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A Confusion-Aware Intelligent Tutoring System Using Adaptive Learning and Student State Modeling

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Abstract: Online learning platforms have become an essential part of modern education. However, most existing e-learning systems deliver uniform content to all learners without considering individual learning difficulties. One of the most critical challenges faced by learners is confusion. This project presents a Confusion-Aware Intelligent Tutoring System that automatically detects learner confusion levels and provides adaptive explanations accordingly. The system analyzes learner interaction data such as quiz accuracy, response time, number of attempts, and hint usage using machine learning techniques. Based on the detected confusion level (low, medium, or high), the system dynamically provides explanations in multiple formats including simplified explanations, flowchart-based explanations, and step-by-step guidance. The proposed system explain about multiple technical domains such as programming languages, web technologies, and core computer science subjects. Experimental results demonstrate improved learning outcomes, reduced confusion levels, and enhanced learner engagement.

Keyword: Confusion Detection, Intelligent Tutoring System, Adaptive Learning, Machine Learning, Personalized Education, Learning Analytics, Student Modeling, Educational Data Mining,Adaptive Explanation, Personalized Learning System, Confusion level.

I. INTRODUCTION

The rapid advancement of digital learning technologies has significantly transformed modern education by providing learners with flexible, scalable, and accessible learning environments. Despite these benefits, most traditional e-learning systems follow a one-size-fits-all approach and lack the ability to understand individual learner difficulties. As a result, learners who experience confusion during problem-solving often receive no immediate support, which can negatively impact learning outcomes and engagement.

Intelligent Tutoring Systems (ITS) aim to address these limitations by offering personalized learning experiences that adapt to individual learner needs. However, many existing systems rely primarily on static assessments and do not actively monitor learner behavior during learning activities. Confusion is a critical cognitive state that directly affects comprehension and performance. Detecting confusion at the right time and responding with appropriate instructional strategies can significantly enhance understanding and reduce learning frustration.

To overcome these challenges, this project proposes a Confusion-Aware Intelligent Tutoring System that automatically detects learner confusion using machine learning techniques. By analyzing interaction features such as accuracy, response time, hint usage, and number of attempts, the system predicts confusion levels and delivers adaptive explanations in multiple formats. This approach enables personalized learning support, improves learner engagement, and contributes to more effective and intelligent e-learning environments.

II. RELATED WORK

The Confusion aware Intelligent Tutoring Systems have increasingly incorporated affect-aware mechanisms to improve personalized learning experiences. Among various affective states, learner confusion plays a crucial role as it can either support deeper learning or lead to disengagement if not addressed timely. Recent studies have focused on detecting confusion using behavioral interaction data such as response time, hint usage, and error patterns through machine learning techniques. These approaches are non-intrusive and scalable for online learning environments. However, effective integration of confusion detection with real-time adaptive feedback remains an open research challenge.

Research on detecting learners' confusion and other affective states in intelligent tutoring systems has evolved steadily over the years. Early work by D'Mello, Gholson, and Graesser (2007) focused on the automatic detection of affective states such as confusion within intelligent tutoring systems, highlighting the role of cognitive–affective interactions in learning. Building on this foundation, Arguel et al. (2017), in *Inside Out: Detecting Learners' Confusion to Improve Interactive Digital Learning Environments*, explored multimodal indicators of confusion and emphasized how recognizing confusion can enhance the design of interactive learning environments. Later, Abidi et al. (2019) applied machine learning techniques to predict confusion during algebra homework in intelligent tutoring systems, demonstrating improved prediction accuracy using learner interaction data. In the same year, Atapattu et al. (2019) investigated the identification of learners' confusion through language and discourse analysis, showing that textual and conversational cues are strong indicators of confusion. More recently, Liu, Zhang, and Elmagarmid (2024) extended this research to large-scale online learning by using deep learning techniques to identify learners' confusion in MOOCs, reflecting a shift toward more scalable and data-driven approaches for affect detection in modern digital learning platforms.Problem Statement.

III. EXISTING SYSTEM

Existing online learning systems do not automatically identify learner confusion or adapt instructional content based on learner difficulties. As a result, students who struggle with concepts receive the same explanations as others, leading to ineffective learning experiences.The problem addressed in this project is the automatic detection of learner confusion and adaptive explanation delivery to enhance learning effectiveness and personalization**.** Most existing learning platforms provide static educational content such as video lectures, notes, and quizzes. Although some systems track scores and completion status, they do not analyze deeper indicators such as confusion, hesitation, or repeated mistakes.Popular platforms such as MOOCs and Learning Management Systems lack real-time adaptive explanation mechanisms. Learners must rely on self-help resources or external assistance, which limits the effectiveness of online education.

