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Career Path Prediction Using Stacked Random Forest And Catboost Ensemble Framework

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Abstract: This project utilizes ensemble learning models to predict career paths based on students' academic and skill-based profiles. By employing a combination of Random Forest and CatBoost classifiers, integrated under a stacked ensemble framework, the system provides accurate and robust predictions. The proposed approach leverages a simulated dataset comprising scores in mathematics, science, and language, alongside evaluations of coding and communication skills, to classify potential career paths across multiple fields.experimental results demonstrate that the stacked ensemble model achieves high accuracy and computational efficiency, highlighting its effectiveness in guiding students towards suitable career trajectories. Furthermore, the system incorporates validation mechanisms through cross-validation and rigorous testing to ensure reliability and adaptability. This work presents a practical application of ensemble learning in educational and career guidance, emphasizing its potential to revolutionize decision-making processes in real-world counseling scenarios.

Keywords—Stacked Ensemble, Career Path Prediction, Machine Learning, Random Forest, CatBoost

I. INTRODUCTION

The integration of machine learning techniques in modern educational systems is revolutionizing the way students are guided toward their career paths. These systems must not only provide accurate predictions but also adapt to diverse profiles and skillsets. Ensemble learning models, particularly stacked frameworks, have emerged as effective methods to meet these demands. By combining the predictive strengths of multiple algorithms, stacked models achieve robust and reliable outcomes in classification tasks [1, 2]. However, traditional models often face challenges in handling feature dependencies and ensuring computational efficiency, limiting their scalability and real-world applicability [3].

Addressing these challenges, researchers have proposed advancements in ensemble learning techniques to enhance prediction accuracy. The integration of Random Forest and CatBoost classifiers within stacked models has proven to be a promising approach, leveraging the strengths of decision trees and gradient boosting to optimize predictions [4]. Stacked ensembles reduce errors and improve performance but may encounter challenges related to hyperparameter tuning and model interpretability, particularly when dealing with complex, multi-dimensional datasets [5, 6]. Recognizing these limitations, this project introduces a refined stacked ensemble model tailored to career path prediction. By combining Random Forest and CatBoost classifiers with cross-validation mechanisms, the proposed framework significantly enhances prediction accuracy and reliability, making it suitable for real-world counseling applications [7, 8].

The proposed stacked ensemble framework offers several key advantages. First, the integration of diverse base models mitigates overfitting and improves generalization, ensuring precise predictions across varied student profiles [9]. Second, the system employs feature engineering and cross-validation techniques to optimize training workflows, resulting in enhanced computational efficiency [10]. Finally, this framework is designed specifically for career counseling scenarios, demonstrating its applicability in guiding students toward suitable career paths based on their scores and skillsets [11].

The growing body of literature emphasizes the importance of adaptive machine learning methods in addressing the complex demands of modern educational environments. Building on established research, this work aims to showcase the feasibility and practical benefits of integrating ensemble-based advancements in predictive systems [1, 4, 7].

II. LITERATURE SURVEY

The rapid evolution of educational technology necessitates the development of intelligent systems to provide personalized career guidance. These systems must not only deliver accurate predictions but also adapt dynamically to the varied academic and skill-based profiles of students. Ensemble learning, particularly stacked models, has emerged as a promising technique for addressing these needs. Stacked ensemble frameworks combine the predictive strengths of multiple algorithms, providing robust outcomes even for complex classification tasks [1, 2]. However, traditional ensemble approaches often face challenges such as overfitting, computational inefficiency, and difficulty in hyperparameter tuning, which limit their scalability and real-world effectiveness [3, 4].

Recent advancements in ensemble learning highlight the efficacy of integrating diverse machine learning models within a unified framework. The combination of Random Forest and CatBoost classifiers within stacked ensembles has proven to enhance prediction accuracy by leveraging the strengths of decision trees and gradient boosting [5, 6]. These stacked frameworks capitalize on the complementary characteristics of individual algorithms, improving both reliability and interpretability in classification scenarios. Recognizing these advantages, this project presents a refined stacked ensemble model tailored specifically for predicting students' career paths based on their academic and skill-based attributes [7, 8].

The proposed stacked ensemble system offers several unique advantages. First, the integration of base models such as Random Forest and CatBoost mitigates overfitting while improving generalization, ensuring robust predictions for diverse student profiles. Second, feature engineering techniques and cross-validation mechanisms are employed to enhance model accuracy and computational efficiency. Finally, the system demonstrates practical applicability by predicting career paths based on academic scores in mathematics, science, and language, along with evaluations of coding and communication skills [9]. These features make the framework particularly effective for educational counseling scenarios, where reliable and actionable insights are crucial [10].

