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An Improved Hybrid Stacking Ensemble Model for Predicting Student Academic Performance Using Machine Learning

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Abstract: Early prediction of student academic performance is essential for identifying at-risk students and enabling timely intervention strategies. Traditional single machine learning models often struggle to capture complex relationships within educational data. This study proposes a hybrid stacking ensemble model that integrates Random Forest, Support Vector Machine (SVM), and XGBoost as base learners with Logistic Regression as a meta-learner. The model was evaluated using a publicly available student performance dataset. Experimental results demonstrate that the proposed hybrid model achieved an accuracy of 91.13%, an F1-score of 0.877, and an AUC value of 0.965, outperforming individual classifiers. The findings indicate that ensemble learning significantly enhances predictive performance and reliability in academic early warning systems.
Keywords: Academic Performance Prediction, Stacking Ensemble, Hybrid Model, Machine Learning, SMOTE, Early Warning System

I. INTRODUCTION

Educational institutions increasingly adopt data-driven approaches to improve student learning outcomes [7],[8]. Early identification of academically at-risk students enables targeted interventions that can significantly reduce dropout rates and academic failure.

Machine learning algorithms such as Random Forest, Support Vector Machine (SVM), and XGBoost have been widely used for academic performance prediction. Although these models demonstrate promising performance, individual classifiers may suffer from bias, variance, or limited generalization capability.

To overcome these limitations, this study proposes a hybrid stacking ensemble model that combines multiple heterogeneous classifiers to enhance predictive robustness and accuracy.

The key contributions of this research are:

- Development of a hybrid stacking ensemble model for academic performance prediction.
- Application of SMOTE to address class imbalance.
- Comprehensive comparison with individual machine learning models.
- Performance validation using multiple evaluation metrics including AUC and confusion matrix analysis.

II. RELATED WORK

Several studies have explored the application of machine learning techniques for predicting student academic performance. Random Forest and SVM are commonly used due to their ability to model nonlinear relationships. XGBoost has also demonstrated strong predictive capability in structured datasets.

However, single-model approaches often exhibit limitations in handling complex and imbalanced educational data. Ensemble learning techniques such as bagging and boosting have improved predictive performance. Among ensemble methods, stacking has shown superior capability by combining diverse classifiers into a unified predictive framework.

This study extends previous research by implementing a stacking-based hybrid ensemble and evaluating its performance using comprehensive metrics.

III. METHODOLOGY

1) Dataset

The study utilizes the Student Performance Dataset containing demographic, academic, and social attributes of students [1]. The target variable was derived from the final grade (G3), where students scoring below 10 were labeled as “At Risk.”

2) Data Preprocessing

The following preprocessing steps were performed:

- Categorical features were encoded using Label Encoding.
- Feature scaling was applied using StandardScaler.
- SMOTE (Synthetic Minority Over-sampling Technique) was used to balance the dataset [2].

3) Proposed Hybrid Model

The proposed stacking ensemble consists of:

Base Learners:

- Random Forest [3]
- Support Vector Machine (SVM) [4]
- XGBoost [5]

Meta-Learner:

- Logistic Regression

The stacking approach combines predictions from base models and feeds them into the meta-learner to generate the final classification output [6].

4) Evaluation Metrics

Model performance was evaluated using:

- Accuracy
- Precision
- Recall
- F1-Score
- Confusion Matrix
- ROC Curve
- Area Under Curve (AUC)

IV. RESULTS AND DISCUSSION

1) Model Performance Comparison

The proposed hybrid stacking model was compared with individual machine learning models including Random Forest, SVM, and XGBoost.

Table 1. Performance Comparison of Machine Learning Models

Model	Accuracy (%)	Precision	Recall	F1 Score
Hybrid Stacking	91.13	0.833	0.926	0.877
Random Forest	89.87	0.806	0.926	0.862
SVM	88.60	0.821	0.852	0.836
XGBoost	88.60	0.821	0.852	0.836

As shown in Table 1, the hybrid stacking model achieved the highest accuracy and F1-score, demonstrating improved predictive capability compared to standalone classifiers.

2) Confusion Matrix Analysis

To further evaluate classification performance, a confusion matrix was generated for the hybrid model.