Traditional learning systems often do not detect learner confusion, so students struggle without timely support. They usually provide static explanations that remain the same for all learners, regardless of understanding. Because of limited personalization, individual learning needs are not addressed effectively. This leads to reduced learner engagement, as students lose interest when content feels irrelevant or too difficult. Over time, these issues contribute to higher dropout rates, especially in long-term or self-paced learning environments.

IV. PROPOSED SYSTEM

The proposed Confusion-Aware Intelligent Tutoring System is designed to enhance personalized learning by automatically detecting learner confusion and adapting instructional content accordingly. The system continuously monitors learner interaction parameters such as quiz accuracy, response time, number of attempts, and hint usage. Using machine learning techniques, the system classifies the learner's confusion level into low, medium, or high. Based on the detected confusion level, the system dynamically provides adaptive explanations in multiple formats, including simple explanations, flowchart-based conceptual explanations, and detailed step-by-step guidance. This approach ensures that learners receive appropriate instructional support at the right time, thereby improving conceptual understanding, reducing frustration, and enhancing overall learning effectiveness.

The proposed system provides personalized learning experiences by adapting content to each learner's needs. It detects learner confusion in real time using machine learning techniques and delivers suitable explanations based on the level of confusion. By offering adaptive support, the system improves learner engagement and helps in better understanding of concepts. It also reduces frustration and minimizes the chances of learners dropping out. The system supports multiple technical subjects and domains, making it flexible and versatile. Overall, it is scalable and well suited for modern online education platforms.

V. METHODOLOGY

The proposed Confusion-Aware Intelligent Tutoring System follows a structured methodology to provide personalized learning support by detecting and addressing learner confusion. Initially, learners register and select a course or topic from the system. As learners interact with the learning content and attempt quizzes, the system continuously collects interaction data such as accuracy, response time, number of attempts, and hint usage. This data is pre-processed and analysed using a supervised machine learning model to predict the learner's confusion level, which is classified as low, medium, or high. Based on the detected confusion level, the system dynamically selects and delivers an appropriate explanation strategy, including simple explanations, flowchart-based conceptual explanations, or detailed step-by-step guidance. Learner performance and confusion scores are stored in the database for progress tracking and future personalization, thereby enabling an adaptive and effective learning experience.

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The processed features are analysed using a supervised machine learning model to predict the learner's confusion level, which is classified into low, medium, or high. The confusion level is computed using a weighted confusion score that combines multiple learning indicators.The confusion score is calculated using the following weighted equation:

Confusion Score=w1(1−Accuracy)+w2(Normalized Response Time) +w3(Hint Usage)

A. ER Diagram

The ER diagram represents the data structure of the Confusion-Aware Intelligent Tutoring System. It models how students interact with learning content, assessments, and adaptive explanations. The Student entity stores learner details, while the Course entity groups related subjects. Each course contains multiple Topics, and every topic is associated with a Quiz to assess understanding. Student quiz attempts generate Performance data such as score, accuracy, and response time. This performance is analyzed to determine the Confusion Level, which categorizes learners as low, medium, or high confusion. Based on the detected confusion level, the system provides appropriate Explanations to improve learning outcomes. This structured design enables adaptive and personalized learning.

