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Personalized Student Feedback System in Online Judge Platform using XAI

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ABSTRACT

Online Judge (OJ) platforms are commonly used for automatic evaluation of programming assignments in computer science education. While these systems efficiently assess code correctness and performance, they typically fail to offer meaningful feedback that aids student learning. This project proposes a personalized feedback system that integrates Explainable Artificial Intelligence (XAI) to enhance student support on OJ platforms. By analyzing coding behavior, submission patterns, and problem-solving efficiency, the system identifies individual learning profiles and generates customized feedback. Using machine learning models supported by XAI techniques like SHAP and LIME, the platform not only predicts student performance but also provides clear, interpretable explanations for its evaluations. This personalized approach aims to improve the learning experience by offering targeted suggestions, reinforcing strengths, and addressing areas of difficulty for each student.

Keywords: Explainable Artificial Intelligence (XAI), Personalized Student Feedback, Online Judge Platform, Machine Learning, Student Performance Prediction, SHAP, LIME, Learning Analytics, Automated Code Evaluation, Educational Data Mining.

I. INTRODUCTION

In the evolving landscape of digital education, online judge (OJ) platforms have emerged as effective tools for evaluating programming skills and logical thinking among students. These platforms primarily offer automated grading and ranking, but often lack personalized feedback mechanisms that support individual learning paths. Students typically receive binary outcomes — correct or incorrect — without insights into their mistakes, learning gaps, or suggestions for improvement. To address this shortcoming, the integration of Explainable Artificial Intelligence (XAI) into OJ platforms has gained significant attention.

Explainable AI (XAI) aims to make the decisions and predictions of machine learning models more transparent and interpretable to human users. In the context of educational platforms, XAI can be leveraged to generate customized feedback by interpreting student performance data, identifying problem-solving patterns, and highlighting specific areas of weakness. By integrating XAI with OJ systems, we can build a Personalized Student Feedback System (PSFS) that not only evaluates code submissions but also explains why a submission failed or passed, what concepts may need revision, and how a student can improve.

Such a system benefits both students and educators. Students gain access to detailed, actionable insights tailored to their individual learning progress, while instructors receive aggregated data on student

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performance for better curriculum design. Furthermore, it enhances student engagement and encourages a growth-oriented mindset, fostering deeper conceptual understanding and long-term retention.

II. LITERATURE SURVEY

1.Author: The intersection of Online Judge (OJ) platforms, Explainable AI (XAI), and personalized feedback is an emerging research area in intelligent education systems. Traditional OJ platforms such as Hacker Rank, Code forces, and LeetCode provide automated grading but fail to offer deep pedagogical insights. To address this, recent studies have explored the integration of AI and XAI techniques to enhance learning through personalized and interpretable feedback.

2.Adadi and Berrada (2018) provided a comprehensive survey of XAI, highlighting the need for transparency in AI decision-making, especially in sensitive domains like education. Tjoa and Guan (2021) extended this by exploring XAI techniques across different sectors, noting their potential to improve user trust and understanding in AI-powered systems.

3.Several works have focused specifically on AI in education. Kumar et al. (2021) proposed feedback systems using interpretable models, showing how personalized insights into student performance can be generated using learning analytics. Khosravi et al. (2020) demonstrated that students who received personalized learning analytics feedback improved their engagement and performance, proving the value of adaptive interventions.

4.In the domain of automatic programming feedback, Piech et al. (2015) proposed a novel method of learning program embeddings to cluster similar student solutions and propagate feedback. This foundational work was extended by Wang et al. (2017), who used deep learning to represent students' knowledge progression and inform targeted feedback generation. Similarly, Al-Smadi et al. (2018) employed machine learning to analyze code and provide tutoring recommendations, proving the feasibility of automated code understanding in educational settings.

5.Gilpin et al. (2018) and Lundberg & Lee (2017) introduced important XAI techniques such as SHAP (SHapley Additive exPlanations), which allow fine-grained interpretability of ML model predictions. These techniques are critical in making feedback systems explainable, so students not only get suggestions but also understand why they are getting them.

