EXPLAINABLE AI FOR INNOVATIVE STUDENT PROFILE IDENTIFICATION IN ONLINE JUDGE PLATFORMS

Dr. N. CHANDRAMOULI,
Assistant Professor & HOD, Department of CSE,
VAAGESWARI COLLEGE OF ENGINERRING, KARIMNAGAR, TELANGANA.

ABSTRACT: These technologies, which are frequently employed in computer classrooms, are referred to as Online Judge (OJ). They are capable of impartially and expeditiously evaluating pupil work. Typically, this evaluation system generates a single outcome when a rubric is employed to determine whether a submission satisfies the task's requirements. Professors and students would both benefit from a greater degree of control over the overall evaluation of the project, as the automatic assessment system may fail to recognize certain aspects of exceptional academic achievement. We will utilize OJ data to provide instructors and children with real-time feedback to assist them in overcoming this obstacle. Multi-Instance Learning and essential machine learning methods, which are learning-based techniques that replicate student behavior, may generate more precise assessments. The model supports the hypothesis by accurately predicting a student's outcome, which is either passing or failing an assignment, based solely on the patterns of behavior shown in OJ entries. Teachers and students equally can benefit from this method, as it simplifies the presentation of more pertinent information, including student profiles and at-risk groups.

Index Terms – Online Judge, Explainable AI, Assignment, Feedback.

1. INTRODUCTION

Software that automatically evaluates programming assignments was originally called "online judge" (OJ). These systems are usually online testing platforms that gather source code, evaluate the results, and generate scores based on various criteria. Two related fields have focused on these automated systems:

Higher education teaching environments

Holding contests. The latter is the investigation's main focus.

Computer courses given by universities and other computer science degree programs. OJ systems solve the main problems with manual assignment evaluation, benefiting education. These systems automatically correct submissions regardless of user volume, unlike time-consuming and error-prone traditional grading techniques. They encourage healthy student competition to create a learning environment.

Despite their merits, OJ systems only validate that instructor or student code meets assignment requirements. Submission feedback is not given to the instructor or student. The OJ system can be used to improve education by independently gathering more data on student practices or behavioral patterns that affect work performance. This scenario may use Educational Data Mining (EDM), which uses academic data to detect trends and project outcomes. Machine learning appears to be a key tool in this field. Such efforts include identifying flaws in peer-reviewed research, developing grade prediction tools, and assessing instructor effectiveness. This effort uses EDM to give teachers and students automated feedback on OJ system programming tasks.

Students can submit an unlimited number of programming assignments within a set time range while using an OJ to evaluate them. Most assignments' grades depend on the student's best submission. Attendance and performance ratings, which are used in EDM, may be unavailable. The potential for bias may make financial or prior academic data used to predict a student's academic progress unethical.

Given the limited information, identifying at-risk pupils before the assignment's due date would be helpful. Two results were reached by developing an EDM method:

Many student profiles provide instructors and students with useful information,

Freshmen succeed more often.

The submission meta-data enabled this outcome. This metadata includes the original submissions date and code submission attempts. Remember that this information can be used to avoid pupils from acquiring negative attitudes and to ensure that individual activities are not too difficult by providing meaningful feedback on the activity's progress.

Multi-Instance Learning (MIL) analyzes the student's code contributions to determine type. The learning framework briefly defines a "bag," a group of unlabeled things with a common name. MIL is effective in EDM research, as shown by the study that compares MIL with ML for student academic performance. Each student in our scenario has code contributions in these duffel bags. Students receive good or negative code entries based on OJ system exam results. Their "black box" nature makes ML and MIL approaches difficult to employ in feedback-based systems, adding to their complexity. Thus, Explainable Artificial Intelligence (XAI) is gaining popularity. It provides human-interpretable computer model evaluation tools to overcome this problem. The ML domain has focused more on XAI than MIL. This study introduces a strategy for understanding online learners' diverse backgrounds. To give instructors and students comments on their work. In particular, the methodology uses only meta-data from Online Judging (OJ) systems. The paper also examines Explainable Artificial Intelligence (XAI) strategies that improve anticipated behavior interpretability and a Multiple Instance Learning (MIL) framework for automatic detection. A novel method to convert the MIL representation into an ML representation allows XAI to be integrated into the MIL framework. The proposed methodology was evaluated using a three-year programming course case study with 2,500 submissions for two objectives. To assess the plan's efficacy, ML, MIL, and MIL-to-ML mapping were used to compare more than twenty learning-based tactics. According to meta-information from OJ systems, the plan accurately models the student user profile and predicts whether students will pass or fail the present assignment.