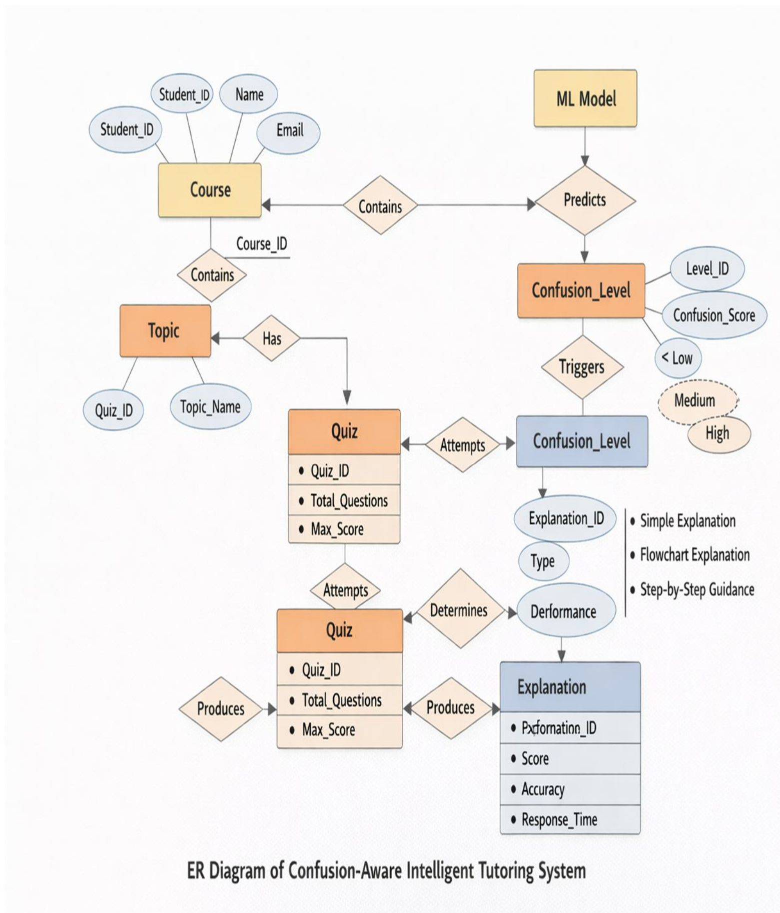

Fig 1.1 ER Diagram

B. Project Flow Diagram

The Process Flow Diagram illustrates the complete operational workflow of the *Confusion-Aware Intelligent Tutoring System*. The process begins with the user login or registration, ensuring authenticated access to the system. After successful login, the student selects a course and topic and starts viewing the learning content. The student then attempts quizzes related to the selected topic. Based on the quiz responses and interaction patterns, the machine learning model analyzes the learner's performance to detect the confusion level. If high confusion is detected, the system provides adaptive explanations using simplified content, hints, or step-by-step guidance. If confusion is low, the learner continues with normal learning progression.

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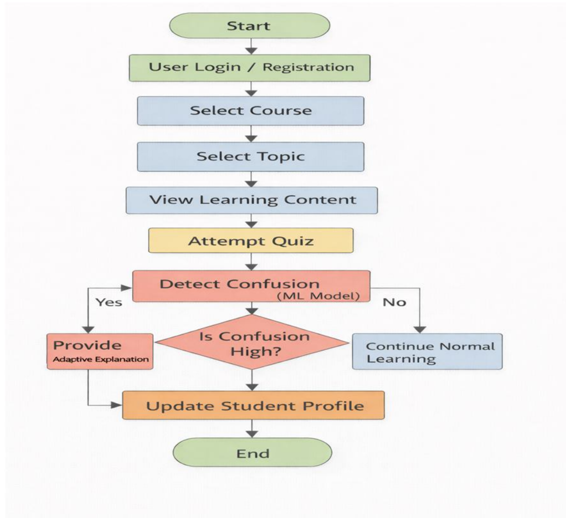

Fig 1.2 Project Flow Diagram

C. Use Case Diagram

The Use Case Diagram illustrates the functional interaction between users and the Confusion-Aware Intelligent Tutoring System. The system involves two primary actors: Student and Admin. The diagram represents how each actor interacts with the system to achieve specific goals. The Student actor can perform use cases such as Register/Login, Select Course, Select Topic, View Learning Content, Attempt Quizzes, Receive Performance Evaluation, and Obtain Adaptive Explanations based on their confusion level. These use cases support personalized learning by continuously assessing the student's understanding and providing suitable instructional support. The Admin actor is responsible for administrative tasks such as Managing Courses and Topics, Managing Users, Uploading Learning Content, and Monitoring Student Performance. The Admin ensures the system remains updated, organized, and functional. Overall, the use case diagram clearly defines system functionality, user roles, and adaptive learning behavior.

