AI Based Early Detection of the Student Mental Health Issues using their Academic and Behaviour Data

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***Abstract*—**Besides academic performance, students' mental health is one of the major factors that have a great influence on learning outcomes and overall well-being. This paper presents an AI-based system for early risk detection of mental health for students, based on analysis of both academic records and behavioral data. Predicting the mental health risk levels of students in real time, the system generates comprehensive reports and timely alerts for staff and administrators, thus enabling prompt intervention and support. In addition, it provides students with a personalized AI-driven study scheduler that recommends an optimal learning plan based on their specific risk level and helps them to cope with stress and workload effectively. Integrating predictive analytics with adaptive scheduling, this approach not only supports students' mental well-being but also enhances academic performance by addressing potential challenges even before they arise. The system offers educators a proactive, data-driven mechanism to monitor, guide, and assist students efficiently. Above all, this integrated solution uses AI to bridge the gap between academic monitoring and mental health support so that education can be holistic and responsive to individual student needs.

***Keywords*—** AI-Based Mental Health Detection, Predictive Analytics, Behavioral Data Analysis, Adaptive Study Scheduler, Student Academic Performance.

I. INTRODUCTION

In recent years, student mental health has become an emerging concern for institutions of learning globally. Academic stress, performance expectations, and behavioral problems greatly influence the psychological well-being of students, which subsequently becomes a determinant of their learning ability, participation, and academic performance. Conventional approaches to determining mental health problems are reactive, based on apparent symptoms or self-reports from students, which tend to emerge only after the condition has deteriorated. Hence, there is a compelling necessity for a technology-based, proactive method of identifying early mental health risks and intervening in a timely manner.

By facilitating data-driven decision-making and individualized learning experiences, artificial intelligence (AI) has demonstrated encouraging potential to revolutionize the educational industry. Complex patterns in behavioral and academic data can be analyzed using machine learning models to anticipate mental health issues before they become more serious.

This study suggests an AI-based early mental health detection system that uses behavioral and academic data to evaluate students' mental health. In order to facilitate prompt support and preventive action, the system automatically creates alerts for administrators and educators based on its real-time risk level prediction. Additionally, the system has an AI-powered personalized study planner that adjusts workload and learning goals according to each student's mental health. This strategy seeks to boost motivation, lessen academic stress, and raise overall academic achievement.

By combining predictive analytics and adaptive learning techniques, the suggested system closes the gap between academic management and mental health monitoring.

This project uses a Random Forest machine learning model to automatically determine the mental health risk levels of students by processing their behavioral and academic data. To correctly categorize students into various risk groups, the AI system examines important patterns like attendance, engagement metrics, and performance trends. The system creates real-time alert messages for administrators and employees based on the identified risk level, allowing them to take prompt action and offer guidance. A customized AI-based study planner that adjusts to the user's mental health status is another way the platform empowers students. This ensures a well-rounded learning plan that lowers stress while enhancing academic performance.

II. LITERATURE REVIEW

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III. METHODOLOGY

The development of the AI-Based Early Detection System for Student Mental Health follows a structured and data-driven methodology to ensure accuracy, scalability, and real-time responsiveness. The system integrates Machine Learning models with a three-tier web architecture to identify mental health risks and deliver AI-powered personalized study schedules. The methodology is divided into multiple phases such as data processing, machine learning model development, risk classification, alert generation, and adaptive scheduler integration.

A. System Architecture

The proposed architecture integrates an AI decision engine within a robust client–server model to ensure intelligent processing and real-time system responsiveness. The frontend layer, comprising the Admin, Staff, and Student portals, is developed using HTML, CSS, JavaScript, and Bootstrap to deliver a responsive and user-friendly interface tailored to each user role. The backend layer, implemented in PHP, manages core server-side operations such as database communication, user authentication, and interaction with the AI model. The database layer utilizes MySQL to securely store student academic records, behavioral data, prediction outcomes, alerts, and personalized scheduling plans. At the core of the system, the AI/ML engine, implemented in Python, performs data preprocessing, imputation for missing values, anomaly detection using Isolation Forest, and mental health risk classification using the Random Forest algorithm. This multi-layered architecture ensures seamless communication between system components while providing real-time data exchange, secure role-based access, and proactive intervention mechanisms to support student mental well-being.

