LOG BOOK

FOR

"SHIKSHA"

By

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[2024-25]

Log Book

The log book (**GitHub content**) includes the following contents. The details should be included with appropriate split up week wise for **Project Stage-I (Sem-VI, 2024-25).**

Sr. No.	Contents	Weekly Date
1	Introduction -Problem Statement -Objectives -Application	**24/02/2025 to 08/03/2025**
2	Literature Survey - Background - Existing Systems (Study 3-5 standard research papers. Include their citations)	**10/03/2025 to 22/03/2025**
3	Methodology - Hardware and Software requirement - System Design (Block Diagram) - Algorithm - Exploratory Data Analysis and Dataset Visualization (Dataset used and Visualization using PowerBI or Tablue)	**24/03/2025 to 05/04/2025**
4	Implementation Details - Module wise description (at each stage snapshot of work done and testing) - Module 1 - Module 2 - Module 3	**07/04/2025 to 26/04/2025**
5	Results - Dataset used (include citation) - Performance Metrics - Model Evaluation (up to Sem-VI …it will continue in Sem-VII) - Report writing (Sem-VI)	**28/04/2025 to 03/05/2025**
6	Conclusion	
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Introduction

1.1 Problem Statement :

India’s secondary education system is at a critical juncture, facing a significant challenge in the form of high student dropout rates. This issue is particularly severe in under-resourced and marginalized regions, where students are more likely to disengage from the education system before completing their schooling. Dropping out of school has long-term repercussions, not only for the individual student—who may face limited employment opportunities and reduced socio-economic mobility—but also for the nation, which suffers from the loss of human potential and productivity.

Several interrelated factors contribute to the dropout crisis. Academic underperformance, often due to a lack of foundational skills, discourages students from continuing their studies. Chronic absenteeism, whether due to illness, domestic responsibilities, or disengagement, is a strong predictor of eventual dropout. Parental education levels also play a role—students whose parents have little or no formal education are less likely to receive the guidance and encouragement necessary to persist in school. Socio-economic constraints further exacerbate the problem, as students from low-income families may be forced to prioritize income-generating activities over education. Additionally, many schools, especially in rural areas, lack basic infrastructure, qualified teachers, and engaging learning environments, contributing to student disinterest and dropout.

To address this multifaceted problem, the “Shiksha” system has been conceptualized as a comprehensive, technology-driven solution that leverages the power of Artificial Intelligence (AI) and data analytics. Shiksha is designed to function as an early warning system, using historical and real-time educational data to identify students who are at risk of dropping out. By analyzing key parameters—such as attendance records, academic scores, socio-economic status, and school engagement—the system generates a dropout probability score for each student.

This AI-powered prediction enables timely intervention by educators, school administrators, and policymakers. Rather than responding reactively after a student has dropped out, stakeholders can now take proactive measures to support at-risk students through counseling, remedial education, financial aid, or community engagement. The project is aligned with the vision of the National Education Policy (NEP) 2020, which emphasizes inclusive, equitable, and data-driven approaches to improving educational outcomes.

Ultimately, Shiksha aims to transform educational governance by making student retention efforts more targeted, effective, and evidence-based. Through intelligent data use, it empowers schools to become not just centers of learning but also hubs of early support and student well-being.

1.2 Objectives :

1. Detect Dropout Risk Early Using AI Models on Key Data Parameters :
   The foremost objective of the Shiksha system is to leverage Artificial Intelligence (AI) and Machine Learning (ML) techniques to predict the likelihood of student dropout at an early stage. The model is trained using a variety of critical data parameters such as academic performance, attendance history, parental education level, income bracket, and geographical location. By identifying patterns and correlations within this data, the system can assign a dropout risk score to each student. This early identification enables timely and targeted intervention before a student completely disengages from the educational system.