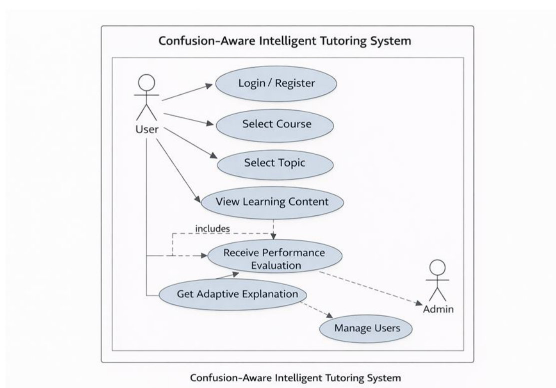

Fig 1.3 Use Case Diagram

VI. IMPLEMENTATION

The Confusion-Aware Intelligent Tutoring System is implemented as a web-based application using a modular architecture. The frontend provides an interactive interface for user login, course selection, quizzes, and adaptive explanations. The backend, developed using Python, handles application logic, user requests, and data processing. Learner interaction data such as accuracy, response time, and number of attempts is collected during assessments. A supervised machine learning model analyses this data to predict the learner's confusion level. Based on the predicted confusion, the system dynamically selects an appropriate explanation type. The explanation content is retrieved from a structured dataset and displayed to the learner. All user activity, confusion scores, and performance data are stored in a database for progress tracking and future personalization. The integrated system is tested to ensure reliability and effective adaptive learning support.

A. System Overview

The confusion-aware intelligent tutoring system is a web-based learning platform designed to provide personalized and adaptive education by identifying learner confusion in real time.

The system allows learners to select courses and attempt quizzes while continuously monitoring their interaction behaviour. Learner performance data such as accuracy, response time, and number of attempts is analysed using a machine learning model to determine the learner's confusion level.

Based on the predicted confusion level, the system dynamically provides suitable explanations in multiple formats, including simple explanations, flowchart-based explanations, and step-by-step guidance. The system stores learner progress and confusion history in a database to support continuous improvement and personalized learning experiences. This approach enhances learner understanding, engagement, and overall learning effectiveness.

B. Frontend Implementation

The frontend provides all user interactions, including login, course selection, quiz interfaces, dashboards, and adaptive explanation display. Components are designed to dynamically update based on learner actions. User experience principles such as clarity, simplicity, and responsiveness are followed to ensure ease of use for learners.

C. Backend Implementation

The backend manages system workflows and decision logic. It processes user requests, retrieves learning content, invokes the machine learning model for confusion prediction, and selects the appropriate explanation. REST APIs are used for communication between frontend and backend, ensuring smooth data flow.

D. Confusion Detection

The confusion detection model is implemented using supervised learning algorithms. Features such as accuracy, response time, and number of attempts are normalized and fed into the model. The trained model predicts confusion levels in real time, enabling immediate adaptive feedback.

E. Explanation Engine

The explanation engine maps confusion levels to explanation types. It retrieves explanations from the dataset and presents them in different formats such as text-based, flow-based, and step-by-step guidance. This engine ensures that learners receive the most suitable explanation based on their understanding level.

F. Database Design

The database stores structured data including user details, learning history, quiz performance, confusion scores, and explanation content. Proper indexing and normalization are applied to support efficient queries and analytics. The database plays a crucial role in personalization and progress tracking.

VII. RESULTS

The experimental evaluation of the Confusion-Aware Intelligent Tutoring System demonstrates a significant improvement in learner performance after the introduction of adaptive explanations. Learners initially showed moderate to high confusion levels, reflected by lower quiz accuracy and longer response times. After the system applied confusion-aware adaptive explanations, there was a noticeable increase in quiz accuracy and a gradual reduction in response time across learning sessions. High-confusion learners benefited most from step-by-step explanations, Further analysis reveals that the system effectively reduced learner confusion levels over time. Confusion scores consistently decreased as learners interacted with adaptive content, indicating improved conceptual clarity and engagement.

The results confirm that integrating machine learning-based confusion detection with adaptive explanation strategies enhances personalized learning outcomes compared to traditional static e-learning systems. Overall, the proposed system proves to be effective in identifying learner difficulties and providing timely instructional support.

