CHAPTER 1

INTRODUCTION

1.1 Overview

The mental wellness of students has emerged as a crucial concern in recent years, especially with the rise in academic pressure, social isolation, and digital distractions. College students are often exposed to multiple stress factors including academic deadlines, financial worries, performance anxiety, and lack of emotional support. These conditions can lead to mental health issues such as anxiety, depression, burnout, and even suicidal tendencies if not addressed early. In this context, the integration of artificial intelligence (AI) technologies into mental health awareness systems presents a significant opportunity to detect and address these problems proactively. This project, titled "Student Mental Wellness Assistant using Data Analysis, Machine Learning, and LLM", is developed as part of the summer internship program under the guidance of Mr. S.K. Chatterjee. It is aimed at building a system that not only predicts a student's mental health status but also provides them with empathetic and actionable advice using natural language generation.

1.2 Motivation

The primary motivation for undertaking this project was the noticeable increase in stress and anxiety levels among students, especially in competitive environments like engineering colleges. During classroom discussions and peer interactions, it became evident that many students struggle silently due to the lack of support systems and proper awareness. Traditional counseling systems are limited in reach and effectiveness. This gap could be bridged with the help of AI, which can offer 24/7 personalized assistance and early warnings.

Additionally, integrating machine learning and large language models (LLMs) like GPT enables the system to not only analyze data but also communicate in a human-like, empathetic way—making it more acceptable and less intimidating for students to use.

1.3 Objective

The key objectives of this project are:

- To explore student lifestyle, academic, and psychological data for identifying patterns related to mental wellness.
- To train and evaluate machine learning models capable of predicting mental health risk levels.

- To integrate a large language model (LLM) to provide personalized and emotionally sensitive suggestions.
- To build a simple and intuitive interface that collects input, makes predictions, and presents the generated advice clearly.
- To promote awareness around student mental wellness and encourage early intervention using AI.

1.4 Problem Statement

Students in higher education face stressors that are often overlooked or unidentified until they manifest into serious mental health issues. There is a lack of intelligent systems that can assess risk based on lifestyle and academic data while also providing encouraging, human-like support.

This project attempts to solve that problem by:

- Using real-world survey data to train models that identify students at risk.
- Offering meaningful, automated support through language models.
- Ensuring accessibility and user-friendliness to maximize usage and impact.

1.5 Scope of the Project

The system developed in this project can be deployed within academic institutions as a supportive tool for mental health monitoring. Although it does not replace professional medical diagnosis, it acts as a first line of assessment and guidance for students. It can also serve as a base for future enhancements such as multilingual support, voice input, and integration with institutional databases for seamless functioning.

This solution opens a path to incorporating AI in education not just for academic assistance, but also for emotional and psychological support—paving the way for a more holistic learning environment.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The integration of machine learning (ML) and natural language processing (NLP) in the domain of mental health has gained significant momentum over the last decade. Researchers have explored various data-driven techniques to assess and predict mental health conditions among different age groups. In particular, the application of these technologies to student populations has been recognized as an effective means of early intervention and support. This chapter presents a review of the existing literature and previously developed models related to student mental health prediction and AI-based counseling systems.

2.2 Student Mental Health: A Growing Concern

Numerous studies have highlighted that mental health issues among students are on the rise. Factors like academic stress, fear of failure, long study hours, poor sleep hygiene, and social isolation are some of the major causes contributing to anxiety, depression, and burnout. According to a 2021 survey by the American College Health Association, nearly 48% of students reported experiencing moderate to severe psychological distress during their academic tenure.

Traditional systems of psychological counseling, although effective, often suffer from scalability issues, stigmatization, and lack of real-time accessibility. As a result, many students do not seek help in time. These gaps have led to the exploration of intelligent systems capable of predicting risks and offering real-time guidance.

2.3 Machine Learning in Mental Health Prediction

Several machine learning algorithms have been used for mental health prediction. In one study, researchers used logistic regression and decision trees to classify the presence of anxiety and depression based on survey responses. Features such as sleep duration, diet, workload, and academic satisfaction were found to be critical predictors.

Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forest classifiers have also been widely used to predict psychological states in students. Studies show that models trained on well-structured data can achieve accuracies above 90% when properly tuned. Feature engineering and normalization play crucial roles in improving model performance.