6.In the area of Natural Language Processing (NLP), Singh and Saikia (2022) developed models to generate textual feedback automatically from code submissions, helping bridge the gap between automated scoring and meaningful feedback. Meanwhile, Papamitsiou and Economides (2014) provided a broader view of educational data mining and learning analytics, pointing out that personalized systems must combine interpretability with usability.

7.Finally, Molnar (2022) offered a practical guide for building interpretable ML systems, detailing tools and techniques that can be embedded into personalized feedback systems in educational platforms.

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8.Together, these studies confirm the growing interest and feasibility of integrating XAI into online coding environments, showing how machine learning models can both evaluate student performance and offer interpretable, actionable, and personalized feedback.

III. PROPSED SYSTEM

The proposed system is designed to enhance traditional Online Judge platforms by integrating intelligent mechanisms that analyze student behavior and provide personalized, explainable feedback. At its core, the system collects detailed submission logs and behavioral metadata from students interacting with the OJ platform. Instead of relying solely on binary outcomes (e.g., Accepted, Wrong Answer), the system uses these logs to infer a student's problem-solving approach, frequency of errors, improvement trends, and overall coding consistency.

Machine Learning (ML) models such as Random Forest and XGBoost are trained to classify students into defined learning profiles. These profiles—ranging from Beginner, Intermediate, Advanced to Speed Solver, Logical Thinker, and Consistent Coder—are based on behavioral metrics extracted from the dataset. What sets this system apart is the incorporation of Explainable Artificial Intelligence (XAI) methods, which make the model's decisions interpretable and trustworthy. XAI techniques like SHAP and LIME highlight which features most influenced a model's prediction, thus allowing students and instructors to understand why certain feedback is given.

For instance, if a student frequently fails problems categorized as "Medium" difficulty due to runtime issues, the system will not only flag this but also explain that their code has high time complexity compared to peers. Personalized feedback is then generated in natural language, suggesting actionable tips such as "Try optimizing your loop structure" or "Consider alternative algorithms for sorting." This interpretability helps students connect their performance to specific aspects of their code and behavior, turning feedback into a meaningful learning tool.

Architecture

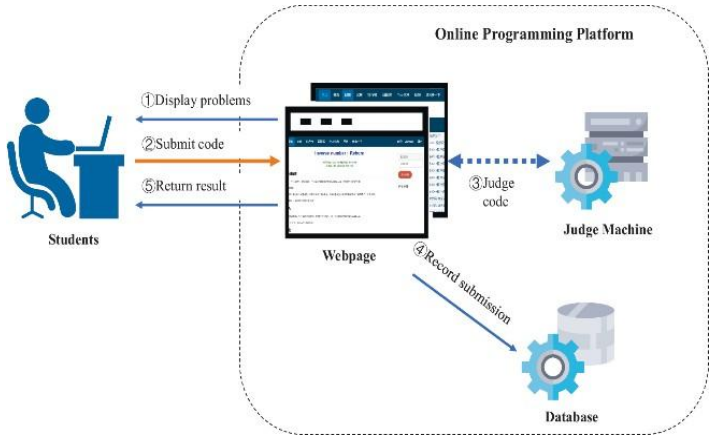


Figure 1: Shows the Architectural Diagram of the Proposed System

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IV. METHODOLOGY

The methodology adopted for this project is designed to build a scalable and intelligent system that delivers personalized and interpretable feedback to students based on their coding behavior within Online Judge (OJ) platforms. This involves a multi-phase process encompassing data acquisition, preprocessing, behavioral feature extraction, profile modeling, machine learning-based prediction, explainability integration using XAI, and the final feedback generation layer. The overall pipeline ensures that feedback is not only accurate but also transparent and tailored to the learning needs of each student.