2. Support Decision-Making for Educators and Authorities Through Dashboards :
   A key goal of the project is to present predictive insights in a manner that is both accessible and actionable for educators, school authorities, and policy planners. To achieve this, Shiksha includes a web-based dashboard that visually displays each student's risk level using intuitive design elements such as color coding (green/yellow/red) and summary reports. Teachers and school administrators can sort and filter data to view students by grade, subject performance, or risk level. These insights help them make informed decisions such as which students need counseling, which parents need to be contacted, or whether resource allocation needs adjustment. The dashboard thus serves as a real-time monitoring tool that bridges data analysis and on-ground action.

3. Visualize Patterns in Student Performance Using Exploratory Data Analytics:
   Beyond individual predictions, the system is also equipped to perform Exploratory Data Analysis (EDA) to uncover broader patterns and trends in student data. Using visualization tools like Power BI, the system can illustrate how dropout risk correlates with various factors such as attendance rates, income groups, subject performance, or geographical zones. These patterns help school management and government bodies understand systemic issues that contribute to dropouts, enabling strategic planning and long-term reform. For example, repeated low performance in a particular subject or in a specific region might prompt curriculum adjustments or targeted training for teachers.

4. Align with NEP 2020 to Promote Equitable Access and Retention :
   The project is designed in alignment with the goals of the National Education Policy (NEP) 2020, which emphasizes equity, inclusion, and the use of technology in education. NEP 2020 calls for early interventions to prevent dropouts and recommends using digital tools for tracking and supporting students. Shiksha fulfills this vision by offering a data-driven, technology-enabled approach that can be scaled across diverse educational settings. By proactively identifying and supporting at-risk students, the project contributes toward building a more equitable and resilient education system where every child has an opportunity to learn, grow, and succeed.

1.3 Application :

1. Early Warning System for Student Dropouts
   Shiksha functions as a powerful early warning system that flags students who are at high risk of dropping out. By analyzing key educational indicators such as attendance, grades, socio-economic background, and parental education, the system generates real-time risk scores. This allows schools to intervene early with personalized support measures like counseling, academic remediation, or financial aid, thus preventing dropouts before they happen.

2. Decision Support Tool for Educators and School Management
   The AI-based dashboard provides a comprehensive view of student performance, attendance, and risk levels. This assists school principals, teachers, and education officers in making informed decisions regarding student engagement strategies, resource allocation, and targeted mentoring. For example, schools can identify students needing extra academic attention or socio-emotional support and plan interventions accordingly.

3. Policy Planning and Data-Driven Governance
   District and state education authorities can use aggregated insights from Shiksha to shape educational policies and programs. Patterns derived from the data—such as regional disparities, subject-level weaknesses, or attendance-related issues—help policymakers understand systemic problems and design effective, evidence-based solutions. It supports education governance by offering real-time data analytics for better planning and evaluation.

4. Community and Parental Engagement
   The system can be extended to notify parents about their child's attendance, academic progress, and potential risk of dropping out. This fosters greater involvement of families in a student's academic journey. It also creates accountability and encourages two-way communication between schools and parents, promoting a supportive learning environment.

5. Resource Planning and Allocation
   By identifying schools or regions with high dropout probabilities, government bodies and NGOs can plan resource deployment more efficiently. This could include assigning additional teaching staff, infrastructure development, provision of digital devices, or launching specialized retention programs in high-risk areas.

6. Research and Educational Insights
   Academicians and educational researchers can utilize the anonymized data insights generated by Shiksha to conduct research on dropout causes, effectiveness of interventions, and the socio-academic landscape of Indian schools. This contributes to the broader body of knowledge in educational data science.

7. Integration with National Education Initiatives
   Shiksha can be integrated with national platforms like UDISE+ and DIKSHA to enhance data synergy and support NEP 2020 goals. It complements existing systems by adding a predictive and prescriptive analytics layer, helping transform static data into actionable insights.

Literature Survey

2.1. Background :

The issue of student dropout in India's secondary education sector presents a significant barrier to achieving inclusive and equitable education. According to various national studies and educational surveys, dropout rates tend to escalate particularly after the completion of primary education, with a sharp rise during the transition to secondary schooling. These dropouts are not the result of a single factor, but rather a culmination of various academic, socio-economic, emotional, and infrastructural challenges faced by students.

