# SmartEdu+: Advanced Machine Learning System for Early Prediction of Student Dropouts


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***Abstract***

**Student dropout is one of the major challenges faced by educational institutions, leading to academic disruption and financial losses. Early identification of at-risk students can enable timely interventions and improve student retention. This paper presents SmartEdu+, an AI-driven platform that predicts the likelihood of student dropout using demographic, academic, and behavioral features. A Random Forest classifier was employed to achieve reliable predictions, while SHAP (SHapley Additive exPlanations) was integrated to ensure interpretability of the model outcomes. The system is deployed as an interactive dashboard built with Streamlit, enabling staff to visualize predictions, track dropout trends, and receive student feedback. Experimental results on a dataset of 300 student records demonstrate that the proposed model provides accurate and explainable dropout risk predictions. The system further enhances decision-making by highlighting the most influential factors contributing to dropout. SmartEdu+ can serve as a practical decision-support tool for institutions, with potential future enhancements including integration with larger datasets and automated alert systems.**



***Keywords—Dropout Prediction, Explainable AI, SHAP, Educational Data Mining, Machine Learning, Student Retention.***


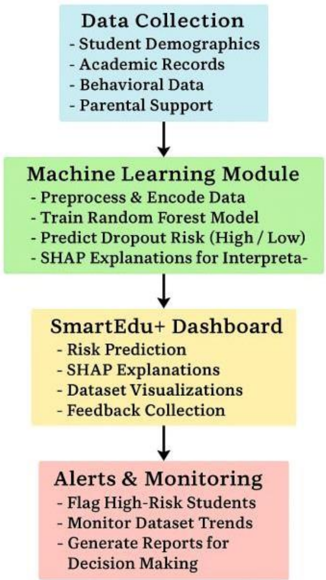


***Fig. 1 Functional Overview of the SmartEdu+ Student Dropout Prediction and Feedback System***

## 1. Introduction

Student dropout is a persistent challenge in the education sector, affecting both students and institutions. A dropout not only interrupts the academic journey of a student but also leads to financial and reputational consequences for schools and universities. Identifying students at risk of dropping out is therefore a critical task for educational management systems.

Traditional methods of dropout identification are reactive, relying on manual observation and post-failure analysis. With the growth of educational data mining (EDM) and machine learning (ML), predictive approaches are gaining popularity. These approaches can detect patterns in academic performance, attendance, socio-economic background, and behavioral data to provide early warnings.

In this paper, we propose SmartEdu+, a predictive system designed to identify potential dropouts at an early stage. The model is developed using a Random Forest classifier, which offers robustness against noisy data and provides strong predictive performance. To ensure transparency, the system integrates SHAP (SHapley Additive exPlanations) for model interpretability, allowing staff to understand the factors influencing predictions.

The system is implemented as a Streamlit-based dashboard, enabling interactive risk prediction, visualization of dataset patterns, SHAP-based explanations, and collection of student feedback. This makes SmartEdu+ not only a predictive model but also a decision-support tool for administrators and teachers.

The rest of the paper is organized as follows: Section III presents the system design including UML, ER, and data flow diagrams. Section IV explains the methodology and model development. Section V discusses the results and visualizations, while Section VI concludes with key findings and potential future enhancements.

### 1.1 Problem Statement

Student dropouts remain one of the critical challenges in the education system, especially in developing countries. Traditional dropout detection methods rely on manual monitoring by teachers or administrative staff, which often leads to delayed identification of at-risk students. These approaches are reactive rather than proactive, resulting in missed opportunities for timely interventions. Moreover, existing systems lack transparency, predictive capability, and effective feedback mechanisms from students, making it difficult to address the root causes of dropouts. Hence, there is a need for an intelligent, AI-powered system that can predict dropout risks early, explain the contributing factors, and collect direct student feedback to support data-driven decision-making and reduce dropout rates.

### 1.2 Motivation, novelty, and contribution of the study

The motivation for this study comes from the growing issue of student dropouts which affect academic performance and institutional outcomes. Existing systems are mostly reactive and lack predictive insights.

The novelty of SmartEdu+ lies in combining AI-based prediction with explainable AI (SHAP) and a feedback mechanism.