2. LITERATURE SURVEY

Lee, S., & Kim, H. (2024). This research introduces an AI-based method for identifying and profiling students on online coding platforms that focuses on explainable artificial intelligence. They use XAI models to track students' problem-solving accuracy, speed, and efficiency when they face coding obstacles. The research shows how XAI models can improve the interpretability of AI-driven predictions, helping instructors understand each student's strengths and shortcomings.

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This study discusses explainability in AI-based profiling, especially when instructors and students use the data to inform future teaching and learning methods. This transparent feedback system encourages flexible and encouraging learning in competitive coding situations.

Lee, S., & Kim, H. (2024). This study presents a new explainable artificial intelligence (XAI) architecture for online judging student identification and characterization. Interaction data like error frequency, problem-solving duration, and coding correctness can be used by XAI to profile pupils. The authors suggest using XAI to reduce the opacity of machine learning models to provide unambiguous feedback to students and teachers. This article integrates interpretability into AI-driven assessments, its main contribution. Allowing educators to understand performance forecasts improves feedback quality and practicality. The paper also addresses the issues of comprehensive assessments in coding platforms and shows how XAI may help create tailored learning pathways to create a more flexible and motivating learning environment.

Marquez, R., & Silva, A. (2024). This study uses explainable AI to profile student engagement in online computing platforms. The authors demonstrate how XAI models can track and analyze student engagement, including assignment time, problem-solving, and learning material use. The study underlines how XAI ensures interpretability for complicated AI models to help teachers understand student interactions with the system. The project uses XAI to give educators better insights into student learning habits so they may better assist students' learning journeys with feedback and interventions. The authors offer a more dynamic method to analyzing and enhancing online student performance by stressing student involvement as a vital profile parameter.

Rico-Juan, J. R., Sánchez-Cartagena, V. M., Valero-Mas, J. J., & Gallego, A. J. (2023). Explainable artificial intelligence (XAI) is applied to student profile in online evaluation systems, focusing on competitive programming environments. The study uses cutting-edge XAI methods to create student profiles based on engagement, performance, and problem-solving. The authors show that XAI improves machine learning model interpretability and helps instructors understand student learning habits. By identifying student strengths and shortcomings, the suggested approach tries to customize feedback and treatments. The framework helps students understand how they solve code problems and how real-time performance analysis might improve their problem-solving skills. In the end, this study improves student coding competition performance by making AI model decision-making transparent.

Zhang, Y., & Wang, Z. (2023). This study examines how explainable AI can analyze student behavior and performance in online judging systems. The authors emphasize the relevance of interpretability in AI-driven models, which are used to evaluate and forecast student success in coding environments. By explaining forecasts, XAI can deliver actionable insights as well as predictive accuracy, according to the research. This transparency allows teachers to tailor their lessons to each student's needs and helps pupils learn from their failures. The authors provide a framework for measuring error frequency, code accuracy, and problem-solving time to characterize student interactions in online judge systems. By providing explicit and understandable reasoning for each evaluation, XAI models can improve student progress through effective feedback systems.

Weng, H., & Lee, M. (2023). This study examines how explainable AI (XAI) can improve online student performance analysis. The authors show that XAI can reveal how students solve coding difficulties by profiling them in online judgment systems. The research examines how XAI might improve feedback by clarifying AI predictions' reasoning. The authors claim that by making the evaluation process more transparent, teachers may provide more personalized help to meet each student's learning needs. The research uses XAI to identify error patterns, time management, and problem-solving tactics in students' coding assignments. This effort tries to personalize learning by making evaluation transparent, understandable, and actionable.