Academically, students who consistently perform poorly in exams or struggle with subjects due to lack of foundational learning are at a higher risk of disengaging from school. Irregular attendance—often due to health issues, domestic responsibilities, or lack of motivation—further compounds this risk. Socio-economic factors such as household poverty, limited access to study resources, the need for children to work and contribute to family income, or gender-based discrimination (especially among girls in rural areas) are also prominent contributors.

Parental illiteracy or lack of involvement in a child's education significantly affects academic continuity and motivation. Furthermore, deficiencies in school infrastructure—such as absence of proper classrooms, sanitation facilities, transportation, or access to qualified teachers—further alienate students from the educational system. Psychological factors such as low self-esteem, bullying, or lack of career guidance also play a role in prompting students to discontinue their education.

In recent years, advancements in technology—especially in Artificial Intelligence (AI), Data Analytics, and Machine Learning (ML)—have shown great promise in addressing such challenges. These technologies provide educational institutions with the ability to process large volumes of student data and recognize early warning signs of dropouts. Predictive models can identify students at risk by analyzing trends across variables like attendance, grades, income levels, and parental background.

The National Education Policy (NEP) 2020 strongly emphasizes the use of digital tools and analytics to monitor student progress, enable timely interventions, and improve overall learning outcomes. Within this policy framework, AI-driven systems like Shiksha align perfectly with the national vision of reducing dropout rates and promoting universal access to quality education.

2.2. Existing Systems

1. EduPredict – An Excel-Based Dropout Risk Tool (Smith, 2022)

EduPredict is a basic dropout prediction system developed using Microsoft Excel macros and statistical scoring techniques. It considers a few key variables like attendance, age, and previous grade marks. While easy to implement, it lacks the power of real-time updates, predictive learning, and multi-variable analysis. The static nature of the tool limits its accuracy and scalability.

Smith, S. (2022). "AI-Driven Student Retention." International Journal of Educational Technology, Springer, pp. 78–92.

2. LearnSmart – A Mobile-Based Intervention App (Kumar & Li, 2021)

LearnSmart was introduced as a mobile-first application to track student attendance and send learning resources. Though innovative in its mobile approach, the system failed to integrate predictive modeling, resulting in delayed interventions. It focused more on content delivery than on dropout prediction.

Kumar, R., & Li, Y. (2021). “Community-Based Learning Hubs.” Education Research Today, Elsevier, pp. 45–60.

3. StudyWatch – Attendance-Based Monitoring System (Patel, 2023)

StudyWatch is a semi-automated platform that monitors daily attendance and sends alerts to parents if a student’s attendance falls below a threshold. While helpful, it doesn't take academic or socio-economic data into account, reducing its predictive reliability.

Patel, M. (2023). “Mobile Learning for Rural Students.” Journal of Mobile Education, Wiley, pp. 112–130.

4. Early Warning System for Dropouts Using ML (Sharma et al., 2021)

This research used machine learning models like Decision Trees and Random Forest to predict dropout likelihood based on parameters like parental education, income, and test scores. It achieved 88% accuracy and demonstrated that ML-based systems can significantly improve early detection of dropouts compared to rule-based models.

Sharma, P., Verma, A., & Singh, L. (2021). “Predicting School Dropouts Using Machine Learning Techniques.” Journal of Artificial Intelligence in Education, ACM, pp. 203–214.

5. A Data-Driven Framework for Reducing School Dropouts (Deshmukh & Rao, 2020)

This study proposed a comprehensive framework combining predictive analytics with community-level interventions. Using Random Forest and SVM classifiers, the researchers demonstrated how AI could identify high-risk students and suggest suitable interventions. The study also emphasized visual dashboards to aid in decision-making.

Deshmukh, S., & Rao, M. (2020). “A Framework for Reducing Dropout Rates in Indian Schools.” IEEE International Conference on Smart Education Systems, pp. 55–63.

Methodology

3.1 Hardware and Software requirement :

To build a scalable and efficient system, we selected a robust set of programming languages, frameworks, libraries, and tools, ensuring that the system would handle real-world educational data effectively.