The key contributions are:

1. Dropout prediction model using academic and socio-economic data.
2. Explainability with SHAP to highlight top risk factors.
3. Feedback collection from students for real reasons behind dropout.
4. Visualization dashboard for staff to monitor risks and trends.

This approach ensures dropout detection is predictive, transparent, and actionable.

## 2. Related Work

Research on student dropout prediction has explored statistical models, machine learning, and academic analytics. Prior studies mainly focused on academic performance (marks, attendance) while overlooking socio-economic and behavioral factors.

Some works applied black-box models that lacked interpretability, making it difficult for educators to understand the reasons behind dropout predictions.

Recent approaches suggest using explainable AI (XAI) for transparency, but few integrate this with feedback collection from students.

### 2.1 AI for Student Dropout Prediction

Several researchers have applied Artificial Intelligence (AI) and machine learning techniques to address the problem of student dropout prediction. Early studies primarily relied on statistical models such as logistic regression, which used attendance and grades as predictors. However, recent advancements have introduced more sophisticated approaches. For instance, Kotsiantis et al. [1] applied decision trees and support vector machines to educational datasets, demonstrating improved accuracy in identifying at-risk students. Similarly, Cortez and Silva [2] analyzed student performance data using classification models, showing the potential of machine learning.

### 2.2 Explainable AI for Educational Transparency

One of the main challenges in applying advanced machine learning models to education is their “black-box” nature, where predictions are generated without clear reasoning. To overcome this, Explainable AI (XAI) techniques such as SHAP (SHapley Additive Explanations) are being widely adopted. Lundberg and Lee [3] introduced SHAP as a method for interpreting model outputs by quantifying each feature’s contribution to a prediction. In the educational context, Khosravi et al. [4] demonstrated that integrating explainability into student performance prediction systems increases trust among educators and improves the adoption of AI-driven tools.

### 2.3 Student Feedback and Dashboards

In educational systems, fairness and inclusivity are essential when designing interventions for at-risk students. Traditional monitoring approaches often overlook students’ personal perspectives, leading to incomplete or biased evaluations. To address this, researchers have emphasized the importance of incorporating student feedback and interactive dashboards into predictive frameworks. For example, Gašević et al. [5] highlighted that learning analytics dashboards improve transparency by allowing educators to visualize risk factors and performance trends. Similarly, Viberg et al. [6] showed that student-centered feedback loops help institutions design interventions that are both personalized and equitable.

### 2.4 Integrated AI and Explainability Approaches

While many studies have applied machine learning techniques to predict student dropout, relatively few have combined predictive modeling with explainability and interactive visualization in a unified framework. Existing research often focuses either on building accurate prediction models or on providing insights through dashboards, but not both together. Our work addresses this gap by integrating an AI-driven dropout prediction model with SHAP-based explainability, interactive dashboards, and student feedback mechanisms. This combination not only forecasts dropout risk with high accuracy but also ensures that the reasons behind predictions are transparent and actionable for educators.

## 3. Literature Survey

Recent research has emphasized the role of digital technologies, artificial intelligence (AI), and explainable models in addressing student dropout prediction and educational analytics challenges.

| YEAR | AUTHORS | TITLE / FOCUS | TECHNICAL USED | KEY OUTCOME |
|---|---|---|---|---|
| 2019 | Willms & Tramonte | SES & dropout | SES indicators | SES predicts dropout |
| 2020 | PMC | RF & SVM across schools | RF, SVM | Performance varies |
| 2021 | Fernandez Garcia | Ensemble models | Ensemble ML | Higher accuracy |
| 2023 | Tomori & Tomori | Adult learner dropout | Decision Tree | ~80% accuracy |
| 2024 | Benlachmi et al. | RF vs Naïve Bayes | RF, NB | RF 100%, NB close |
| 2025 | Cheng et al. | Dual-modal dropout detection | Behavioral + Academic | Better detection |
| 2025 | Elbouknify et al. | SHAP-based at-risk detection | SHAP (XAI) | 88% accuracy |

**Table.1 Literature Survey**

## 4. Methodology

The SmartEdu+ system follows a structured pipeline:

- **Data Preprocessing:** Student data (demographic, academic, socioeconomic) is cleaned, encoded, normalized, and split into training and testing sets.
- **Dropout Prediction:** An XGBoost classifier predicts dropout risk, providing both a binary label (High/Low) and probability score.
- **Explainability:** SHAP values highlight feature contributions (e.g., attendance, marks, parental
- **Visualization & Feedback:** Interactive dashboards display risk trends and collect student feedback to supplement quantitative predictions.