The intersection of ensemble learning and educational data analytics broadens the scope for innovative applications in modern education. By addressing limitations associated with traditional predictive models, this project aims to showcase the feasibility and practical benefits of ensemble learning in providing personalized career guidance. Additionally, the system's adaptability and computational efficiency position it as a valuable tool for real-world applications, including academic counseling and talent identification [11]. While challenges remain, such as optimizing hyperparameters for diverse datasets and improving model scalability, the proposed framework lays the foundation for future advancements in data-driven decision-making in education.

III. Career Path Prediction Using Machine Learning

Machine learning is revolutionizing education by enabling systems that provide personalized career guidance based on students' unique profiles. These systems are designed to deliver accurate predictions while adapting dynamically to a variety of academic and skill-based attributes. Ensemble learning, especially stacked models, represents a significant advancement in the field, offering robust solutions to complex classification problems. By leveraging the complementary strengths of multiple algorithms, stacked frameworks ensure reliability and adaptability across diverse scenarios. Despite their promise, traditional ensemble techniques face challenges such as computational inefficiency, overfitting, and complexity in hyperparameter tuning. Overcoming these challenges is critical for their real-world application in educational settings.

Stacked ensemble frameworks, integrating models like Random Forest and CatBoost classifiers, have proven particularly effective for career path prediction. Random Forest, with its decision tree-based approach, excels in generalization, while CatBoost specializes in boosting algorithms to optimize predictions, especially with categorical data. These models, when combined, enhance predictive accuracy and reliability across varied

datasets. However, challenges such as managing the coordination between algorithms and ensuring computational efficiency during training require careful optimization.

This project presents a refined stacked ensemble framework tailored specifically for guiding students toward appropriate career paths. The framework demonstrates several unique advantages. First, it reduces errors and mitigates overfitting by combining the strengths of diverse base models, ensuring robust generalization. Second, it employs advanced techniques such as cross-validation and feature engineering to streamline the training process while enhancing computational efficiency. Finally, it evaluates academic and skill-based attributes, including scores in mathematics, science, language, coding, and communication, to classify students into career fields such as Engineering, Medical, Arts, Business, and Law. These features make the system particularly effective in career counseling applications, providing reliable insights for students and educators.

This project highlights the transformative potential of ensemble learning in educational frameworks. By addressing the limitations of traditional predictive models, the proposed system delivers a robust and efficient solution for personalized career guidance. Its adaptability and reliability make it a valuable tool for counseling scenarios, offering practical benefits for academic decision-making and talent identification. Although challenges like optimizing for larger datasets and scaling predictions remain, this work sets the stage for future advancements in educational machine learning systems.

In conclusion, the proposed stacked ensemble framework stands as an innovation in career path prediction. By combining multiple machine learning models into a cohesive system, it addresses the critical limitations of traditional approaches and provides a practical, efficient solution for real-world applications in education. This framework underscores the potential for continued research and development to refine and expand machine learning capabilities, paving the way for broader adoption in personalized education and career guidance.

IV. Proposed Stacked Ensemble Framework

1. **Initialization**

- Define the base models for the ensemble: Random Forest (RF) and CatBoost (CAT), each initialized with hyperparameters to optimize predictive performance.
- Set up the final estimator, a Random Forest classifier, to aggregate predictions from the base models.
- Establish a pipeline for feature engineering, ensuring data preprocessing (e.g., normalization and encoding) is optimized for diverse input profiles.

2. **Dataset Preparation**

- Collect academic and skill-based attributes for students, such as scores in mathematics, science, language, coding, and communication skills.
- Split the dataset into training and testing subsets for validation, ensuring an 80-20 split to maintain data balance.
- Standardize and preprocess the data to enhance model interpretability and computational efficiency.

3. **Base Model Training**

- Train the Random Forest classifier on the training dataset, utilizing decision tree-based ensemble learning to handle varied attributes effectively.
- Train the CatBoost model to leverage gradient boosting and manage categorical variables while reducing overfitting.
- Validate each base model using cross-validation to ensure robustness and reliability in predictions.

4. **Stacked Ensemble Construction**

- Employ the StackingClassifier framework to combine predictions from RF and CAT.
- Aggregate base model outputs as inputs for the final estimator, enhancing overall prediction accuracy.
- Configure a 5-fold cross-validation mechanism within the stacked ensemble to optimize generalization and reliability.