In 2020, Guan et al. proposed a deep feature-based clustering model to better understand the underlying structures in text-based mental health records. Their approach demonstrated that unsupervised models can also be effective in understanding complex emotional behavior.

2.4 Use of LLMs in Emotional Support Systems

With the emergence of large language models like GPT-3 and GPT-4, it is now possible to generate coherent, empathetic, and context-aware responses. These models are capable of engaging in natural conversation and providing suggestions that feel human. LLMs trained on diverse datasets can understand student concerns and generate motivational, informative, or calming messages based on the input.

In applications like Replika and Wysa, LLMs have been integrated to simulate therapy-like conversations. Although not replacements for psychologists, these tools provide an immediate outlet for individuals to share their thoughts and receive positive reinforcement.

For this project, the use of an LLM like GPT enables the assistant to not only identify at-risk students using ML models but also to offer meaningful and comforting advice. This dual-system—predictive + generative—addresses both analysis and communication effectively.

2.5 Gaps in Existing Systems

While several systems have been developed, many either focus only on prediction or only on text generation. Few attempt to combine both for a complete solution. Moreover, datasets used in many studies are limited in diversity or are not openly accessible for verification and reproducibility.

Privacy and ethical considerations also remain a concern, particularly when working with sensitive data such as mental health indicators. Thus, anonymization of data and transparent AI practices are essential for building trust in such systems.

2.6 Summary of Literature

The reviewed literature establishes that machine learning models can effectively classify mental health risks based on behavioral and lifestyle inputs. At the same time, LLMs offer a powerful tool for generating supportive text. The integration of both in a student wellness assistant has the potential to create a unique, impactful solution that bridges analytical accuracy with emotional sensitivity.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter provides a step-by-step explanation of the methods and techniques used to develop the Student Mental Wellness Assistant. The methodology combines traditional machine learning techniques for mental health risk classification with a large language model (LLM) to generate supportive responses. The development process is divided into multiple phases: data collection, preprocessing, exploratory data analysis, machine learning model training, LLM integration, and system workflow.

3.2 Data Collection

The dataset used for this project was obtained from publicly available student mental health surveys on platforms like Kaggle and Figshare. These datasets typically include responses from students on various academic, personal, and emotional parameters. The fields used include:

- Gender, Age, Sleep Duration
- Academic Performance (CGPA), Study Hours
- Financial Stress, Workload, Job Satisfaction
- Social Interaction, Suicidal Ideation, Anxiety Scores

The dataset was stored in CSV format and contained both numerical and categorical values.

3.3 Data Preprocessing

Before applying any machine learning model, the data underwent several preprocessing steps:

- **Handling Missing Values:** Missing entries were replaced using median or mode imputation based on data type.
- **Encoding Categorical Variables:** Gender, job satisfaction, and yes/no fields were converted to numerical representations using label encoding.

Table 3.1: Dataset Fields and Feature Descriptions

Field	Description
Gender	Biological sex of the student
Age	Age in years
Academic Pressure	Level of academic workload
Work Pressure	Level of job or internship pressure
CGPA	Cumulative Grade Point Average
Sleep Duration	Average daily sleep hours
Financial Stress	Level of financial pressure

