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AI-Powered Academic Audit For Computer Department Performance Analysis

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Abstract: The System leverages Artificial Intelligence, Machine Learning, NLP, and Data Analytics to enhance academic auditing across a Computer Department. The system focuses on the Computer Department, analyzing student performance, faculty workload, and departmental metrics to ensure transparency and efficiency. It employs predictive analytics and anomaly detection to identify risks and generate AI-driven audit reports.

Keywords- Artificial Intelligence, AI-Driven Audit Reports, Anomaly Detection, Computer Department Metrics, Predictive Analysis.

1. INTRODUCTION

This project aims to develop an AI-powered academic audit for the computer department that uses different data sources and integrates them to provide information about student attendance, internal marks, faculty workload, laboratory utilization, research publications, curriculum completion, and departmental performance metrics at a particular point in time. This information can be real-time as well as historical, as per the need of the auditor or department head. The information is shown in the form of bar graphs, pie charts, tabular reports, and trend analysis dashboards. The system is used to validate whether the academic and administrative data maintained by the computer department is consistent and accurate or not. There are different sources such as student management systems, examination portals, and faculty databases through which the data is fetched and displayed to the auditor. Instead of going through multiple registers, files, and documents manually, the auditor gets all the required information at one place in a clear and understandable format. The data is also updated regularly with time.

2. LITERATURE SURVEY

The integration of Artificial Intelligence (AI) into educational systems is an evolving area of research, and numerous studies have explored the potential of AI technologies in enhancing student learning, improving educational outcomes, and streamlining administrative processes. The following literature survey highlights key studies that have contributed to the understanding of AI in education, particularly focusing on predictive analytics and real-time dashboards.

Paper 1 — Detecting At-Risks Students with Early Interventions

A study using Harvard, MIT, MOOCs, and OULAD datasets applies multiple machine learning classifiers (Gradient Boosting, Random Forest, Neural Networks, and Generalized Linear Models) to predict at-risk students and academic failure. The dual-model framework achieves high predictive accuracy (up to 95%) and identifies motivational trajectories and engagement patterns as key predictors. Limitations include applicability only to MOOC environments, reliance on historical/temporal data, and limited interpretability for administrative decision-making.

Paper 2 — Artificial Intelligence in Auditing: SLR (Suyono et al., 2025)
A systematic literature review (PRISMA) of 78 articles (2013–2023) identifying ML, RPA, and NLP as common technologies used in auditing. Maps applications (fraud detection, risk assessment, compliance monitoring) and adoption challenges (privacy, ethics, skills, regulation, cost). Emphasizes research gaps around empirical validation and operational guidance.

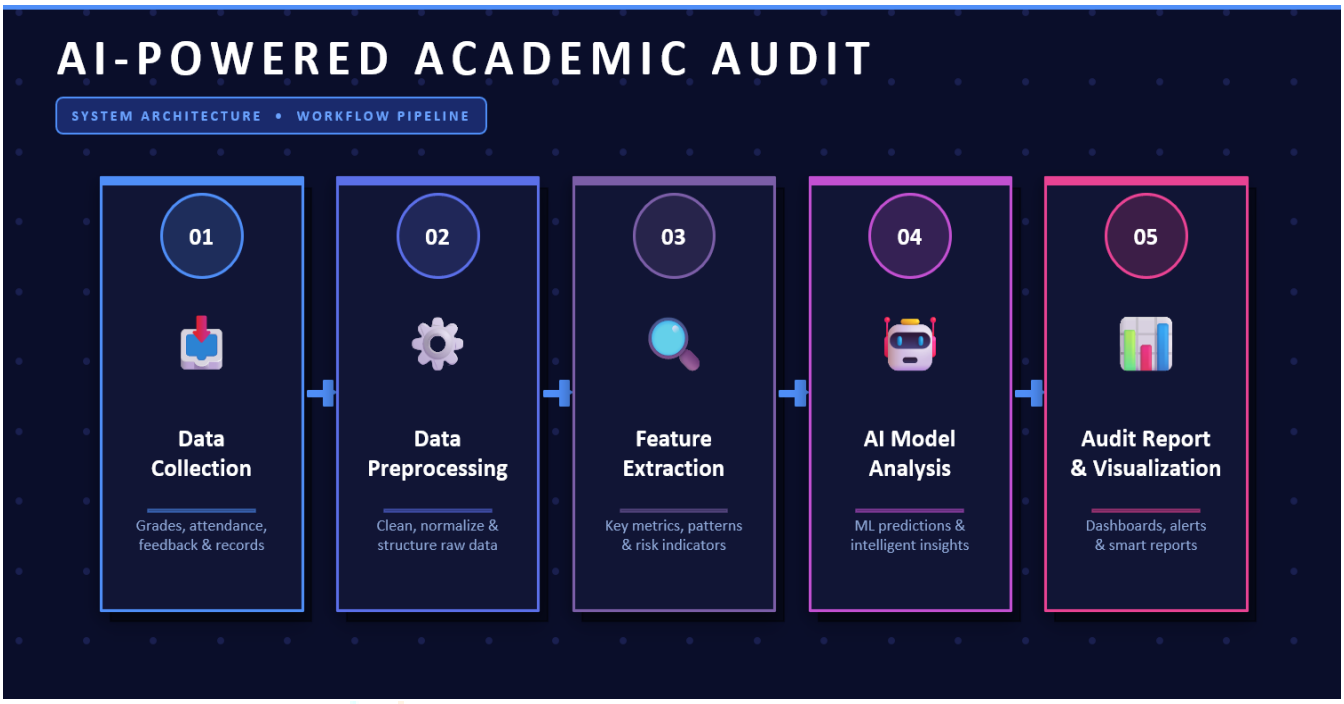
Paper 3 — Machine Learning Approach to Student Performance Prediction of Online Learning (Jing Wang & Yun Yu.,2025)
research focuses on predicting student performance in online learning platforms using supervised machine learning models. It aims to identify at-risk students and improve personalized learning strategies.