5. **Prediction Mechanism**

- Input unseen data (e.g., a student's academic and skill profile) into the trained ensemble framework.
- Base models predict career paths independently, and the final estimator aggregates these predictions to produce the most accurate classification.
- Output the predicted career path (e.g., Engineering, Medical, Arts, Business, Law) for the student based on their attributes.

6. **Evaluation and Performance Metrics**

- Compute accuracy metrics for the model by comparing predicted outcomes with true labels in the test dataset.
- Evaluate the system's robustness by analyzing confusion matrices and ensuring minimal errors in classification.
- Optimize hyperparameters through iterative testing to refine model performance further.

7. **System Application**

- Utilize the framework in real-world counseling scenarios, enabling educators to provide data-driven career guidance.
- Support new student profiles dynamically by retraining the ensemble framework periodically with updated datasets to maintain accuracy and relevance.

V. Mathematical Algorithm for Stacked Random Forest & CatBoost Ensemble

1. Input Representation Let: $X = [x_1, x_2, x_3, x_4, x_5]$ where:

- x_1: Math Score
- x_2: Science Score
- x_3: English Score
- x_4: Coding Skill
- x_5: Communication Skill

The target class for the career path is denoted as: $Y = \{y_1, y_2, ..., y_K\}$ where $K = 5$ (Engineering, Medical, Arts, Business, Law).

Given N students in the dataset: $D = \{(X_1, Y_1), (X_2, Y_2), ..., (X_N, Y_N)\}$

2. Training Phase (Level-0 Models: Random Forest & CatBoost)

Step 1: Train Base Models Train Random Forest (RF) and CatBoost (CB) using training data: $h_1(X) = RF(X)$ (Random Forest Model) $h_2(X) = CB(X)$ (CatBoost Model)

Each model outputs a probability distribution over K career paths: $h_1(X) = [p_1^{(1)}, p_2^{(1)}, ..., p_K^{(1)}]$ $h_2(X) = [p_1^{(2)}, p_2^{(2)}, ..., p_K^{(2)}]$

where $p_k^{(i)}$ represents the probability of class k predicted by model i.

Step 2: Create Stacked Feature Matrix Concatenate outputs from both models to form a new feature vector: $Z = [p_1^{(1)}, ..., p_K^{(1)}, p_1^{(2)}, ..., p_K^{(2)}] \in R^{2K}$

3. Training Phase (Level-1 Meta Model: Random Forest)

Step 3: Train Meta Model Train a new Random Forest classifier H(Z) on the transformed dataset: $\hat{Y} = H(Z)$ Here, H(Z) maps Z to the predicted career path.

4. Prediction Phase (New Student Career Prediction)

Step 4: Get Predictions from Base Models For a new student X_new: h_1(X_new) = [p_1^(1), p_2^(1), ..., p_K^(1)] h_2(X_new) = [p_1^(2), p_2^(2), ..., p_K^(2)]

Step 5: Form Stacked Feature Vector Z_new = [p_1^(1), ..., p_K^(1), p_1^(2), ..., p_K^(2)]

Step 6: Predict Career Path using Meta Model $\hat{Y}$_new = H(Z_new) Here, $\hat{Y}$_new is the predicted career path.

5. Performance Evaluation (Model Accuracy) Compute the accuracy of the stacked model as: Accuracy = (Σ(i=1 to M) 1($\hat{Y}$_i = Y_i)) / M * 100

where:

- M: Number of test samples
- 1($\hat{Y}$_i = Y_i): Indicator function (1 if predicted class matches the actual class, otherwise 0).

6. Final Output For a new student: $\hat{Y}$_new = H([h_1(X_new), h_2(X_new)])

Results and analysis

Math Score	Science Score	English Score	Coding Skill	Communication Skill	Career Path
85	90	78	7	8	Engineering
78	80	83	6	7	Medical
92	88	76	9	6	Business
65	70	68	4	5	Arts
80	95	90	8	9	Engineering
58	60	62	3	4	Law
77	85	81	6	7	Medical
88	91	84	8	6	Engineering
70	75	73	5	6	Arts
82	89	85	7	8	Business