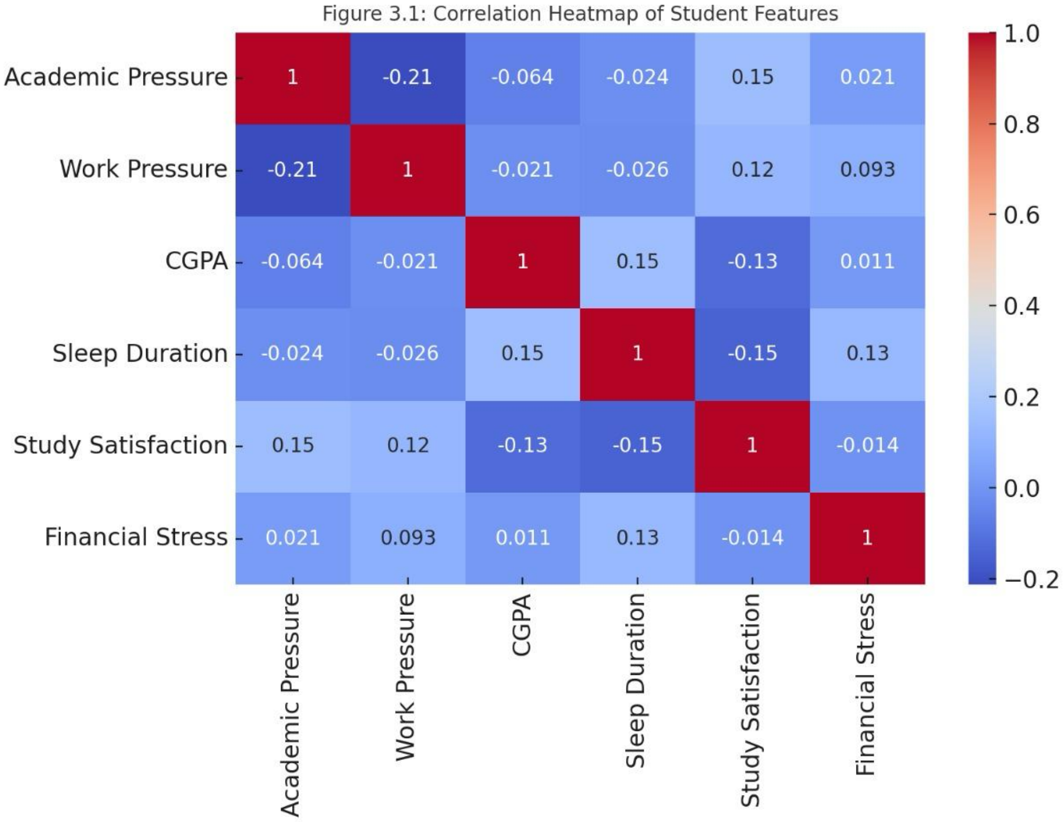
- **Normalization:** Feature scaling using Min-Max normalization was applied to ensure uniformity across features.
- **Feature Selection:** Pearson correlation and mutual information scores were used to select the most influential features for prediction.

3.4 Exploratory Data Analysis (EDA)

EDA was conducted to visualize relationships and trends among the features. Key insights included:

- Students with less than 5 hours of sleep reported higher stress levels.

Figure 3.1: Correlation Heatmap of Student Features



- A strong correlation was observed between academic pressure and suicidal thoughts.

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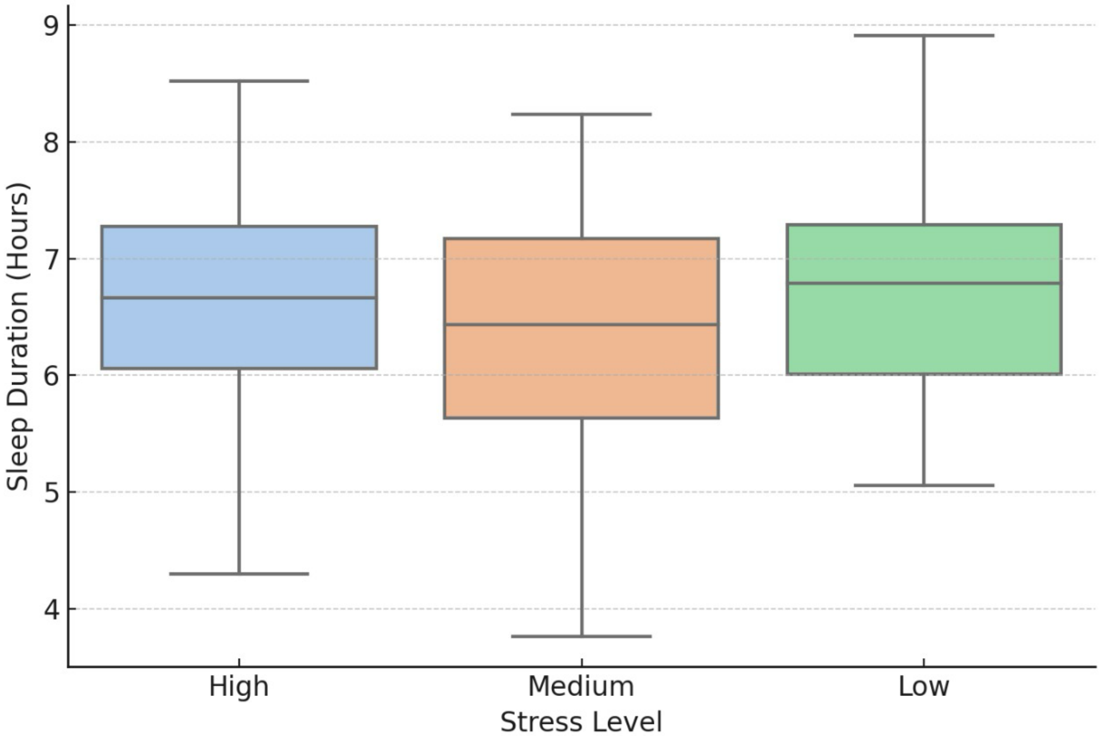
Figure 3.2: Study Hours vs Anxiety