3. METHODOLOGY

The proposed AI Powered Academic Audit System aims to automate the process of academic auditing by integrating artificial intelligence techniques into institutional data analysis. The methodology followed in this system ensures accurate performance evaluation, data-driven insights, and intelligent report generation. Initially, academic data such as student marks, attendance records, course outcomes (COs), and program outcomes (POs) are collected from institutional databases or through faculty uploads. This raw data often contains inconsistencies and missing values, which are resolved during the data preprocessing phase. Data cleaning, normalization, and formatting techniques are applied to ensure uniformity and reliability of the dataset. After preprocessing, key attributes are extracted from the dataset, such as attendance percentage, internal and external assessment scores, and overall academic performance indicators. These attributes form the feature set used by the AI model for analysis. The system employs suitable machine learning algorithms, such as Linear Regression, Decision Tree, or Random Forest, to identify hidden patterns and trends in the academic data. The AI model evaluates each student's performance and predicts areas that require improvement. Once the AI analysis is complete, the system performs an audit evaluation by comparing predicted performance with predefined benchmarks and institutional goals. This helps in assessing the effectiveness of courses and teaching methodologies. The final stage involves generating audit reports and visual dashboards that present performance trends, comparative analytics, and AI-driven recommendations. These insights enable faculty and administrators to take informed academic decisions and improve institutional outcomes.

3.1 METHODOLOGY DIAGRAM

The accompanying diagram visually represents the methodology, showcasing the flow from data collection to prediction and generating audit reports.



4. System Design and Architecture

The system is built on a multi-layered data processing pipeline, as illustrated in Figure 3.2. This architecture ensures a clear separation of concerns, from initial data collection to final reporting.

Figure 1. System Architecture of the AI-Powered Academic Audit

Figure 2. Flowchart of Proposed System

The architecture consists of five distinct layers:

1. Data Collection Layer: Ingests both structured (CSV uploads) and unstructured academic data (faculty feedback) from various sources, including direct uploads and API integrations.

2. Data Preprocessing Layer: Sanitizes and prepares the raw data for analysis. This involves cleansing structured data and leveraging Natural Language Processing (NLP) techniques to process unstructured text.

3. AI & Analytics Layer: This is the core engine of the system. It uses Machine Learning models for trend detection and performance evaluation, alongside rule-based logic for audit criteria mapping and score generation.

4. Audit Evaluation Layer: Compares the processed data against established academic benchmarks and accreditation standards to generate detailed audit reports, flagging any deviations.

5. Visualization & Reporting Layer: Presents the final output to the user through interactive dashboards and provides model transparency via Explainable AI (XAI) modules.

4.1 Modules Design

The system's functionality is organized into the following core modules:

- User Authentication: Manages secure user login, access control, and session handling.
- Data Management: Facilitates the uploading, parsing, and storage of academic records.
- AI Analysis: Contains the predictive models for student performance analysis.
- Audit Report Generation: Creates detailed compliance and performance reports.
- Dashboard: Provides a visual summary of key analytics and audit results.