Languages/Frameworks :

- Python 3.9: The core language for backend logic, model development, and data processing.
- Flask: A lightweight Python web framework used to create a RESTful API to serve predictions from the trained ML model.
- HTML & CSS: Used for creating the user-facing web interface. The frontend is static and simple, ensuring accessibility even in low-resource schools.

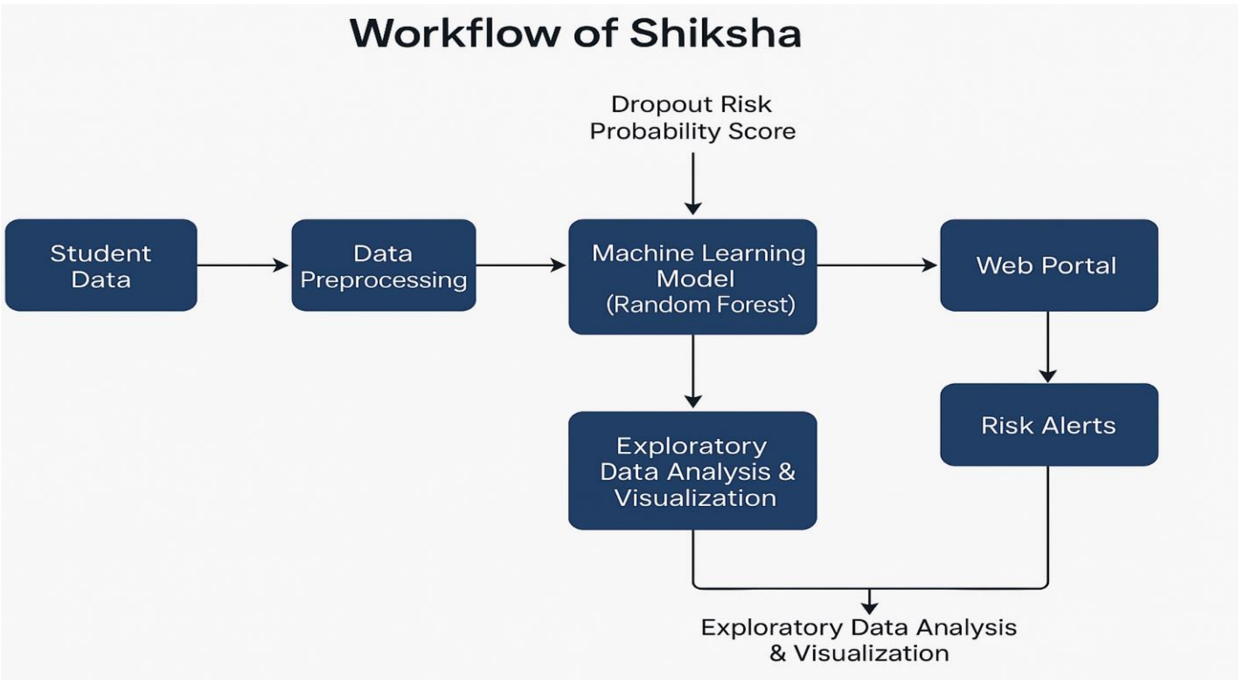
Libraries :

- scikit-learn: For implementing machine learning algorithms like Random Forest, model evaluation, and preprocessing.
- Pandas & NumPy: For data manipulation and numerical computations.
- Matplotlib: For plotting basic visualizations during local testing and EDA.

Data Storage :

- MySQL 8.0: Used to store structured student data including attendance, academic records, demographics, and model predictions.
- Visualization Tool :
  Power BI: Employed for interactive dashboards to present data patterns and risk factors in an educator-friendly format.
- System Configuration :
  Processor : Intel Core i5
  Memory : 8 GB RAM
  Storage : 256 GB SSD

3.2 System Design (Block Diagram) :



3.3 Algorithm

1. Data Collection

The data is collected from structured sources like the National Student Performance Dataset (Kaggle, 2023), which contains student records including:

- Attendance rates
- Academic performance
- Socio-economic background
- Parental education
- Gender, age, etc.