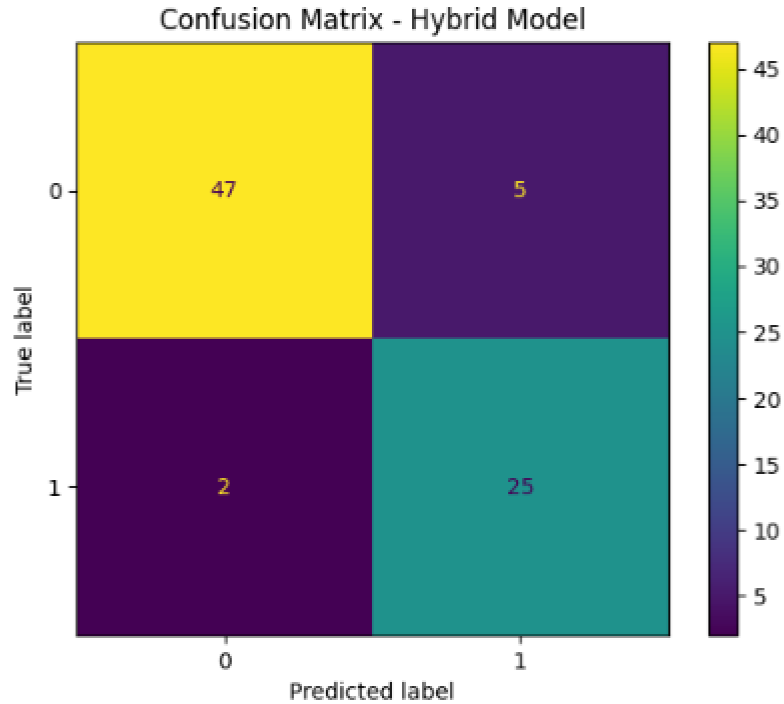

Figure 1. Confusion Matrix of Hybrid Stacking Model

The confusion matrix indicates that only two at-risk students were misclassified. The model correctly identified 25 at-risk students and 47 non-risk students. The low number of false negatives highlights the effectiveness of the model in detecting academically vulnerable students.

3) ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve was plotted to assess the discriminative ability of the model.

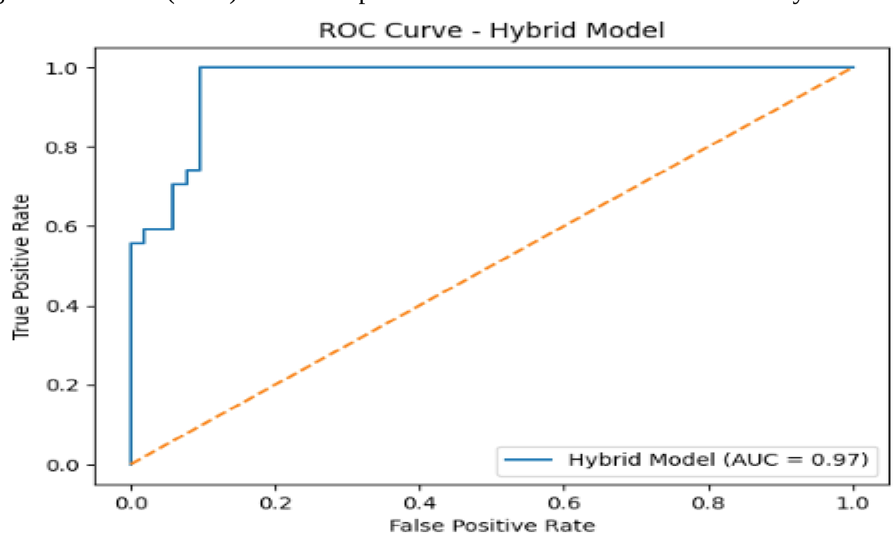

Figure 2. ROC Curve of Hybrid Stacking Model

The ROC curve analysis yielded an AUC value of 0.965, indicating excellent classification performance and strong separability between at-risk and non-risk students [10]. An AUC above 0.90 confirms the robustness of the proposed ensemble approach.

Overall, the experimental results demonstrate that stacking ensemble learning significantly improves predictive robustness compared to individual machine learning models.

V. CONCLUSION

This study proposed a hybrid stacking ensemble model for predicting student academic performance. The integration of Random Forest, SVM, and XGBoost through a Logistic Regression meta-learner resulted in improved classification performance.