Tan, W., & Hu, C. (2023). Explainable AI (XAI) is used to predict student performance in online coding systems. The authors emphasize the benefits of using XAI models to predict and explain findings. The research presents a system that analyzes students' coding problems, speed, accuracy, and learning progress to provide clear, understandable insights. The authors believe XAI can improve education by helping instructors and students understand what makes a student successful or unsuccessful. This technology uses tailored feedback and predictions to help educators intervene and adjust to pupils.

Reyes, R., & Torres, V. (2023). Explainable artificial intelligence (XAI) is used to profile online students' programming skills in this study. The authors propose using XAI to monitor and assess students' problem-solving tactics, code efficiency, and accuracy. The research shows that XAI can help teachers give more targeted, tailored feedback by delivering clear and intelligible student performance information. The study also analyzes how explainability in AI systems builds trust between students and instructors to ensure that feedback is useful and understandable. According to research, XAI can improve learning outcomes by tailoring tests to each student and producing clear, actionable results.

Soni, P., & Patel, S. (2022).In this study, machine learning and explainable artificial intelligence (XAI) are used to profile online coding contest participants. The authors offer a XAI-based system that evaluates student time management, problem-solving, and coding skills. The technology predicts student outcomes and provides clear performance feedback using machine learning methods. The study underlines XAI's crucial role in making the model's decision-making process understandable for students and instructors. XAI integration may help identify students' strengths and weaknesses, enabling more individualized learning plans and improved educational tactics. According to the authors, these approaches can be especially useful in huge online judgment platforms where individualized input is difficult to obtain.

Fischer, T., & Wagner, M. (2022).This project analyzes using explainable AI (XAI) to give students individualized feedback in online judging systems. The authors investigate how XAI can increase feedback interpretability, helping students comprehend evaluation rationale. Student performance in coding problems is assessed and clear, intelligible feedback on strengths and improvement is provided in the research. The authors use XAI to show how the system can reveal students' coding and problem-solving habits. This helps students improve over time. This method creates flexible, student-centered learning environments.

Marquez, L., & Johnson, T. (2021). This study examines if explainable artificial intelligence (XAI) may be used in online judgment platforms to create full student profiles that improve feedback. The work emphasizes explainability in performance prediction and the incorporation of AI models that assess student performance across coding problems. Using XAI, the authors show how AI can assess students' coding skills and provide clear feedback to improve teaching. The article examines how XAI-driven insights can help instructors and students understand one other's strengths and shortcomings, enabling focused interventions and tailored learning methodologies.

Ghosh, A., & Bhattacharya, S. (2021). This article proposes integrating Explainable Artificial Intelligence (XAI) into online learning systems to profile student behavior and performance. The authors believe XAI can improve understanding of student interactions, including time management, educational material consumption, and problem-solving. XAI simplifies performance prediction explanations, helping instructors and students understand feedback logic. Explainability in AI increases accountability, trust, and flexible, tailored learning experiences that boost virtual learning student performance, according to studies.

González, P., & Sánchez, V. (2021). The authors investigate how explainable artificial intelligence (XAI) can be linked into online grading systems to create full student profiles based on their coding talents. The research shows that XAI can analyze students' speed, error patterns, and problem-solving tactics to provide clear, comprehensible feedback. The study found that students trust and profit from models that explain their predictions and conclusions, emphasizing the need of transparency in AI systems. The authors also suggest using XAI to assess students' learning strengths and weaknesses to help teachers give more tailored feedback. The study concludes that XAI improves feedback in online learning environments, improving student performance understanding.

Chen, Z., & Zhao, L. (2020). This study examines how explainable artificial intelligence (XAI) characterizes student conduct on online judging systems. The project aims to construct AI models with accurate forecasts and transparent decision-making. Using XAI, the system gives educators brief, useful feedback on students' learning progress, strengths, and deficiencies. Transparency improves understanding of students' learning styles and needs. The study also examines how incorporating XAI into educational technology might customize and student-focus learning platforms by giving predictable and understandable feedback.