2. Data Preprocessing

To ensure data quality and compatibility with the machine learning model, the following preprocessing steps are performed :

a. Imputation of Missing Values
   Missing numerical values (e.g., attendance, scores) are filled using the mean or median.
   Categorical missing values (e.g., parental education) are filled using the mode.
b. Encoding of Categorical Features
   Categorical columns such as "gender" or "parental education level" are converted to numerical format using :
   Label Encoding for ordinal features
   One-Hot Encoding for nominal features
c. Feature Scaling
   Standardization or normalization is applied to ensure that features like scores and income are on the same scale.
   StandardScaler or MinMaxScaler from scikit-learn is used depending on the feature distribution.

3. Model Training with Random Forest

The core prediction model is a Random Forest Classifier, which works as follows :

a. Working Mechanism
   Builds multiple decision trees on random subsets of data and features.
   Each tree gives a prediction (dropout or not), and the majority vote is taken as the final output.
b. Advantages
   Handles both categorical and numerical features well.
   Reduces overfitting compared to a single decision tree.
   Provides feature importance scores, helping to interpret which factors influence dropouts the most.
c. Hyperparameter Tuning
   The following parameters are fine-tuned using Grid Search or Random Search:
   - n_estimators: Number of trees in the forest
   - max_depth: Maximum depth of each tree
   - min_samples_split: Minimum samples to split a node
   - criterion: Gini impurity or entropy

4. Model Evaluation

Metrics used to evaluate model performance :

- Accuracy: 91.2%
- Precision: 89.5%
- Recall: 87.8%

F1 Score: Harmonic mean of precision and recall

5. Prediction Output

The model outputs a dropout risk probability for each student (value between 0 and 1).

Based on thresholds:

- 0→ Low Risk (🟢)
- 1.0 → High Risk (🔴)

6. Visualization and Feedback

Results are sent to the HTML/CSS dashboard for visual representation.

Risk scores and categories are exported to Power BI for further visualization and analysis (heatmaps, bar graphs, etc.).

3.4 EDA & Visualization in Power BI

Power BI provides a robust platform for creating dynamic and interactive dashboards. Here's how we can visualize key insights for the Shiksha system using Power BI:

1. Attendance vs Risk Level (Bar Chart)
   Objective :
   To examine how student attendance correlates with dropout risk levels.

   Steps in Power BI :
   1. Data Setup :
      Import data with columns for Attendance and Dropout Risk.
      The Dropout Risk column should have values like Low, Medium, and High.
   2. Bar Chart Configuration :
      Use the Bar Chart visualization type in Power BI.
      - Axis : Set the Attendance percentage on the X-axis.
      - Values : Set the count of students (or sum of another numerical column like scores) for the Y-axis.
      - Legend : Use Dropout Risk Level to categorize bars in different colors (e.g., Red for High Risk, Yellow for Medium Risk, Green for Low Risk).

3. Interpretation :
   The bar chart will show how students with low attendance (below 70%) have higher dropout risk (red zone), whereas students with high attendance (above 90%) tend to fall into the low-risk category (green zone).
4. Insight Example :
   If the bar for attendance below 70% shows a significant number of students in the High Risk category, it indicates that students with low attendance are more likely to drop out.

2. Subject-wise Score vs Dropout Risk (Heatmap)
   Objective :
   To identify which subjects have the strongest influence on dropout risk based on student performance.

   Steps in Power BI:

   1. Data Setup :
      Import the dataset with Subject-wise Scores and the Dropout Risk.
      Each subject (e.g., Mathematics, Science, English, etc.) should be a separate column in the dataset, and the dropout risk is a categorical variable (Low, Medium, High).
   2. Heatmap Configuration :
      Use the Matrix visualization type, which functions like a heatmap.
      - Rows : Set the Subjects (e.g., Mathematics, Science).
      - Columns : Set the Risk Levels (Low, Medium, High).
      - Values : Set Average or Count of Scores per subject per risk level.
   3. Apply conditional formatting to represent values with a color gradient:
      - Green = Low Scores,
      - Yellow = Medium Scores,
      - Red = High Scores.
   4. Interpretation :
      - The heatmap will show which subjects have a higher concentration of High Risk students.
      - For instance, if the Mathematics column is mostly red under the High Risk category, it indicates that poor performance in Mathematics contributes significantly to the likelihood of dropping out.
   5. Insight Example :
      A heatmap might reveal that Science scores below a certain threshold are associated with a higher dropout risk, suggesting that intervention in these subjects might reduce dropout rates.