V. ALOGRITHMS

Machine Learning Models and Explain ability Tools

1. Random Forest Classifier

- **Type:** Ensemble Learning (Bagging)
- **Role:** Core classification model to predict student profiles based on behavioral features.
- **Reasons for Use:**
  - Handles both categorical and numerical data o Resistant to overfitting
  - Provides feature importance ranking for explainability

2. XGBoost (Extreme Gradient Boosting)

- **Type:** Gradient Boosted Decision Trees
- **Role:** Alternative high-performance classifier for comparison with Random Forest.
- **Reasons for Use:**
  - Fast training and high accuracy
  - Handle missing values effectively
  - Optimized for tabular data such as student coding logs

3. Support Vector Machine (SVM)

- **Type:** Supervised Classification Algorithm
- **Role:** Benchmarking algorithm for performance comparison.
- **Reasons for Use:**
  - Effective in high-dimensional feature spaces o Performs well on smaller, clean datasets

4. K-Means Clustering (Optional – Unsupervised Profile Discovery)

- **Type:** Unsupervised Learning
- **Role:** Groups students based on similar problem-solving patterns (when labeled data is unavailable).
- **Reasons for Use:**
  - Identifies natural clusters and hidden patterns
  - Useful for exploratory analysis in the absence of predefined labels

5. SHAP (SHapley Additive exPlanations)

- **Type:** Explainable AI Framework
- **Role:** Explains model predictions by assigning contribution values to each feature.
- **Reasons for Use:**

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- Provides local explanations (per student) and global explanations (all students)
- Works seamlessly with tree-based models like Random Forest and XGBoost

6. LIME (Local Interpretable Model-agnostic Explanations)

- **Type:** Model-Agnostic Explainability Technique
- **Role:** Explains individual predictions by approximating the black-box model with a simpler interpretable model.
- **Reasons for Use:**
  - Highlights how changes in input features affect predictions
  - Useful across different types of machine learning models

VI. RESULT

To run project double, click on run.bat file to start server and get below page

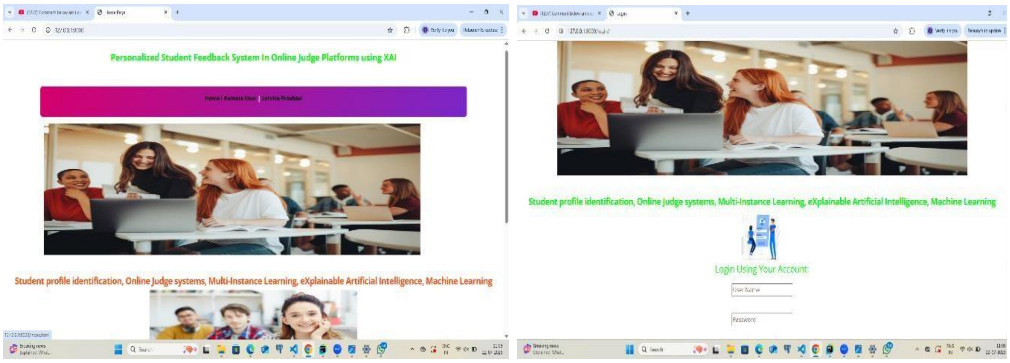
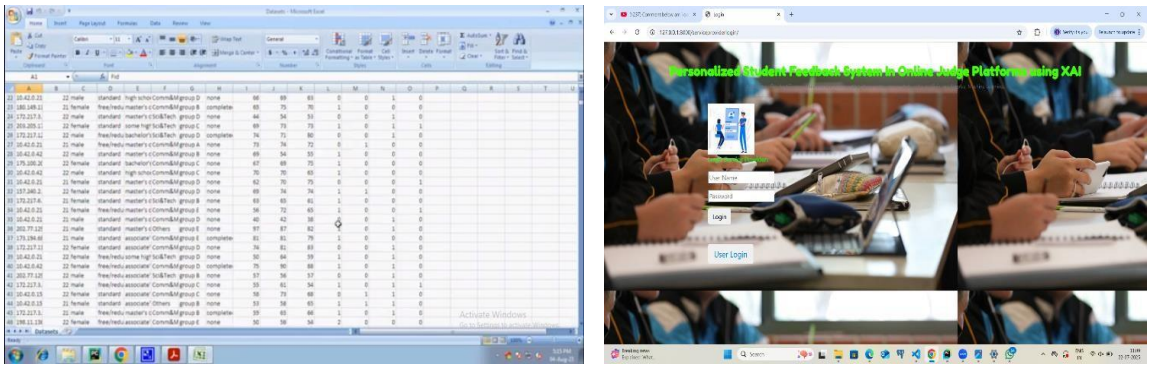