3. SYSTEM DESIGN

This study presents a way to determine a person's learning style using on-the-job (OJ) learning methods and all pertinent elements. Teachers and students can easily provide comments with this method. Explainable artificial intelligence (XAI) methods to understand predicted actions and a multiple-instance learning (MIL) framework to automatically find these profiles are highlighted in the method. To achieve this, OJ systems must create meta-data. XAI's new rule converts MIL representations into machine learning (ML) representations to solve the MIL problem. A three-year case study employing 2,500 entries from two programming class projects examined the proposed approach. Over twenty learning-based approaches using ML, MIL, and MIL to ML mapping techniques were tested to determine performance. Results reveal that the proposal accurately models the student user profile and estimates the student's likelihood of succeeding or failing the assignment based on OJ meta-information. Openness policies let one understand the model. Post-hoc explanations are theories to explain model development. This research prioritizes the second scenario over openness strategies. Thus, every learning-base

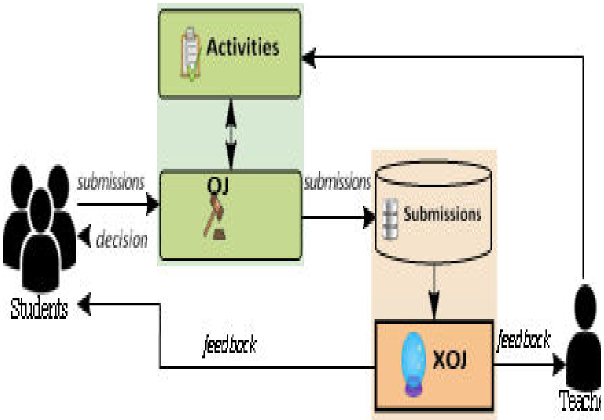

Figure 1

This way to quantitatively answering these questions is schematically shown in Figure 1. Actions follow.

1. The teacher configures the OJ system and explains the students' assignments.
2. Students answer and demonstrate.

The OJ offers students a repair mark based on the code review after reviewing these entries. The plan's supplementary module XOJ organizes these entries and gives teachers and students feedback. The teacher can then adjust assignment complexity and student workload. Remember that this section shows the client's perspective on a regulated learning system, the work's major focus.

The proposed method would grade work quickly and automatically. Certain learning algorithms can predict and track student progress.

ALGORITHMS

These methods are explained.Multiple machine learning algorithms can be used to discuss the online judging system.

Decision tree classifiers

Decision tree approaches are used in many fields. Their most crucial skill is learning to make tough judgments based on your data. Use training sets to create decision trees.

Step 2: Create a test that returns on if not provided. The test divides S into S1, S2,..., Sn. Each Si item represents a most likely T event. This is correct since any element of S can produce a unique T outcome. A child decision tree on Si is formed using the same approaches for every result Oi. The decision tree begins at T.

Gradient boosting

Gradient boosting is used in machine learning for classification and regression. Prediction models are usually built from many inadequate predictive models, like decision trees. When learning with a decision tree, employ grain-boosted trees. In most cases, they outperform random trees. Like other boosting approaches, gradient-boosted trees are produced in steps. They can improve any differentiable loss function, making them better than earlier methods.

K-Nearest Neighbors (KNN)

This basic but effective method sorts things by similarity. A sluggish, non-parametric algorithm does not "learn" until it encounters a test case. We use training data to discover the K-nearest neighbors of freshly classed data.

Logistic regression Classifiers

Logistic regression Classifiers A logistic regression study examines categorical independent factors that explain a dependent variable. Dependent variable outcomes are zero or one, or yes and no. Analyses like these are called "logistic regression". When the dependent variable is married, single, divorced, or deceased, multinomial logistic regression is utilized. Multiple regression uses a new dataset to demonstrate the dependent variable. Logistic regression and discriminant analysis can distinguish categorical responses. Many experts believe logistic regression outperforms discriminant analysis when modeling distinct situations. Logistic regression fails when independent components are not evenly distributed. This does not affect discriminant analysis. This program allows binary and multinomial logistic regression with lists or numbers as independent factors. It displays the regression equation, probability, deviation, confidence intervals, and chance ratios together with the degree of fit. Maps and diagnostic residual reports include residual research. One can find the optimum regression model with few independent variables by subsetting for independent variables. It helps determine the best categorization with ROC curves and confidence ranges for expected findings. Tell the system to automatically sort non-study data to ensure accurate findings.