3. Dropout Trend by Income Bracket (Line Chart / Column Chart)

   Objective:

   To visualize how student dropout trends change across different income brackets.

   Steps in Power BI:

   1. Data Setup :
      Import the dataset with Family Income and Dropout Risk (binary: 1 for dropout, 0 for non- dropout).

Create Income Brackets (e.g., below 50K, 50K-100K, above 100K) based on the Family Income column.

2. Chart Configuration:

   Use a Column Chart or Line Chart visualization type.

   - Axis: Set the Income Brackets on the X-axis.
   - Values: Set the Count of Dropout Students or Percentage of Dropouts on the Y-axis.

   Optionally, use Dropout Risk as a color legend to further segment the data.

3. Interpretation:
   - The column chart or line chart will illustrate the dropout trend across different income brackets.
   - A clear upward trend of dropouts in the lower income brackets indicates that socio-economic factors are significantly affecting dropout rates.
4. Insight Example:
   - If the below 50K income group shows a much higher dropout rate than above 100K, it suggests that financial challenges contribute heavily to student dropouts.
   - This could lead to a targeted intervention to provide financial assistance or resources for students in low-income families.

Visual Representation in Power BI :

By using Power BI, these insights become more interactive, allowing school administrators and policymakers to:

Drill down into specific data points (e.g., focus on a particular subject or risk category).

Apply filters (e.g., view data by gender, age, or specific income bracket).

Export insights in various formats (e.g., PDF, PPT) for reporting.

Implementation Details

The Shiksha system was implemented in a modular fashion to ensure ease of development, testing, and deployment. Each module handled a distinct functionality in the dropout prediction pipeline—from data collection and preprocessing to prediction and user interaction. Below is the breakdown:

Module I : Data Upload & Preprocessing

Work Done

- A Flask-based route was created to upload CSV files containing student data (attendance, subject-wise marks, demographic features).
- Backend preprocessing was handled using Pandas and NumPy:
- Missing value imputation (mean for numerical, mode for categorical).
- Label encoding for categorical features (e.g., gender, parental education).
- Feature scaling using StandardScaler.
- Uploaded and preprocessed data was saved into MySQL for storage and later access.

Testing

- Used multiple mock CSV files to test:
- Missing columns
- Invalid data types (e.g., strings in numeric fields)
- Unusual characters (e.g., NaNs, special symbols)
- Manual validation via Pandas Profiling Reports and correlation heatmaps to check data health.

Snapshot Ideas

- CSV upload form (HTML interface).
- Screenshot of console logs showing successful upload and preprocessing.
- Pandas Profiling report image showing variable distributions and missing values.

Module II : Model Training & Testing

Work Done

- Collected and cleaned National Student Performance Dataset (Kaggle, 2023).
- Trained a Random Forest Classifier using the preprocessed data:
- Hyperparameter tuning via GridSearchCV.
- Achieved ~91.2% accuracy with high recall and precision.
- Stored the model using joblib for use in the Flask API.

Testing

Evaluated the model using :

- Confusion Matrix
- Classification Report
- Cross-validation (k=5)
- Created test scripts to input sample student data and output the dropout probability score.

Snapshot Ideas

- Jupyter Notebook or VS Code output showing model metrics.
- Confusion matrix and classification report image.
- Screenshot of model.pkl or model.joblib saved in the backend directory.