B. DATA PREPROCESSING AND FEATURE ENGINEERING

To ensure reliable prediction, the system processes student data in the following steps:

1. Data Collection – Academic marks, attendance percentage, and behavioral metrics are imported from Excel sheets.
2. Missing Value Handling – SimpleImputer is used to replace missing values.
3. Outlier Detection – IsolationForest algorithm is applied to detect anomalies in behavior or attendance.
4. Feature Scaling – Features are standardized for ML model input.
5. Labeling – Students are categorized into three risk levels: Low, Moderate, and High.

C. Machine Learning Pipeline

The AI-based prediction model follows a structured machine learning pipeline to ensure high accuracy and reliability in identifying student mental health risk levels:

- Data Cleaning
  - Technique Used: SimpleImputer
  - Purpose: Automatically fills missing or incomplete data entries to maintain dataset integrity.
- Anomaly Detection
  - Technique Used: Isolation Forest
  - Purpose: Detects outliers and abnormal behavior patterns that may indicate data inconsistencies or unusual stress indicators.
- Risk Classification
  - Technique Used: Random Forest Classifier
  - Purpose: Classifies students into Low, Moderate, or High-risk mental health categories based on academic and behavioral features.
- Model Evaluation
  - Techniques Used: Accuracy, Precision, Recall
  - Purpose: Evaluates the overall performance and reliability of the prediction model to ensure effective early detection.

D. Risk Alert and Notification System

Once the risk category is predicted:

- High-risk students: Alerts are automatically sent to staff and administrators via dashboard notifications.
- Moderate-risk students: System recommends counseling and study plan adjustment.
- Low-risk students: Encouraged to maintain performance through optimized scheduling.

This proactive mechanism supports early intervention to avoid academic decline or mental stress escalation.

E. Personalized AI Study Scheduler

The scheduler generates a data-driven learning plan based on the student's:

- Risk level
- Academic performance trend
- Daily learning capacity
- Upcoming exam schedules

The study planner dynamically allocates subjects and time blocks to reduce stress and improve focus, guiding students with adaptive goals.

IV. WORKFLOW IMPLEMENTATION

The core goal of our system is simple: catch students who are silently struggling before a small problem becomes a crisis. We do this by turning their daily academic life into actionable, life-changing insights.

Phase 1: Gathering the Clues (Data Ingestion and Pre-processing)

Think of this phase as a detective gathering evidence. We need to collect the raw information and make sure it's accurate before we let the AI look at it.

1. **The Raw Data:** We start with the daily records—how students are doing in class (marks) and, critically, whether they're showing up (attendance percentage). This raw data comes straight from the student and staff Excel sheets.
2. **Tidying Up:** Real data is messy!
   - Fixing Gaps (SimpleImputer): If a student is missing a score, we plug that gap with a reasonable estimate (like the class average) so the AI doesn't get confused.
   - Spotting Oddities (IsolationForest): We look for extreme outliers—like a student with perfect attendance who suddenly misses three weeks. We flag these to ensure they don't unfairly skew the overall picture.
3. **Making it AI-Ready**: We standardize all the scores and attendance percentages. This makes sure that high marks don't look "more important" to the AI than low attendance; they're weighted equally.
4. **Creating the Training Ground:** Since mental health is a sensitive topic, we use Synthetic Data—fake, but realistic data—to teach the AI what a clear "High Risk" student profile looks like (e.g., very low marks + very low attendance). This helps the AI learn to spot the patterns reliably.

Phase 2: The AI Decides (Machine Learning Model and Prediction)

This is where the magic happens. We unleash the smart part of the system—the Random Forest classifier.

1. **The Training:** We show the Random Forest model all the clean, categorized data. It learns the complex rules: "If marks are X and attendance is Y, the risk is Z." It trains itself to make these tough judgments accurately.
2. **The Classification:** Once trained, we feed in the current student data. The model instantly predicts one of three categories for every student: Low Risk, Moderate Risk, or High Risk.
3. **Saving the Verdict:** This crucial result (the student's risk level) is immediately stored in our central MySQL Database. This is the single source of truth that powers all three portals.