The model achieved 91.13% accuracy and an AUC value of 0.965, outperforming standalone classifiers. The proposed approach can serve as an effective academic early warning system for identifying at-risk students.

Future research may focus on:

- Evaluating the model on larger multi-institutional datasets
- Incorporating deep learning architectures
- Developing real-time deployment systems for institutional use

VI. ACKNOWLEDGEMENT

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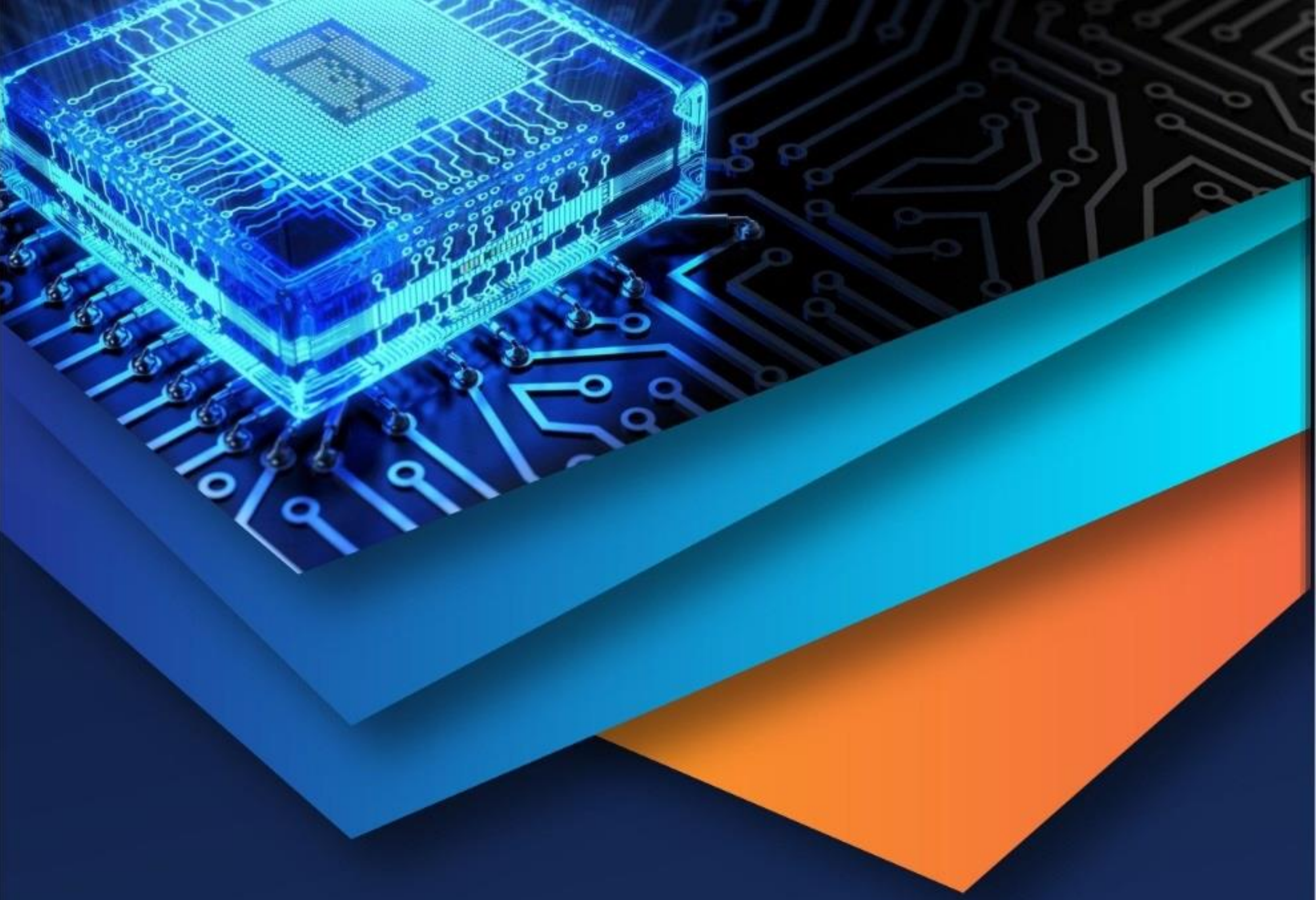

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