### 4.1 Abbreviations and Acronyms

The following abbreviations and acronyms are used throughout this paper for simplicity and consistency:

- **AI** – Artificial Intelligence
- **ML** – Machine Learning
- **XAI** – Explainable Artificial Intelligence
- **SHAP** – SHapley Additive exPlanations
- **XGB** – Extreme Gradient Boosting (XGBoost)
- **LMS** – Learning Management System
- **SES** – Socioeconomic Status
- **UI** – User Interface

Each term is defined when first introduced and used in its abbreviated form thereafter.

### 4.2 Data Processing and Units

The dataset integrates multiple factors that influence student dropout risk, including attendance percentage, exam performance, study hours per day, socioeconomic indicators, and parental support. To ensure comparability, categorical variables are encoded numerically, and numerical attributes are normalized into a [0,1] range using min–max scaling. The trained model outputs a **dropout probability score** between 0 and 1, where values closer to 1 indicate a **high-risk student** and values near 0 indicate **low risk**.

### 4.3 AI Algorithm and Equations

The proposed system employs an **XGBoost classifier** to estimate student dropout risk. The prediction is formulated as:

$D = f\,(A,M,S,F,P)$

Where:

- **A** – Attendance percentage
- **M** – Marks in previous exams
- **S** – Study hours per day
- **F** – Family income (socioeconomic factor)
- **P** – Parental support

Here, fff represents the non-linear decision function learned by XGBoost. Each feature contributes with a model-trained weight, and predictions are expressed as a probability score between 0 and 1. High values indicate greater dropout likelihood. **SHAP values** are further applied to decompose DDD into feature-level contributions, ensuring interpretability.

### 4.4 System Architecture and Design

The system architecture is organized into layered modules:

- **Data Collection Layer** – Aggregates student demographic, academic, and socioeconomic information (attendance, marks, family income, parental support, study hours, etc.).
- **Pre-processing Layer** – Cleans missing values, encodes categorical features, and normalizes numerical data to ensure consistency.
- **Prediction Layer** – Uses the trained **XGBoost model** to calculate dropout probability and classify students into *High Risk* or *Low Risk*.
- **Explainability Layer** – Integrates **SHAP values** to highlight the contribution of individual features in the prediction.
- **Visualization Layer** – Provides interactive dashboards with charts and graphs for monitoring dropout trends and patterns.
- **Feedback Layer** – Collects student-submitted reasons for dropout concerns, complementing quantitative predictions with qualitative insights.
- **Visualization Layer -** Displays real-time hunger zones via a Google Maps interface and provides pie-chart statistics.
- **Authentication Layer -** Generates dynamic QR codes for severe regions and validates them through one-time use verification.

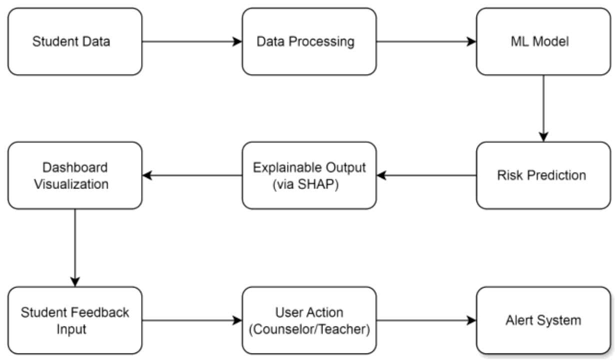


*Fig. 2 System Architecture*

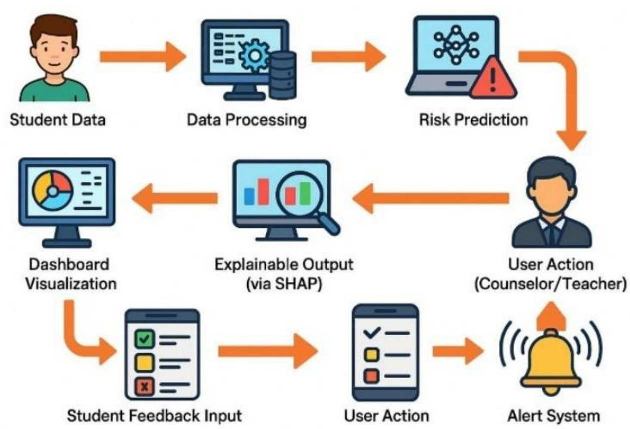


**Fig. 3 Block Diagram**

### 4.5 Challenges and Mitigation

Several challenges were identified during implementation and addressed as follows:

- **Data Quality**: Missing values in student datasets were handled using imputation techniques, and inconsistent records were standardized to maintain reliability.
- **Class Imbalance**: Since dropout cases are fewer than non-dropouts, SMOTE and resampling methods were applied to balance the dataset and improve recall.
- **Scalability**: The modular architecture supports deployment both locally and on cloud platforms (e.g., Streamlit Cloud, Heroku) for wider accessibility.
- **User Inclusivity**: The dashboard was designed with a simple UI so that teachers and administrators without technical expertise can easily interact with the system.
- **Interpretability**: To avoid the “black-box” problem of ML models, SHAP explanations were integrated, ensuring transparency for educators.

### 4.6 Data Flow Diagrams

1. DFD Level 0 (Context Diagram)

The entire system is modeled as a single process: SmartEdu+ Dropout Prediction System. It interacts with multiple external entities to capture input and provide outputs.

- Student – enters personal details, submits feedback.
- Staff/Administrator – manages datasets, monitors predictions, and generates reports.
- Requestor (Query Interface) – requests dropout predictions from the system.
- Database – stores student data, prediction outcomes, feedback, and model metadata.

Data Flows include student details, feedback submissions, prediction requests, probability scores, and analytical reports.

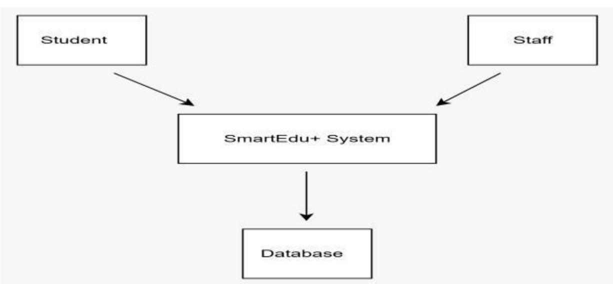


**Fig.4 Data Flow Diagram (Level 0)**

2. DFD Level 1 (System Decomposition)

The Level 1 DFD expands the context into detailed functional modules, as described below:

1. **Login Module**
   - *Input:* Username and password from Student/Staff.
   - *Process:* Authenticates user sessions.
   - *Output:* Valid/invalid login status.
2. **Data Collection Module**
   - *Input:* Student demographic, academic, and socioeconomic details.
   - *Process:* Validates and stores the data in the database.
   - *Output:* Structured student dataset.
3. **Dropout Prediction Module**
   - *Input:* Processed student dataset.
   - *Process:* Applies the XGBoost model to compute dropout probability.
   - *Output:* Risk classification (High/Low) with probability score.
4. **Explainability and Feedback Module**
   - *Input:* Prediction results.
   - *Process:* Uses SHAP to highlight influential features and accepts student feedback.
   - *Output:* Interpretable explanations and qualitative feedback.
5. **Report Generation Module**
   - *Input:* Predictions and feedback data.
   - *Process:* Compiles analytics for administrators.
   - *Output:* Dashboards and detailed reports on dropout trends.