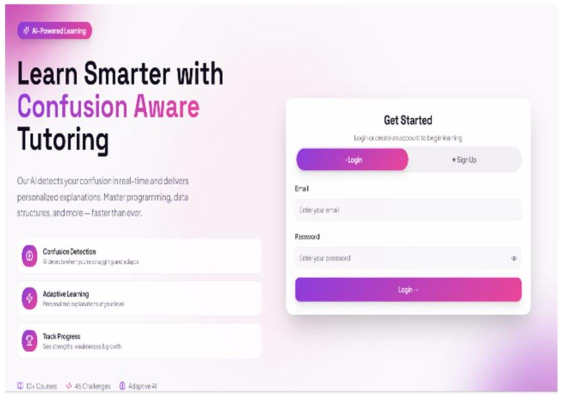

Fig 2.1 Login Page

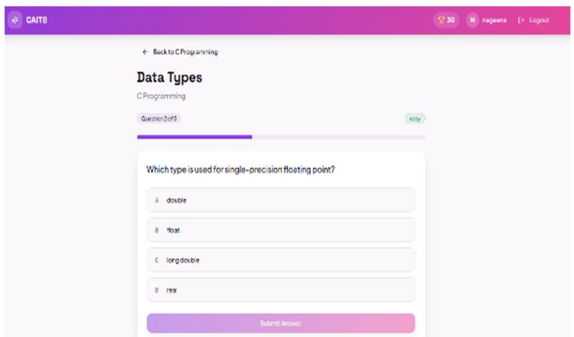

Fig 2.2 MCQ Quiz

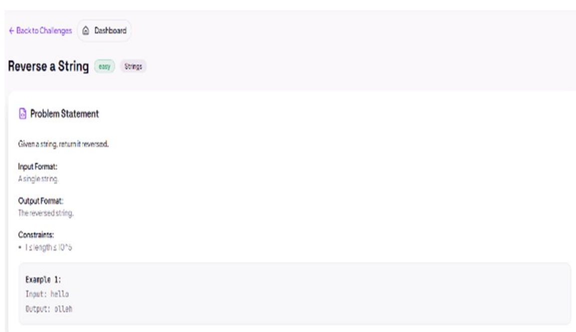

Fig 2.3 Coding Challenge

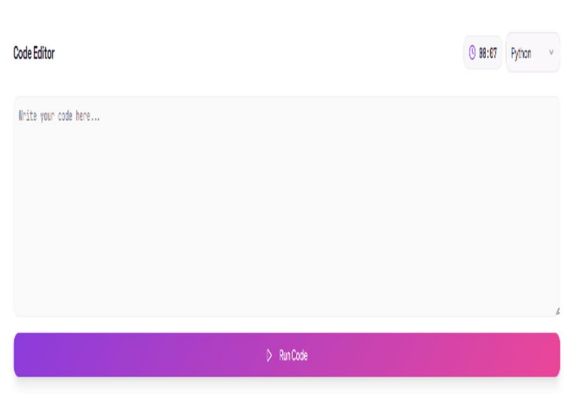

Fig 2.4 Code Editor

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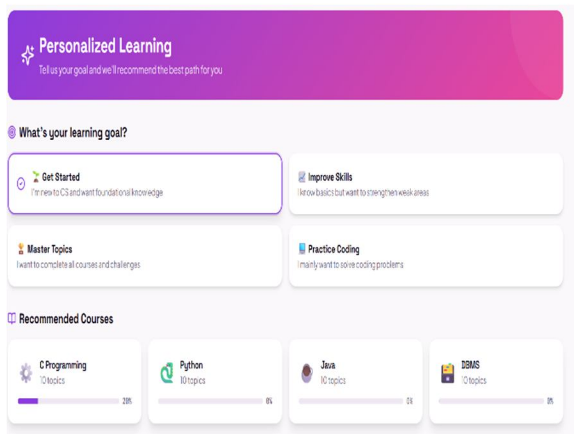

Fig 2.5 Personalized Learning

A. *Confusion Matrix*

A confusion matrix is a performance evaluation tool used to assess the effectiveness of a machine learning classification model. It compares the actual class labels with the predicted class labels, allowing a detailed analysis of model performance. In this project, the confusion matrix is used to evaluate how accurately the system classifies learner confusion levels into Low, Medium, and High categories.

The matrix consists of four key components: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). True Positives represent correctly predicted confusion levels, while False Positives and False Negatives indicate misclassifications. By analyzing these values, the effectiveness of the confusion detection model can be measured and improved.

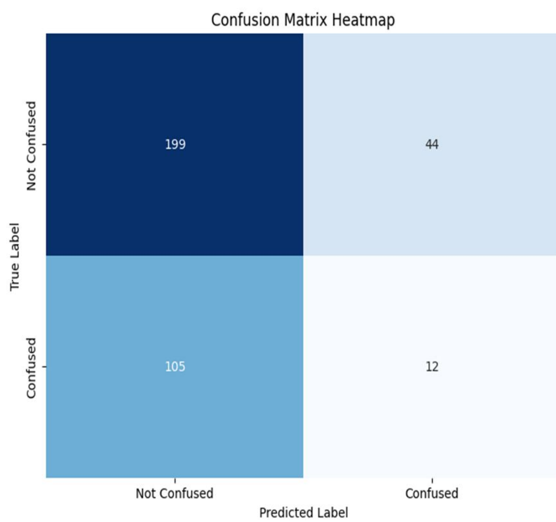

Fig 3.1 Confusion Matrix

B. *ROC Curve*

The Receiver Operating Characteristic (ROC) curve is a graphical representation used to evaluate the performance of a classification model. It illustrates the trade-off between the True Positive Rate (TPR) and the False Positive Rate (FPR) at different classification threshold values. In this project, the ROC curve is used to assess how effectively the machine learning model distinguishes between different learner confusion levels.