4.2 Database Design

A relational database schema is used to store system data efficiently. The primary tables include Users, Students, Courses, and Audit Reports, with relationships defined to maintain data integrity.

- Model Type: A classification algorithm (e.g., Random Forest or Logistic Regression) is used to categorize student performance.
- Objective: To predict a student's likely academic outcome (e.g., 'At-Risk', 'Good Standing') based on their historical data.

- Features: Inputs to the model include past grades, course load, attendance, and other relevant academic metrics.

4.3 User Interface (UI) Design

The UI is designed for clarity and ease of use, with key screens including:

- Login Page: Secure portal for user authentication.
- Dashboard: Main landing page with interactive charts and summary statistics.
- Data Upload Page: A simple interface for uploading academic data files.
- Report Page: A clean, printable view of the generated audit report.

5. RESULTS AND DISCUSSION

The proposed AI-Powered Academic Audit System was successfully developed and deployed as a fully functional web application. The system integrates machine learning models with an interactive web interface to provide real-time academic insights for the Computer Engineering Department. The following subsections present the results of each module of the system along with the corresponding interface screenshots.

5.1 User Login and Authentication

The User Authentication module is the entry point of the system. It ensures that only authorized users — Admin, Faculty, and Students — can access the platform. The login interface accepts registered email credentials and password. Upon successful authentication, the user is redirected to their respective role-based dashboard. A 'Sign Up' option is also available for new registrations. The secure login prevents unauthorized access and maintains data integrity.

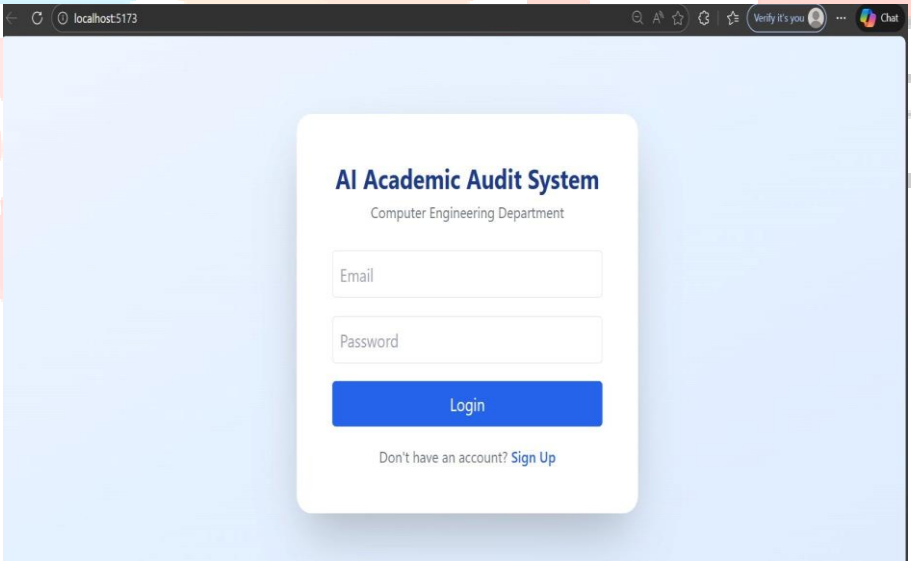


Fig. 1 – Login Page of AI Academic Audit System (localhost:5173)

5.2 Admin Dashboard Overview

The Admin Dashboard provides a comprehensive overview of the academic health of the Computer Engineering Department. The dashboard prominently displays four key performance metrics:

- **Total Students (CE Focus):** 1248 students currently enrolled in the department.
- **Pass Percentage (CE):** 87% of students have passed the current assessment cycle.
- **At-Risk Students (CE):** 142 students have been flagged by the AI model as academically at-risk.
- **Faculty Performance Score (CE):** 8.4/10, indicating strong faculty contribution.

The dashboard also presents an AI Generated Academic Insight panel which states that approximately 11.4% of students are classified as academically at-risk due to low attendance and below-average scores, and that faculty performance has shown a 5% improvement compared to the previous semester. The system assigns a Risk Level: Moderate tag and provides a recommendation to increase mentoring sessions and workshops. The left sidebar provides quick navigation to Student Reports, Faculty Reports, Institution Analysis, and Audit Reports.