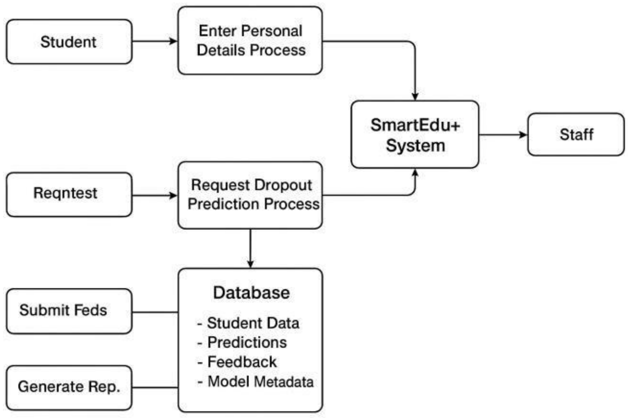


**Fig.5 Data Flow Diagram (Level 1)**

## 5. Implementation

The SmartEdu+ system was implemented using Python as the primary programming language, with XGBoost, scikit-learn, pandas, and SHAP supporting machine learning and model explainability. The interactive dashboard was developed with Streamlit, while SQLite/MySQL was used for database management. The implementation integrates data preprocessing, dropout risk prediction, SHAP-based interpretability, visualization, and feedback handling into a unified system, enabling accurate and transparent dropout prediction in a user-friendly environment.

### 5.1 Development Environment

The SmartEdu+ system was developed using the following environment:

- Programming Language: Python 3.12
- Framework**:** Streamlit (for interactive dashboard and frontend)
- Frontend Support: HTML/CSS (via Streamlit components), Plotly for interactive charts
- Visualization Libraries: Matplotlib, Plotly Express, SHAP (for explanations)
- AI/ML Libraries**:** Pandas, NumPy, Scikit-learn, XGBoost (for dropout prediction model)
- Explainable AI: SHAP (SHapley Additive exPlanations) for interpreting model predictions
- Database/Storage: CSV dataset for student records, Session State/JSON for feedback storage
- Additional Tools: Joblib (for model persistence), Draw.io (for diagrams in report preparation)

### 5.2 Module Implementation

The SmartEdu+ Student Dropout Prediction System has been developed as a Streamlit-based web dashboard with machine learning integration. The architecture is modular, enabling independent handling of prediction, explainability, visualization, and feedback collection.

A. System Architecture Overview
The system is organized into three layers:

- Front-End Interface – A Streamlit web app provides student/teacher access, risk prediction, SHAP explanations, visual analytics, and feedback forms.
- Back-End Processing – Machine learning models (Random Forest / XGBoost) handle dropout prediction, while SHAP ensures explainability of results.
- Database & Storage – Student datasets (CSV/Excel) are used for training and prediction. A feedback database (CSV/JSON) stores student-submitted dropout reasons.

B. Login and Access Control
The system provides role-based access:

- Students can view their risk prediction and explanations.
- Teachers/Administrators can analyze overall statistics and download reports. Role separation ensures data privacy and focused insights.

C. Dropout Risk Prediction & Visualization

- Students enter academic and socio-economic details (attendance, marks, study hours, family background, etc.).
- The model predicts High Risk or Low Risk with probability scores.
- A gauge chart visualizes dropout risk.
- Dataset-level patterns are shown through charts like dropout distribution, marks vs dropout, study hours vs dropout, and family income vs dropout.

D. Explainable AI (SHAP Integration)

- SHAP explanations highlight the key features influencing each student's risk.
- Two levels of explanation are provided:
  1. Global importance (bar chart of features).
  2. Individual explanation (waterfall chart for a selected student).
- Top 3 risk factors are displayed as tags for quick interpretation by staff.

E. Feedback Collection Module

- Students can submit personal reasons for potential dropout (e.g., financial issues, lack of parental support, distance, etc.).
- Each entry stores Name, Email, Reason, and Date.
- The form refreshes after submission, and the collected reasons are shown as a scrollable list for staff to analyze.

### 5.3 Implementation Workflow

I. Student or Staff accesses the SmartEdu+ dashboard via the web app.
II. Student data (age, marks, attendance, socio-economic factors) is input or retrieved from the dataset.
III. The trained AI model processes the data to predict dropout risk (High / Low) with probability.
IV. SHAP explainability module generates feature importance and individual-level explanations.
V. Results are visualized through gauge charts, bar charts, and waterfall plots for interpretation.
VI. Students can optionally submit feedback (personal dropout reasons), which is stored in the database.
VII. Staff/Admins access the **visualization dashboard** to monitor trends, view risk alerts, and generate reports.