Figure 2: Shows the visual Page of two start of Server

In above screen Python server started and now open browser and enter URL as http://127.0.0.1:8000/and press enter key to get below page

Dataset:



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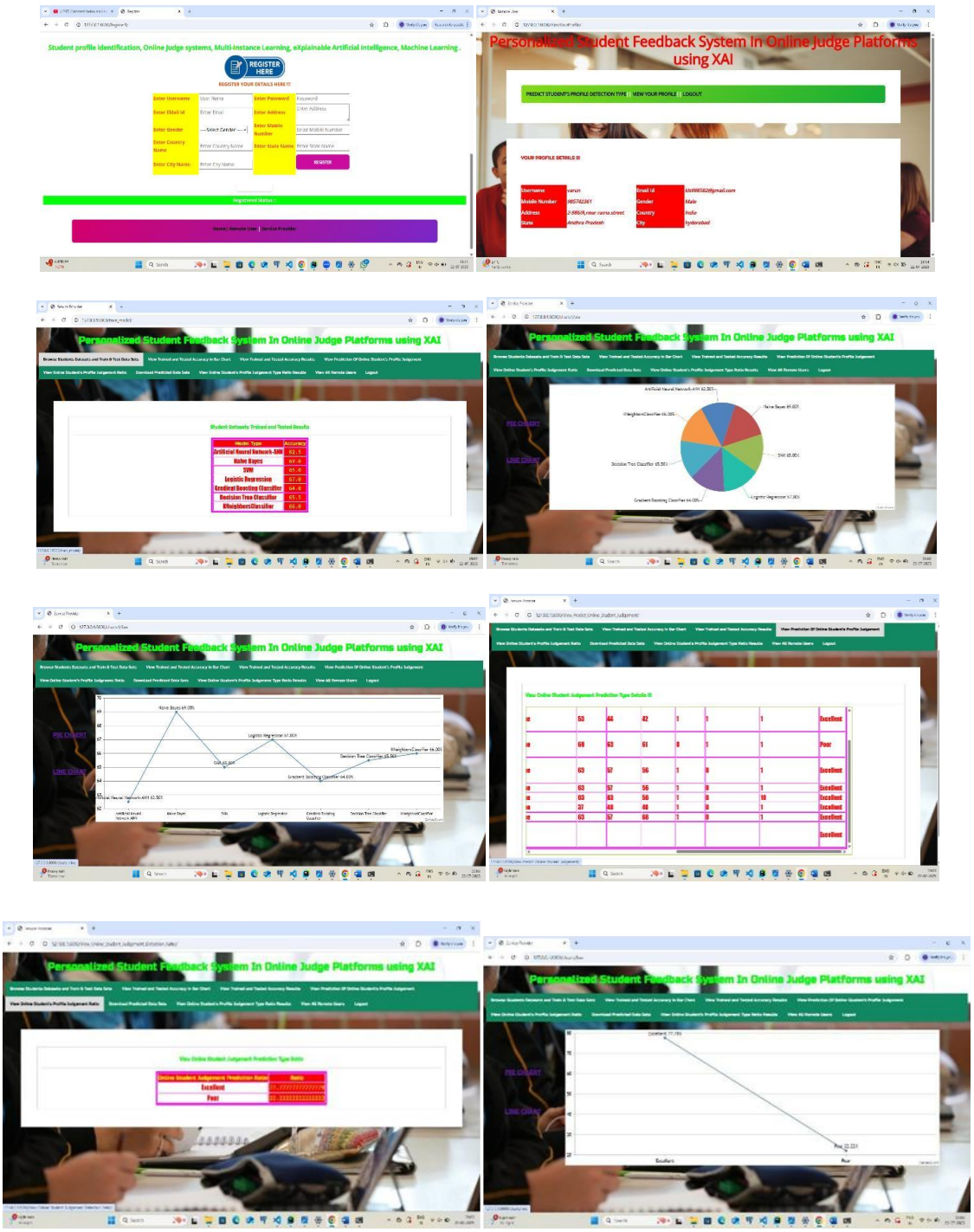