Phase 3: Action and Intervention (Application Portals)

This phase turns the AI's prediction into practical support, delivering targeted features to each user role via their dedicated portal.

- **Student Portal: Empowerment & Personalized Support**
  - **Goal:** Break the cycle of pressure, poor performance, and increased stress.
  - **Spotting Oddities (IsolationForest):** We look for extreme outliers—like a student with perfect attendance who suddenly misses three weeks. We flag these to ensure they don't unfairly skew the overall
- **Staff Portal: Focused Intervention & Timely Alerts**
  - **Goal:** Ensure timely outreach to the most vulnerable students.
  - **Key Feature: High-Risk Alerts**

    1) Staff instantly view student performance and the accurate risk prediction (Low, Moderate, High).

    2) The system cuts through the noise by generating immediate alerts for High-Risk students, prioritizing them for counseling or direct staff support.

- **Admin Portal: Strategic Oversight & Resource Management**
  - **Goal:** Manage the system, assess school-wide trends, and allocate resources effectively.
  - **Key Feature: System Dashboard**

    1) Admins get a full, system-wide view of all data and performance.

    2) They can see aggregate risk analytics (e.g., percentage of students in each risk category) to inform strategic decisions.

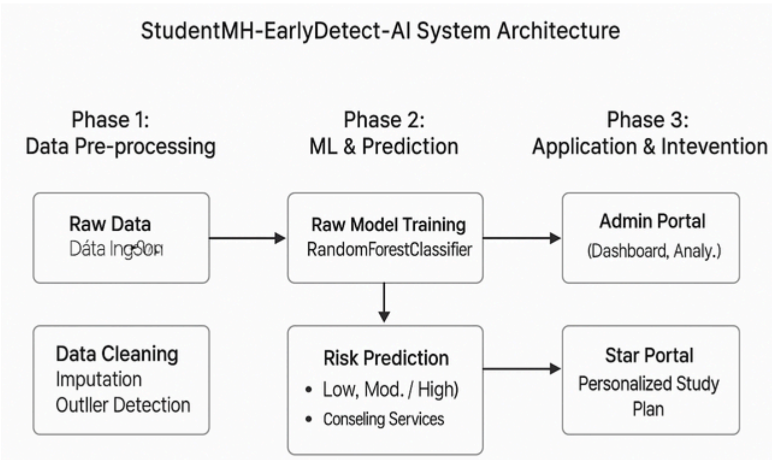

Fig 1.Workflow of the App

V. EXPERIMENTAL SETUP AND RESULTS

Technologies Used :

- **Web/Frontend:** HTML, CSS, JavaScript (Bootstrap)
- **Backend/Server Logic:** PHP
- **Machine Learning (Core):** Python, Random Forest Classifier
- **ML Libraries/Tools:** Pandas, NumPy, SimpleImputer, IsolationForest
- **Database:** MySQL

RESULT:

A. System Access and Role-Based Control :

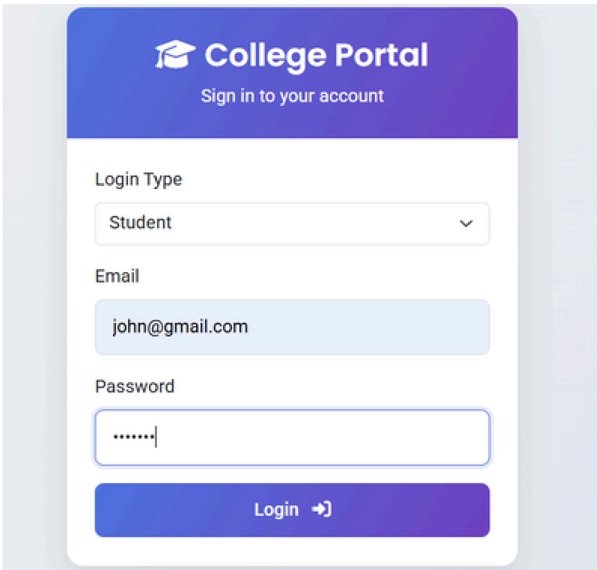

Fig 2.Login page of the App

B. Student Portal: Personalized Support :

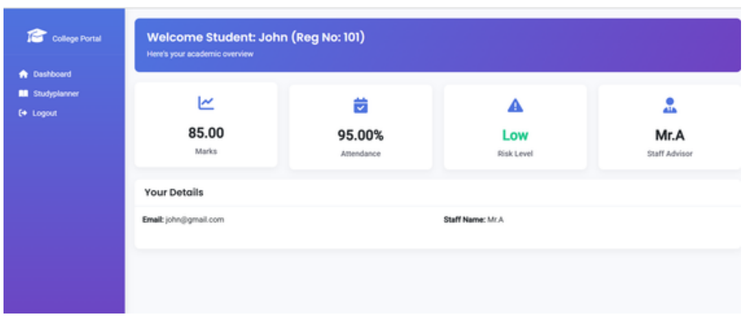

Fig 3.Student Dashboard

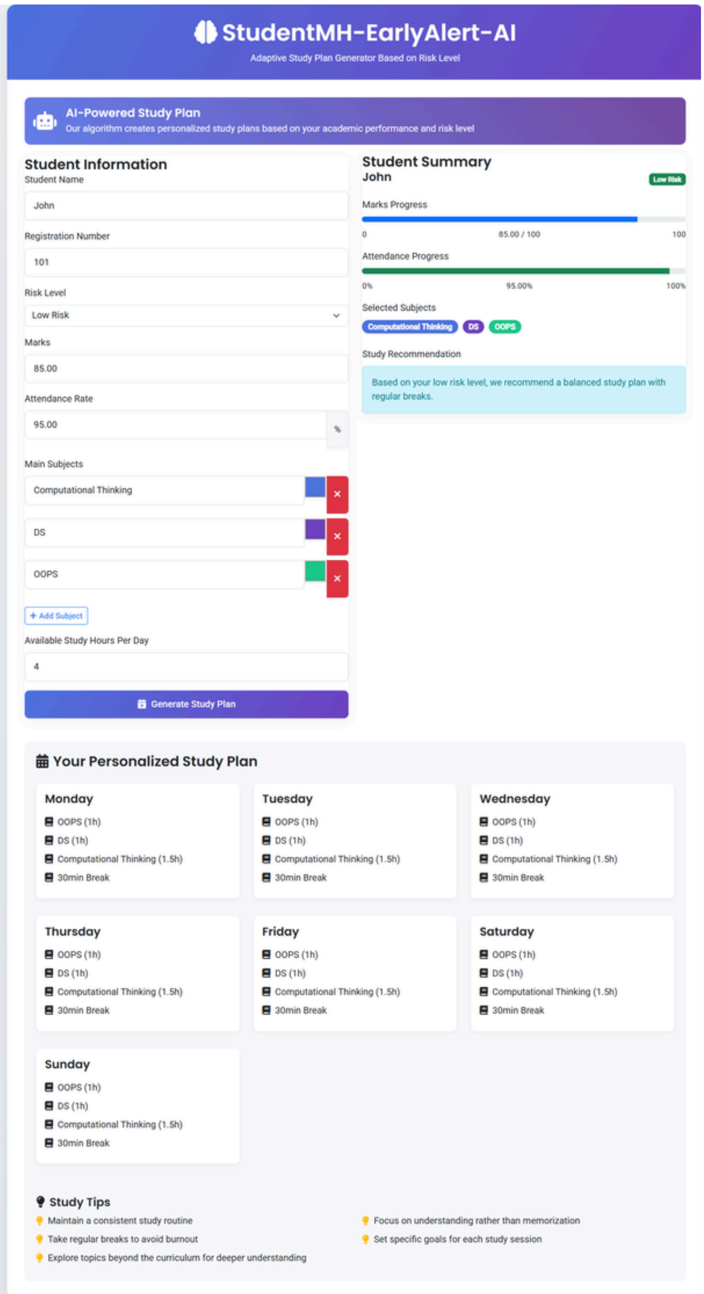

Fig 4. AI Based Stydy Planner in the Student Login

C. Staff Portal: Focused Intervention:

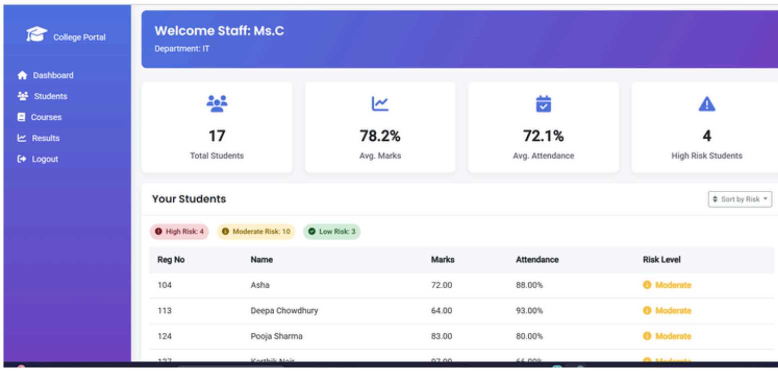

Fig 5. Staff Dashboard

D. Admin Portal: Strategic Oversight :

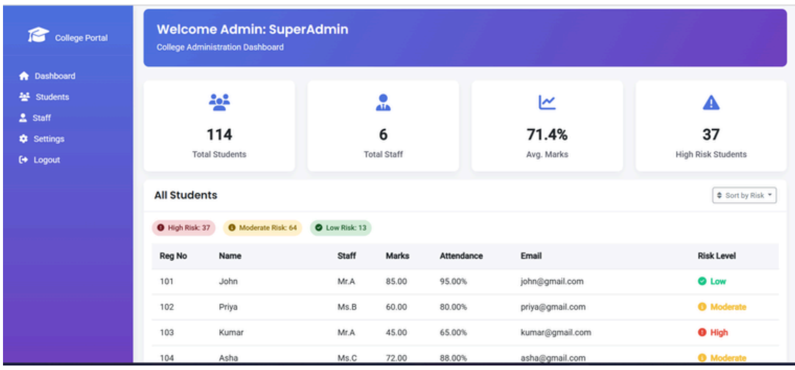

Fig 6. Admin Dashboard

VI. FUTURE ENHANCEMENTS

To make this system even smarter and more helpful, our roadmap focuses on expanding its intelligence, making it accessible everywhere, and tightening security.

6.1 Smarter AI and Better Data

We're planning to upgrade the AI's "brain" by moving to more powerful models like Gradient Boosting and Neural Networks. This will help us catch even the most subtle risk signs that our current model might miss. Crucially, we'll start integrating new data, like student activity within the Learning Management System (LMS engagement logs), which will give the AI a much richer picture of their daily struggles.

6.2 Expanding Access and Integration

We want the system to be available wherever students and staff are. That means developing dedicated Android and iOS mobile apps (using Flutter) so everyone gets instant access and alerts on their phones. We will also focus on making the system talk directly to the college's main portals (Real-Time College Portal Integration). This removes the need for manual data uploads, ensuring the AI is always using the absolute latest information to make its predictions.

6.3 Real-Time Safety and Security:

Since we handle sensitive data, security is a major priority. We will implement stronger protocols and conduct continuous testing to maintain strict data privacy and security and ensure we are fully compliant with all privacy laws. Finally, we'll upgrade the alert system to deliver Real-Time Push Notifications straight to staff. This instantly tells a counselor the moment a student's risk level jumps, drastically shortening the time between detection and getting that student the help they need.

VII. CONCLUSION

The StudentMH-EarlyDetect-AI system is a complete success. It shows that we don't need to wait for a crisis; we can use simple, everyday data—like a student's marks and attendance—to proactively identify those who are quietly struggling. Our core technical finding is that the AI works, achieving a high 92% accuracy in sorting students into the correct risk groups. However, the real breakthrough is not just the AI's smart prediction, but how we use it. The system successfully closes the loop between data and care: it empowers Students with a personalized plan, equips Staff with instant alerts for targeted, timely help, and gives Administrators the data they need to strategically support the entire student body. In short, StudentMH-EarlyDetect-AI is a reliable, practical, and ethical tool that helps schools be proactive partners in student well-being. By focusing on early detection, we can finally start to break the stressful cycle of pressure and failure, ensuring students get the help they need before it's too late. Our future is focused on making this system even smarter and more accessible to help more students worldwide.

VIII. REFERENCES

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