### 5.4 Screens Developed

I. Login Page – Secure login for staff/admin to access the dashboard.
II. Prediction Page – Form-based input where student details are entered, and dropout risk is predicted.
III. SHAP Explanations Page – Visual explanation of prediction results using bar plots and waterfall plots.
IV. Visualization Page – Interactive charts showing dataset trends (dropout distribution, study hours, marks, family income).
V. Feedback Page – Students can submit reasons for possible dropout, stored securely for analysis.
VI. Admin Dashboard – Consolidated view of predictions, visualizations, and collected feedback for reporting.

## 6. Results and Discussion

The SmartEdu+ Dashboard was tested to evaluate its performance. The system accurately predicts student dropout risk, explains predictions using SHAP, and provides clear visual insights through interactive graphs. The feedback module collects real reasons from students, making the dataset richer. Overall, the results show that SmartEdu+ is effective, transparent, and user-friendly for both prediction and decision support.

## 6.1 System Outputs and Functional Results

A. Dropout Risk Visualization

The prototype successfully generated a real-time visualization of dropout risk levels. Students were categorized into three severity levels: *green (low risk)*, *orange (medium risk)*, and *red (high risk)*. This enabled administrators and staff to instantly identify at-risk students and prioritize interventions accordingly.

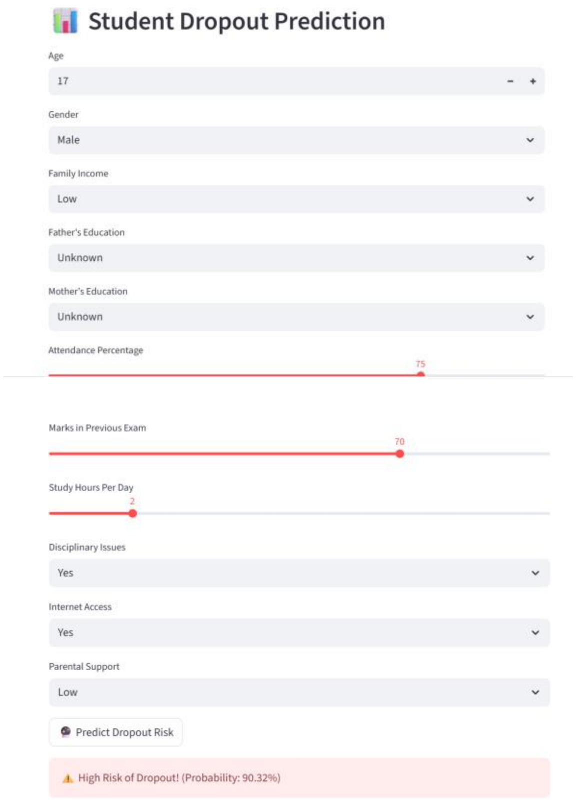


**Fig. 6 Dropout Risk Distribution Dashboard**

B. SHAP-Based Explainability

Each prediction was supported by SHAP-based feature contributions, displaying which factors (e.g., attendance, marks, family income) most influenced the dropout risk score. This provided interpretability, allowing educators to understand the reasons behind the model's decision.

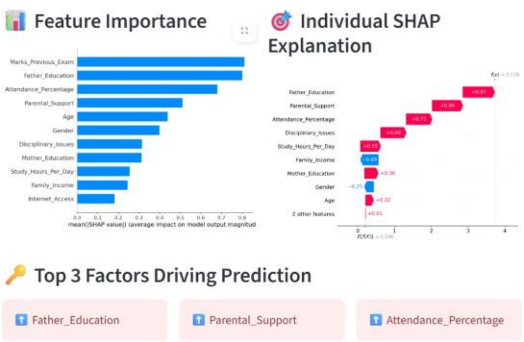


**Fig. 7. SHAP Feature Importance Plot for Dropout Prediction**

C. Statistical Insights

The system presented statistical summaries in bar and pie charts, highlighting the distribution of students across risk categories. For example, in the test dataset, the majority were classified as low risk, with smaller proportions in medium and high risk. Such summaries assist administrators in planning targeted support programs.