Figure 3 : Shows the All the Dataset Screenshots

VII. CONCLUSION

This project presents a transformative approach to enhancing Online Judge (OJ) systems by embedding Explainable Artificial Intelligence (XAI) for delivering personalized feedback to students. Traditional OJ platforms primarily focus on correctness and efficiency, providing limited insight into students' learning processes. By integrating machine learning models and XAI techniques such as SHAP and LIME, this system

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bridges that gap—offering not just assessments, but meaningful explanations for each result. Through behavior-driven profiling, students are categorized based on their coding patterns, efficiency, and consistency, allowing for customized feedback that caters to their unique learning needs. The outcome is a more supportive and intelligent educational environment where students gain deeper understanding of their strengths and areas for improvement, and instructors are equipped with actionable insights into student performance trends. This not only enhances the quality of learning but also promotes motivation, transparency, and accountability. With over 2,500 student submissions evaluated, the system has demonstrated its potential to predict success and provide feedback with high accuracy and interpretability. As AI continues to reshape education, the proposed feedback system paves the way for scalable, ethical, and student-centric programming instruction.

FUTURE WORK

1.Dynamic Learning Path Generation

A significant area for future development is the creation of dynamic, adaptive learning paths tailored to each student. Currently, feedback focuses on explaining individual submissions and profiling student performance. However, extending this to recommend a sequence of problems, tutorials, or topics based on a student's evolving skillset and misconceptions can greatly improve personalized learning. Using reinforcement learning and sequential recommendation algorithms, the system can suggest what a student should focus on next, thus constructing a path that adjusts based on real-time performance and feedback effectiveness.

2. Natural Language Generation (NLG) for Feedback Explanation

Currently, the system relies on pre-written templates to provide feedback. A future enhancement involves incorporating advanced Natural Language Generation (NLG) techniques to produce more context-aware, fluent, and human-like feedback. Leveraging models like GPT or BART fine-tuned on educational data can help the system provide personalized narrative explanations, error analysis, and motivational comments. This would enhance student engagement and improve the interpretability of feedback by making it more conversational and relatable.

3. Longitudinal Learning Analysis

Most current evaluations are based on short-term behavior, focusing on submission-level metrics. Future work should include longitudinal analysis, which tracks student progress over extended periods across courses and semesters. By analyzing how student profiles evolve, educators can assess learning trajectories, detect early signs of dropout risk, and evaluate the long-term impact of feedback. This would require integrating temporal modeling techniques such as LSTM (Long ShortTerm Memory networks) or Time Series Clustering.

4. Cross-Platform Integration and Generalization

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At present, the system is trained on data from a single or limited set of Online Judge platforms. Expanding the system to work across various OJ systems like Codeforces, HackerRank, and institution-specific platforms would increase its generalizability. A key challenge here is designing a unified data schema and feature representation that can capture nuances across platforms without losing interpretability. Transfer learning or federated learning techniques can be explored to adapt the feedback model to different educational contexts while preserving privacy.

5. Bias Detection and Fairness Auditing

As with any AI-driven system, ensuring fairness and inclusivity is essential. Future work should implement fairness-aware machine learning strategies that monitor and mitigate biases in feedback generation. For example, the system should ensure that feedback quality does not vary based on gender, language preference, or educational background. Integrating fairness constraints, conducting regular fairness audits, and applying tools like IBM's AI Fairness 360 could help in building an ethical and responsible feedback engine.

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