, and more insightful student support platforms.

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