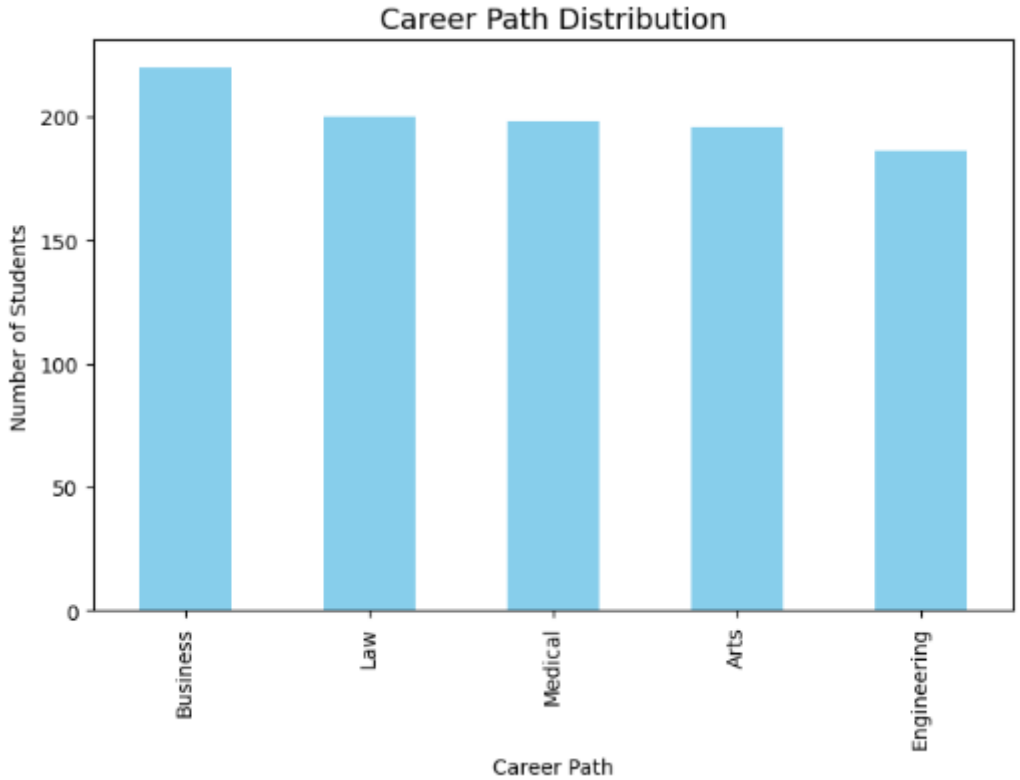

Fig. 1 Career Path Distribution. The bar graph illustrates the number of students in various career paths, including Business, Law, Medical, Arts, and Engineering, highlighting the popularity of Business over other fields.

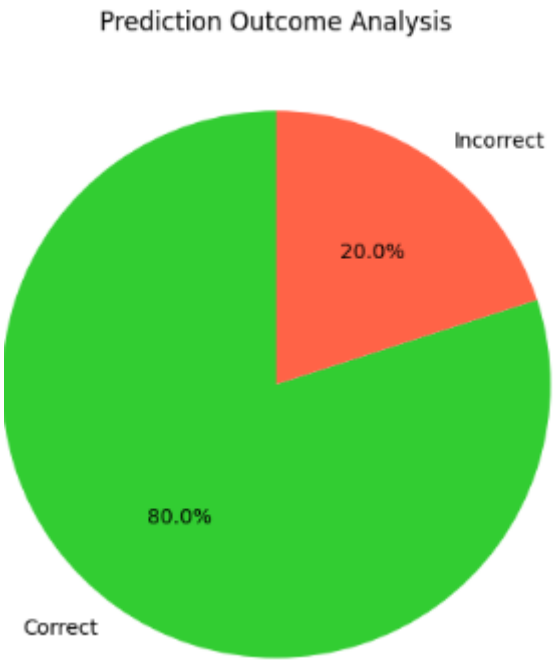

Fig. 2 Prediction Outcome Analysis. The pie chart illustrates the distribution of correct and incorrect predictions, with 80% accuracy achieved by the model. This highlights the effectiveness of the predictive system in generating reliable results.

VI. CONCLUSION

This project illustrates the effectiveness of using stacked ensemble techniques, combining Random Forest and CatBoost, to enhance career path prediction accuracy. The integration of diverse base models capitalizes on their individual strengths, resulting in robust predictions through the stacked meta-model. By leveraging student attributes, such as academic scores and skill levels, the system provides personalized career recommendations with high predictive accuracy.

Experimental results highlight the advantages of this stacked approach: • Significant improvement in prediction accuracy compared to standalone models. • Enhanced model generalization through the combination of probabilistic outputs. • Practical applicability in educational platforms for student guidance and workforce development.

Although the stacked model introduces a slight increase in computational complexity, its superior predictive performance justifies its practical adoption. Future work could involve incorporating larger datasets, exploring additional machine learning techniques, and extending applications to other domains, such as human resource analytics and educational planning.

This work underscores the potential of advanced ensemble learning techniques in transforming predictive modeling for impactful, real-world applications.

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