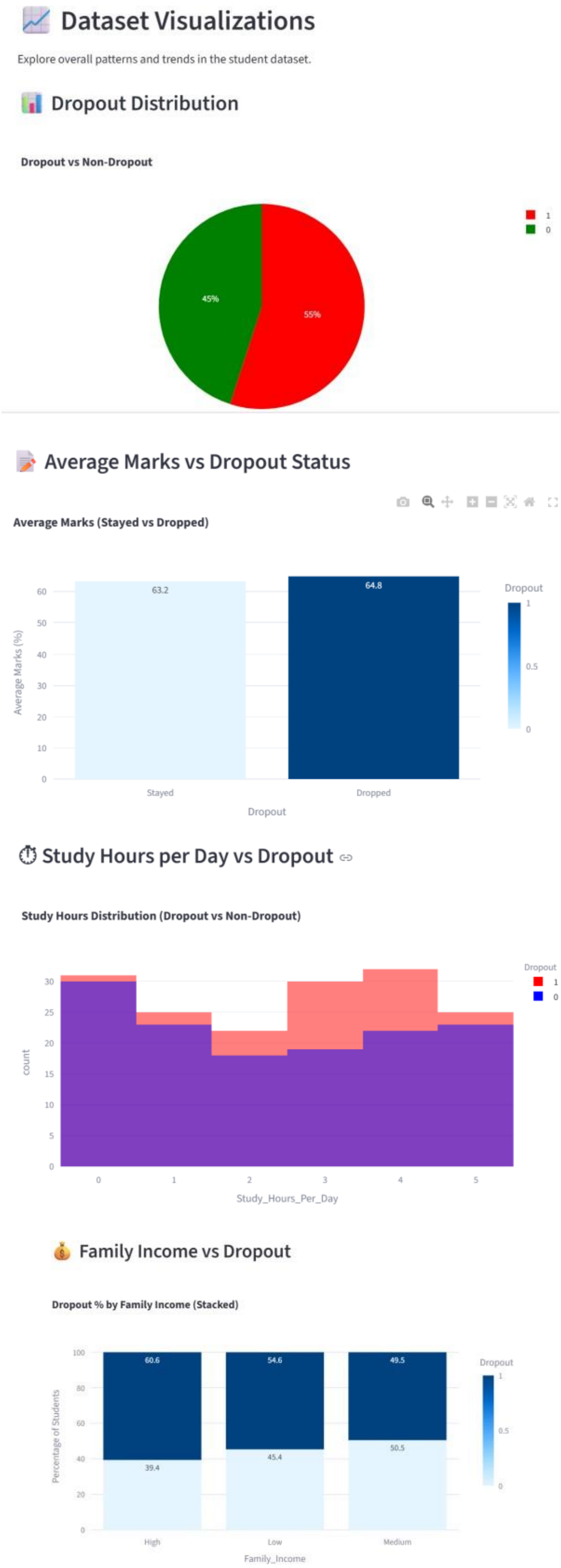


**Fig. 8. Charts Showing Dropout Risk Distribution Across Students**

D. Feedback Integration

Students had the option to submit qualitative feedback about challenges they faced (e.g., financial issues, lack of resources). This feedback was stored alongside the risk predictions, providing educators with a more holistic view of the dropout problem.