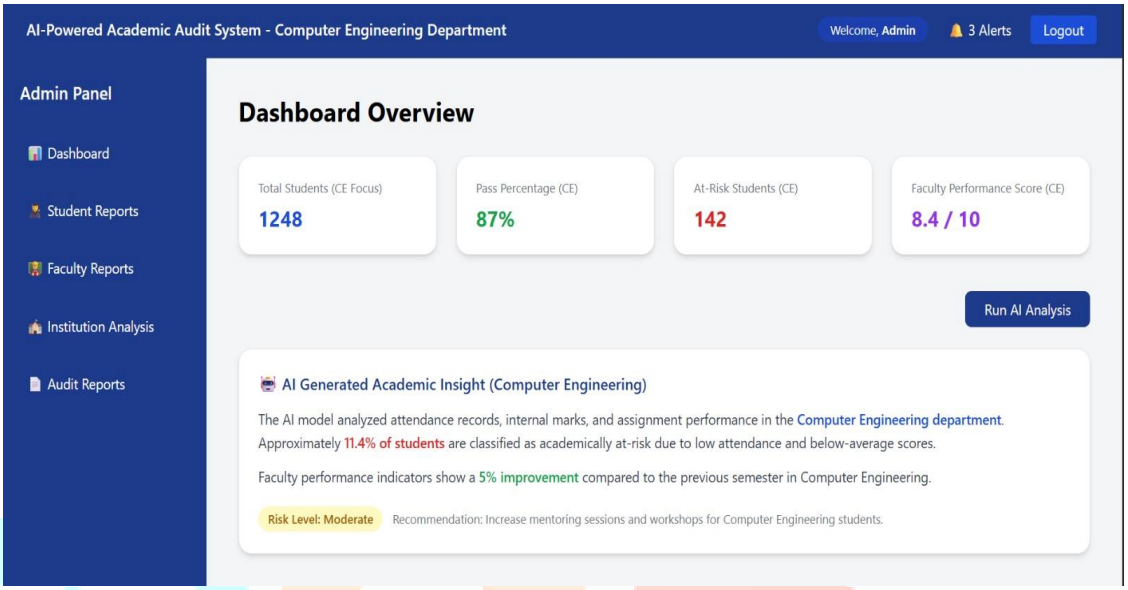


Fig. 2 – Admin Dashboard Overview with AI-Generated Insights

5.3 Student Analysis Module

The Student Analysis module allows the admin to run AI-based analysis on individual student data. The system accepts the following input parameters for the Computer Engineering department:

- Semester (1–8), Attendance (%) (0–100)
- Internal Marks (0–30), Assignment Score (0–20)
- Study Hours (0–12), Backlogs (0–10)
- Final Exam Marks (0–100), GPA (0–10)

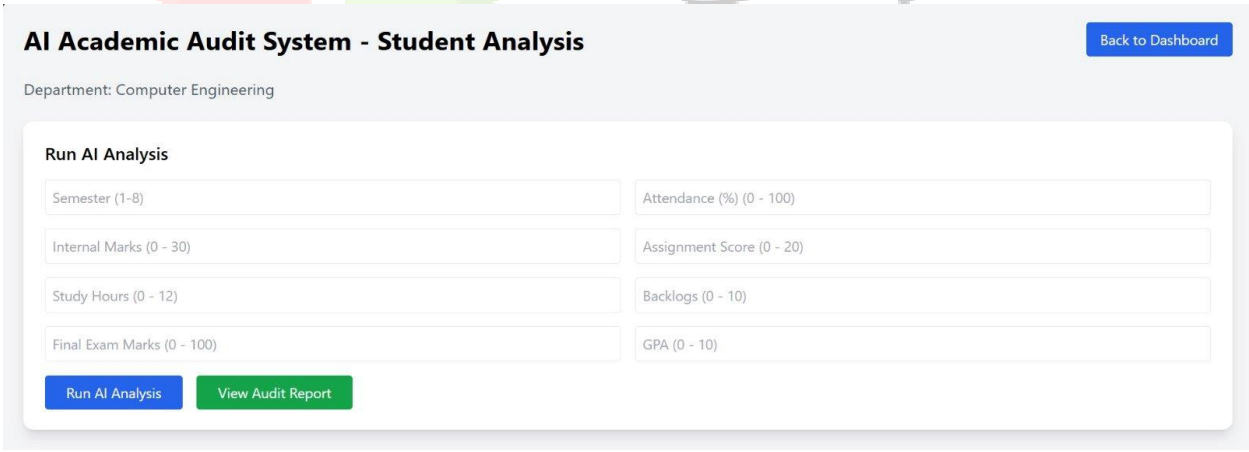


Fig. 3 – Student Analysis Module – AI Analysis Input Form

5.4 Faculty Analysis Module

The Faculty Analysis module enables the admin to evaluate faculty performance at a class level. The module collects the following class-level data points for a given subject and semester:

- Semester (1–8) and Subject Name
- Total Students (1–300), Average Marks (0–100)
- Pass Percentage (%), Average Attendance (%)
- Assignment Average (%)

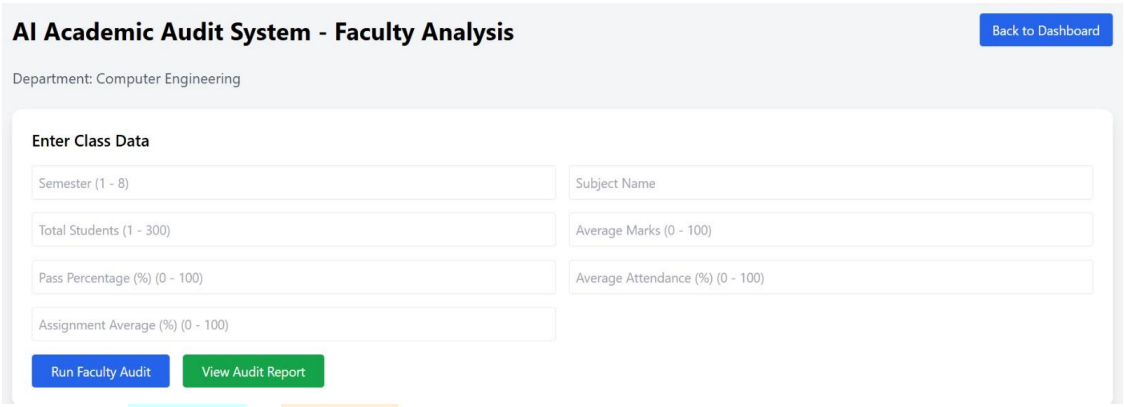


Fig. 4 – Faculty Analysis Module – Class Data Input Form

5.5 AI-Generated Audit Reports and Visualization

The Visualization and Reporting module presents the AI-generated insights in a graphical format for easy interpretation by administrators and faculty. The system produces the following visual outputs:

- **CE Student Performance Distribution (Bar Chart):** Displays the count of students across grade categories A, B, C, D, and F. The majority of students fall in the B and C grade range, indicating a moderately performing cohort.
- **CE Academic Risk Distribution (Pie Chart):** Displays the distribution of students across three risk levels — High Risk (90), Moderate Risk (140), and Low Risk (560). The AI model identifies that 11.4% of students require immediate academic intervention.