The True Positive Rate, also known as Sensitivity or Recall, represents the proportion of correctly identified confusion instances, while the False Positive Rate represents the proportion of incorrectly classified non-confusion instances. A model with better performance produces an ROC curve that moves closer to the top-left corner of the graph, indicating high sensitivity and low false positives. The Area Under the Curve (AUC) provides a single numerical value to summarize model performance, where a value closer to 1 indicates excellent classification capability.

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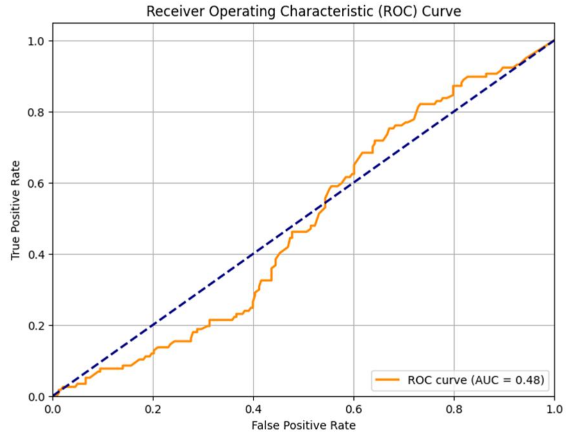

Fig 3.2 ROC Curve

C. Precision - Recall Curve

The Precision–Recall (PR) curve is a performance evaluation graph used to analyze the effectiveness of a classification model, especially when the dataset is imbalanced. It shows the relationship between Precision and Recall for different classification threshold values. In this project, the Precision–Recall curve is used to evaluate how accurately the model identifies learner confusion levels while minimizing incorrect predictions.Precision measures how many of the predicted confusion instances are actually correct, while Recall measures how many of the actual confusion instances are successfully identified by the model. A good model achieves high precision and high recall, resulting in a PR curve that stays close to the top-right corner of the graph. The area under the PR curve provides a summary of model performance, where higher values indicate better confusion detection capability.

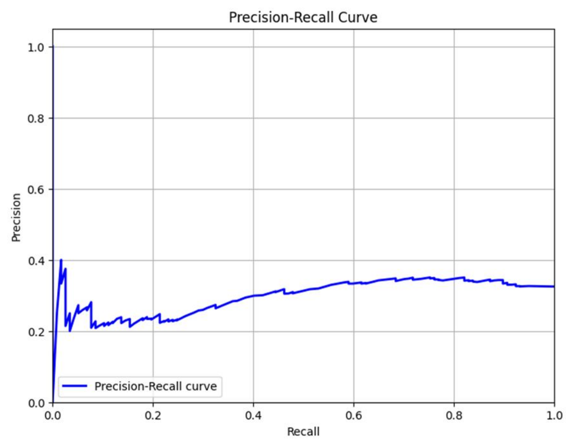

Fig 3.3 Precision – Recall Curve

VIII. CONCLUSION

This project successfully developed a Confusion-Aware Intelligent Tutoring System that enhances personalized learning by identifying and addressing learner confusion in real time. By analyzing learner interaction data such as accuracy, response time, hint usage, and number of attempts, the system effectively predicts confusion levels using machine learning techniques. Based on the detected confusion level, adaptive explanations are dynamically delivered in multiple formats, including simple explanations, flowchart-based conceptual representations, and step-by-step guidance. The results demonstrate improved learner understanding, reduced confusion, and increased engagement compared to traditional static learning systems. The proposed system provides a scalable and flexible solution for intelligent e-learning environments by integrating data-driven confusion detection with adaptive instructional strategies. Its modular architecture allows easy extension to additional subjects and learning domains. Future enhancements may include incorporating deep learning models, emotion recognition, and real-time feedback analytics to further improve personalization and learning outcomes. Overall, the system contributes significantly to the development of intelligent and adaptive educational technologies.

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