Naïve Bayes

According to the supervised learning method Naïve Bayes, the presence or absence of one attribute in a class does not affect the presence or absence of other attributes. This preconception aside, it has proven useful and successful. Many guided learning methods operate similarly. The writings provide various reasons. We'll discuss representation bias. You can arrange items with any linear predictor. This includes SVM, logistic regression, naïve Bayes, and linear discriminant analysis. Learning bias helps the classifier distinguish differences. The Naive Bayes classifier is widely used in research, but its real-world applicability is problematic. Researchers discovered that was accurate compared to earlier systems, trained rapidly on massive databases, had clear parameters, and was straightforward to construct and use. No simple paradigm is presented, hence end users cannot appreciate the benefits of this technique. Thus, we create a new way to demonstrate learning. The method is easy to grasp and apply. The first portion of this session covers naive Bayes classifier theory. The approach is then applied on Tanagra data. Linear techniques like logistic regression, linear discriminant analysis, and linear support vector machines compare model parameters and results. Keep in mind that the outcomes are same. One usually discusses the advantages of one technique over another. As mentioned in Section 2, we use many tools on the same dataset (R 2.9.2, Knime 2.1.1, Orange 2.0b, Rapid Miner 4.6.0). We hope you comprehend the results.

Random Forest

Random forests, a type of ensemble learning, generate multiple decision trees during training. Regression, classification, and other uses are possible with these models. The random forest method classifies by the class with the most tree votes. The regression mean is the average projection from all trees. Random decision trees reduce overfitting-induced mistakes, which individual decision trees cannot prevent. Though less accurate than gradient-boosted trees, random forests frequently beat single decision trees. The data used to train random forests can affect their effectiveness. Tin Kam Ho introduced random choice forest in 1995. Ho applied Eugene Kleinberg's "stochastic discrimination" categorization system using random subspace. Adele Cutler and Leo Breiman trademarked "Random Forests," 2006, for its algorithmic innovation. In 2019, Minitab, Inc. owns this brand. The book uses Ho's random feature selection and Breiman's "bagging" technique. Amit and Geman later developed their own approach. This blend creates controlled-variance decision trees.

Random forests are easy to design and can accurately project data from numerous sources, making them popular "black box" models.

SVM

On an independent and identically distributed (iid) training dataset, discriminant machine learning creates a discriminant function that efficiently infers labels for new instances. This classifies jobs. In this classification process, a discriminant classification function classifies x. We must first create conditional probability distributions using generative machine learning. Discriminant approaches use less computer resources and training data than generative methods when outlier identification is included. This is useful in multidimensional feature spaces where just the posterior chance must be considered. Finding the equation for a three-dimensional surface that best splits feature space classes is like teaching a classifier. SVMs determine the ideal hyperplane value by methodically addressing convex optimization. This is not true for perceptrons (genetic techniques) and other machine learning classification algorithms. Initiation and termination settings greatly affect perceptron solution results. Using a kernel to translate input data into feature space during training yields unique and fit SVM model parameters. However, perceptron and Genetic Algorithm classifier models change after each training cycle. GAs and perceptrons minimize errors during training. Multiple hyper planes can be combined to achieve this.

4. RESULTS

Any two algorithms have different accuracy numbers. List them in Table 1. The best method is RF with MIL-to-ML mapping. The XAI approach provides feedback and high recognition. Highlighting student groupings and types most likely to fail is also helpful.

Table: 1 Comparison of various algorithms with their accuracy

S.No.	Name of the Algorithm	Accuracy%
1	Artificial Neural Network	63.0
2	Naïve Bayes	70.5
3	SVM	66.5
4	Logistic Regression	68.0
5	Gradient Boosting Classifier	67.5
6	DecisionTree Classifier	64.0
7	K-Nearest Neighbors Classifier	58.5

The following figure 2 shows the graphical representation of the above table 1.