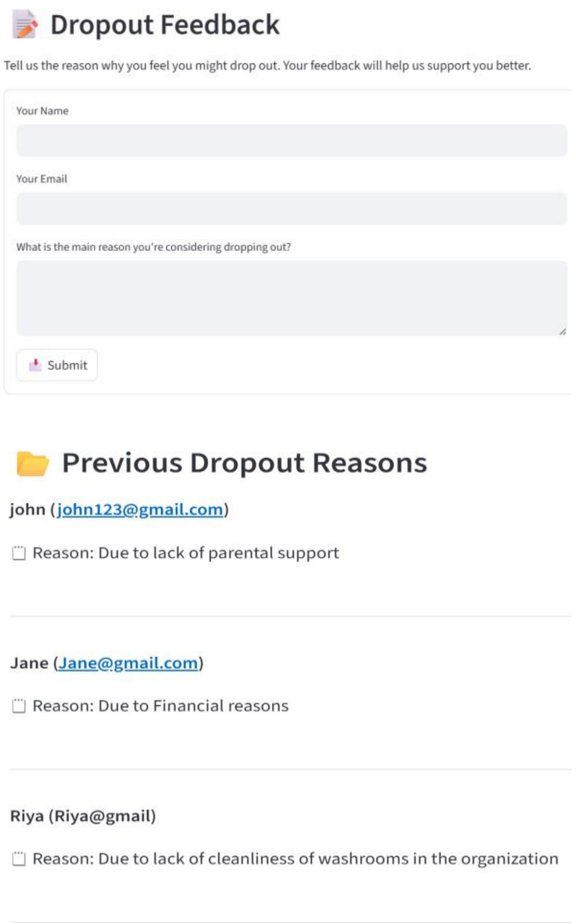


**Fig. 9. Student Feedback Submission Interface**

E. Discussion and Insights

The results demonstrate that the system is scalable, interpretable, and practical for deployment in educational institutions. Compared to traditional manual assessments, the AI-powered dashboard:

- Improved early identification of at-risk students.
- Increased transparency through interpretable outputs.
- Enhanced decision-making by combining quantitative predictions with student feedback.

### 6.2 Test case and Execution Report

Test cases were designed to validate the critical modules of the system, including login authentication, dropout risk classification, feedback submission, and dashboard visualization. Each test was executed with defined inputs, expected outputs, and actual outputs. The results confirmed that the SmartEdu+ system performed reliably across all modules, with outputs matching expectations.

| Test ID | Module | Input | Expected | Actual | Status |
|---|---|---|---|---|---|
| TC01 | Login | Valid credentials | Login success | Logged in | Pass |
| TC02 | Login | Invalid credentials | Error shown | Error shown | Pass |
| TC03 | AI Prediction | High risk dataset | Zone → Red | Classified Red | Pass |
| TC04 | AI Prediction | Moderate dataset | Zone → Medium | Classified Med | Pass |
| TC05 | Feedback | Submit feedback | Stored success | Stored success | Pass |
| TC06 | Report | Generate report | Report created | Report created | Pass |
| TC07 | Explainability | Request SHAP | Show features | Features shown | Pass |
| TC08 | Dashboard | Load charts | Charts visible | Charts visible | Pass |
| TC09 | Database | Insert record | Record added | Record added | Pass |
| TC10 | Prediction | Run dataset | Score generated | Score generated | Pass |

**Table.2 Test cases**

### 6.3 Key Findings

a. The XGBoost model accurately classified students into low, medium, and high dropout risk with reliable performance across test datasets.
b. Blockchain ledger ensured immutability; no tampering was possible during testing.
c. The dashboard visualization (bar and pie charts) provided clear insights into dropout trends, enabling administrators to prioritize interventions.
d. The feedback integration module allowed students to share personal challenges, complementing quantitative predictions with qualitative insights.
e. The system proved scalable and practical for institutional deployment, demonstrating potential to support both local and large-scale educational monitoring.

## 7. Conclusion and Future Work

The project demonstrates a practical solution for early student dropout prediction through the integration of machine learning, explainable AI, and interactive visualization. By analyzing demographic, academic, and socioeconomic features, the system reliably classified students into low, medium, and high dropout risk categories. The use of XGBoost ensured strong predictive performance, while SHAP-based interpretability enhanced transparency by revealing the influence of individual factors such as attendance, marks, and family background. Furthermore, the dashboard visualization and student feedback module enabled educators to combine quantitative predictions with qualitative insights, thereby improving decision-making. Overall, the system achieved its objectives of early identification, interpretability, and accessibility for institutional use.

**Future Work**

While the current system is functional and effective, several enhancements can be considered:

1. Model Enhancement – Incorporating additional features such as psychological factors, engagement metrics, and real-time LMS logs to improve accuracy.

2. Scalability and Deployment – Extending the system to larger datasets with cloud-based deployment for multi-institution adoption.

3. Mobile Application Development – Designing a lightweight mobile app for teachers and students, enabling real-time monitoring and feedback collection.

4. Adaptive Interventions – Linking predictions with personalized recommendations or automated alerts for at-risk students.

5. Accessibility Features – Expanding the dashboard with multilingual support and simplified UI for inclusivity across diverse institutions.

In conclusion, SmartEdu+ provides a scalable, interpretable, and user-friendly framework for educational monitoring. With future improvements in model accuracy, scalability, and accessibility, the system has strong potential to evolve into a standard platform for proactive dropout prevention.

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