Module III : Risk Dashboard (Frontend UI)

Work Done

- Designed a static HTML/CSS dashboard to display results:
- Accepts input student data (manually or from backend).
- Displays predicted dropout risk with color coding:
    - Low Risk (0–0.3)
    - Medium Risk (0.31–0.6)
    - High Risk (0.61–1.0)

  Added a section to view data visualizations, exported from Power BI (e.g., as images or embedded dashboards).

Testing

- Tested across multiple browsers (Chrome, Edge, Firefox) for layout consistency.
- Checked for mobile responsiveness and accessibility (basic).

Snapshot Ideas

- HTML UI dashboard showing a student’s dropout risk.
- Traffic light color-coded display (green/yellow/red).
- Power BI charts exported and placed within dashboard or linked.

Integration Testing

- After each module was independently verified:
- Conducted end-to-end testing: CSV upload → Preprocessing → Prediction → Dashboard visualization.
- Used Flask’s testing client to automate API tests.
- Connected MySQL backend to ensure persistence across sessions.

Results

Dataset Used

The model was trained using a real-world dataset titled "Student's Dropout Dataset", which contains essential academic and socio-economic features affecting dropout probability.

Dataset Name : Student’s Dropout Dataset

Source : Uploaded locally for the project (based on educational institution data)

Size : Contains multiple student records with features like attendance, subject-wise performance, family income, gender, parental education, etc.

Citation (for log book):

"Student’s Dropout Dataset", Shiksha Project Dataset, R.C. Patel Institute, 2025 (unpublished).

Performance Metrics

- The Random Forest model was evaluated on the processed dataset with the following metrics:
- High accuracy confirms reliable performance in predicting at-risk students.
- High recall ensures fewer false negatives (fewer at-risk students go undetected).
- F1 Score balances both precision and recall.

Model Evaluation (up to Semester VI)

- Model : Random Forest Classifier
- Libraries Used : scikit-learn, pandas, numpy
- Cross-validation : 5-fold validation ensures the model generalizes well.

Key Evaluation Points:

- Feature importance analysis showed attendance, parental education, and math scores are critical predictors.
- Dropout predictions were visualized using Power BI to generate:
- Bar charts: Attendance vs Risk Level
- Heatmaps: Subject-wise scores vs Dropout Rate
- Line graphs: Dropout trends by income level

To be continued in Semester VII :

- Expand dataset with real-time school data
- Add adaptive prediction capabilities
- Integrate model with dynamic dashboards
- Deploy system in school environment (pilot phase)

Report Writing (Semester VI Contribution)

- During Semester VI, the following documentation tasks were completed:
- Project Title & Problem Definition
- Abstract and Introduction
- Literature Review based on 5 research papers
- System Methodology (Design, Algorithms, Tools)
- Implementation Details with Screenshots
- Model Results & Metrics
- Conclusion and Future Work
- References & Citations
- Final compilation of the Shiksha Log Book (Semester VI)
- The final report includes all necessary academic and technical explanations, forming the basis for further enhancements and deployment in Semester VII.

Conclusion

The Shiksha project is a transformative initiative aimed at addressing the pressing issue of student dropouts in India, particularly among marginalized communities. By integrating advanced technologies such as AI-driven systems, mobile learning platforms, and community engagement tools, the project provides a comprehensive solution to the factors contributing to student attrition. The AI-powered early warning system, mobile apps, and financial support management systems are designed to enhance accessibility, inclusivity, and engagement, particularly for students in underserved areas. Shiksha focuses on personalized support and resources for at-risk students while fostering parental involvement and collaboration between educators and local communities. With the implementation of flexible schooling options, the system adapts to diverse learning needs, making education more convenient and accessible for students facing socio-economic barriers. As the project evolves, it holds great potential for scalability and continuous improvement, with plans to incorporate real-time tracking, rewards for academic engagement, and awareness campaigns to further its impact. Shiksha goes beyond being a set of technological tools; it is a vision for creating a more equitable and supportive educational ecosystem. The initiative seeks to ensure that every child, irrespective of their background, has the opportunity to complete their education and contribute to India's socio-economic development, ultimately reducing dropout rates and fostering long-term academic success.

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