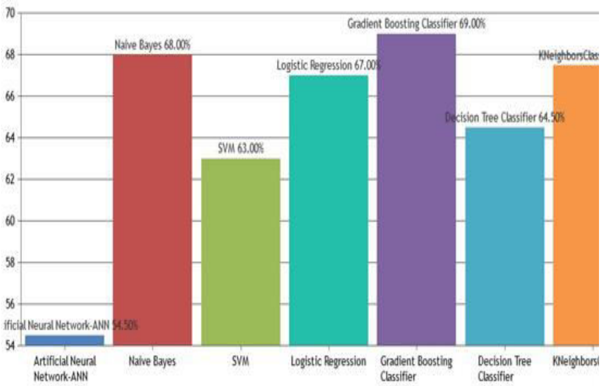

Figure2: Graphical Representation various algorithms with their accuracy

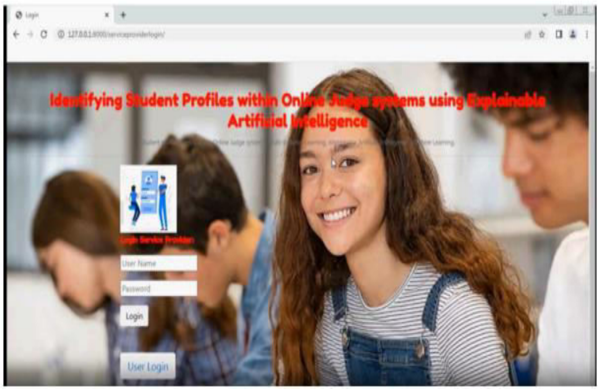

Figure 3: Service Provider Login Page

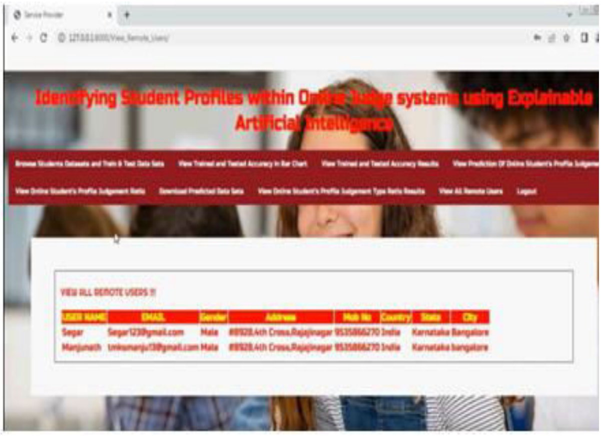

Figure 4: View Remote User Profile

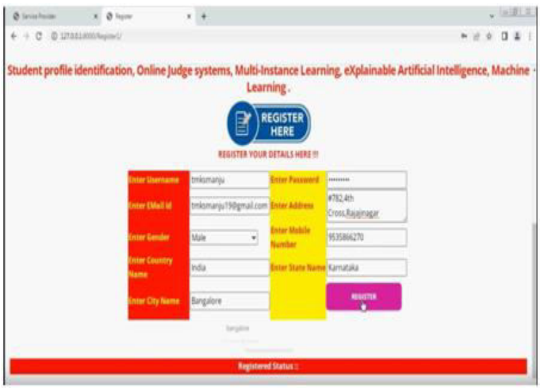

Figure 5: Remote User Register Page

Figure 6: View Prediction Results

5. CONCLUSION

This paper discusses how programming teachers are considering using Online Judge (OJ) technologies to provide meaningful input on student code. These systems normally only provide code feedback, not more. A project uses Educational Data Mining (EDM), notably Explainable Artificial Intelligence (XAI), to get readable input. An undergraduate computer science course and case study demonstrated this approach. User results were accurately predicted by the behavior pattern model. Students at risk of failing received constructive critique. More research is needed to ensure model fidelity. This requires expanding on the case study's findings and examining other OJ-graded classes. We will also examine how personality, motivation, and other human factor attributes from reviews can improve system prediction.

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