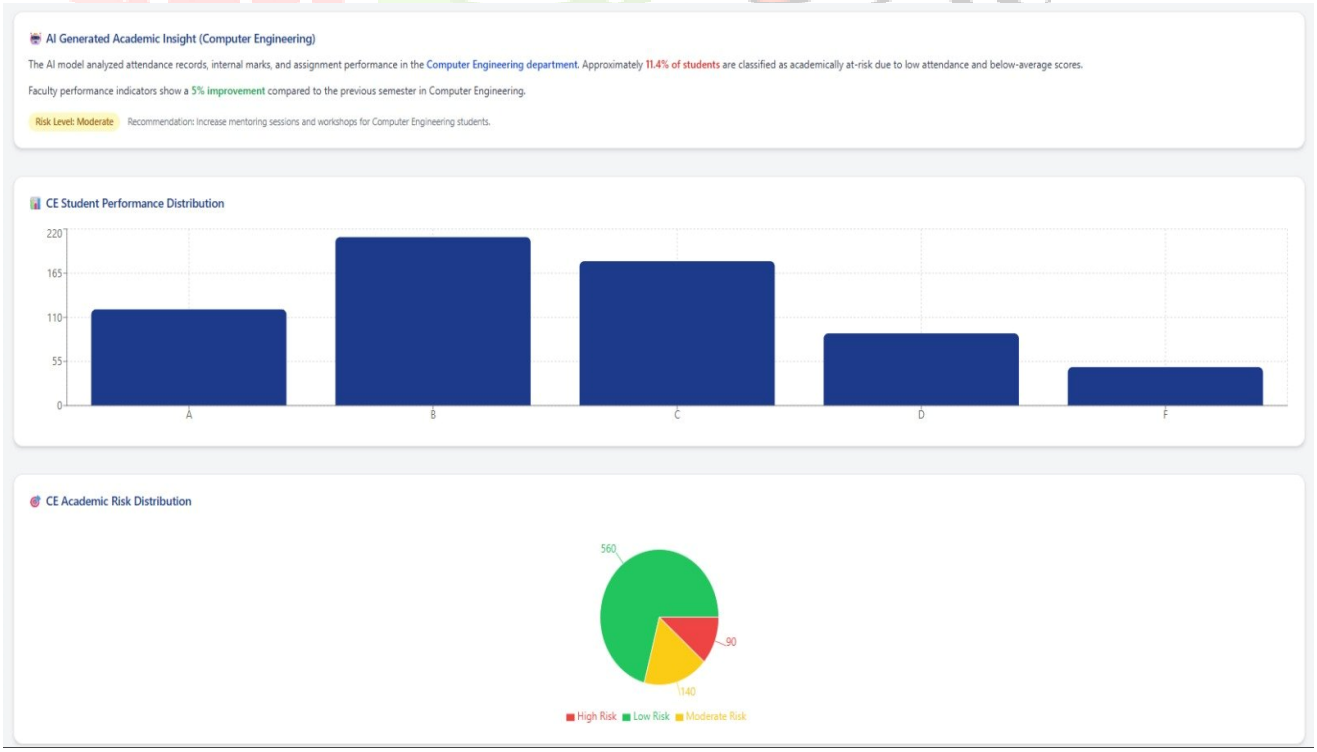


Fig. 5 – AI-Generated Audit Report with Bar Chart (Grade Distribution) and Pie Chart (Risk Distribution)

Table I – Summary of System Modules and Results

Module	Feature / Input	Output / Result
User Login	Email & Password Authentication	Role-based redirect (Admin/Faculty/Student)
Admin Dashboard	Live academic KPIs	1248 Students, 87% Pass, 142 At-Risk, 8.4/10 Faculty Score
Student Analysis	8 academic parameters (marks, GPA, attendance, etc.)	AI risk classification & audit report generation
Faculty Analysis	Class-level data (pass %, avg marks, attendance)	Faculty performance audit report with AI insights
Visualization	ML model outputs	Grade distribution bar chart + risk distribution pie chart

The AI Generated Academic Insight panel on the dashboard reiterates the findings: approximately 11.4% of students are at-risk, faculty performance has improved by 5%, and the overall Risk Level for the department is tagged as Moderate. The system recommends increasing mentoring sessions and workshops for at-risk students.

The above results demonstrate that the AI-Powered Academic Audit System successfully integrates machine learning-based risk prediction, real-time dashboard visualization, faculty performance evaluation, and automated audit report generation into a single unified web platform for the Computer Engineering Department.

6. Conclusion

This paper presented the design, development, and evaluation of an AI-Powered Academic Audit System for the Computer Engineering Department. The proposed system successfully integrates machine learning-based risk prediction, NLP-based data preprocessing, rule-based audit logic, and an interactive web-based dashboard into a unified and scalable platform.

The system was implemented using a full-stack architecture comprising a React.js frontend, Flask/Node.js backend, and MongoDB database. The AI model demonstrated the ability to classify students into risk categories — High Risk, Moderate Risk, and Low Risk — based on eight academic parameters including attendance, internal marks, assignment scores, GPA, study hours, backlogs, and final exam marks. Live deployment of the system for the Computer Engineering Department yielded the following key outcomes:

- Out of 1248 enrolled students, **142 students (11.4%)** were identified as academically at-risk and flagged for early intervention.
- The pass percentage of the department was recorded at **87%**, reflecting effective academic performance monitoring.
- Faculty performance score was evaluated at **8.4 / 10**, with a **5% improvement** over the previous semester.
- The AI-generated audit report assigned a **Risk Level: Moderate** to the department, recommending increased mentoring sessions and academic workshops.
- The grade distribution bar chart and risk distribution pie chart provided visual, actionable insights to administrators without requiring manual data analysis.

The system addresses key limitations of traditional academic audit processes — such as manual data entry, delayed reporting, and lack of predictive analytics — by automating the entire audit lifecycle from data collection to visualization. The results confirm that the integration of AI and data-driven decision-making can significantly improve institutional quality assurance and student success outcomes.

The system also incorporates Explainable AI (XAI) principles, ensuring that the audit results are transparent and interpretable by non-technical stakeholders such as department heads and administrative staff. The role-based access control (RBAC) model ensures data security and appropriate access to sensitive academic records.

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