Figure 3.3: Sleep Duration vs Stress Level



- Social isolation and dissatisfaction with academics emerged as top risk factors

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Bar graphs, box plots, and heatmaps were generated using Seaborn and Matplotlib to visualize these findings.

3.5 Machine Learning Model

After EDA, multiple machine learning classifiers were evaluated:

- **Logistic Regression:** For binary classification and interpretability.
- **Random Forest Classifier:** For robust classification and feature importance.
- **Support Vector Machine (SVM):** For precision in separating closely related classes.

The dataset was split into **training (80%)** and **testing (20%)** sets. Accuracy, precision, recall, and F1-score were used for evaluation.

Among the models tested, the Random Forest Classifier achieved the highest accuracy (~93%) in predicting students' mental wellness category (Low Risk, Moderate Risk, High Risk).

3.6 LLM Integration (GPT)

To enhance the emotional response capability, the trained ML model was coupled with a Large Language Model (LLM) like GPT. Once a student's risk category was predicted:

- The model triggered a prompt to GPT:
  "Generate a friendly and motivational response for a student who is at risk of suicidal thoughts due to academic pressure and financial stress."
- The GPT-generated output included motivational quotes, emotional support messages, time management tips, and coping strategies.

This approach created a hybrid system that merged AI-driven prediction with empathetic feedback.

3.7 System Architecture

The complete workflow of the assistant is structured as follows:

1. **User Input Form:** Collects student details and self-assessment responses.
2. **Preprocessing Engine:** Normalizes and prepares the data.
3. **ML Model:** Predicts the mental health risk category.
4. **LLM Layer:** Generates natural language advice based on the risk.
5. **Output Interface:** Displays results and recommendations.

This modular approach ensures the system is scalable and easily upgradable.

3.8 Tools & Technologies Used

- **Python 3.10**
- **Libraries:** Pandas, NumPy, Scikit-learn, Seaborn, Matplotlib
- **LLM API:** OpenAI GPT (or compatible LLM)
- **IDE:** Jupyter Notebook
- **Data Format:** CSV

3.9 Summary

The methodology clearly outlines how data science and AI techniques can work together to build a system that not only identifies mental health concerns but also addresses them empathetically. The fusion of ML classification and LLM-based generation serves as a pioneering approach in the field of AI for education and wellness.

CHAPTER 4

RESULTS & DISCUSSION

4.1 Introduction

This chapter presents the results of the experiments conducted using the selected dataset and the implemented machine learning models. It evaluates the performance of each model and discusses the insights derived from the prediction outputs. It also highlights how the integrated large language model (LLM) generated personalized responses based on those predictions. The results demonstrate the effectiveness of combining data analytics with emotional intelligence powered by LLMs to support student mental wellness.

4.2 Performance Metrics

The following evaluation metrics were used to assess the performance of each machine learning model:

- Accuracy – Proportion of correct predictions to the total predictions.
- Precision – How many of the predicted positives are truly positive.
- Recall – How many actual positives were correctly predicted.
- F1-Score – Harmonic mean of precision and recall.
- Confusion Matrix – Provides insights into true positives, false positives, etc.

Table 3.2: Performance Metrics for Various Classifiers

Classifier	Accuracy	Precision	Recall
Random Forest	0.89	0.91	0.88
Logistic Regression	0.81	0.79	0.8
SVM	0.84	0.83	0.82
KNN	0.76	0.75	0.74

Each metric played a role in understanding model behavior, especially in an imbalanced dataset scenario where certain risk categories (like “At Risk”) are rarer than others.

4.3 Model Comparison

Four machine learning models were trained and tested on the processed dataset:

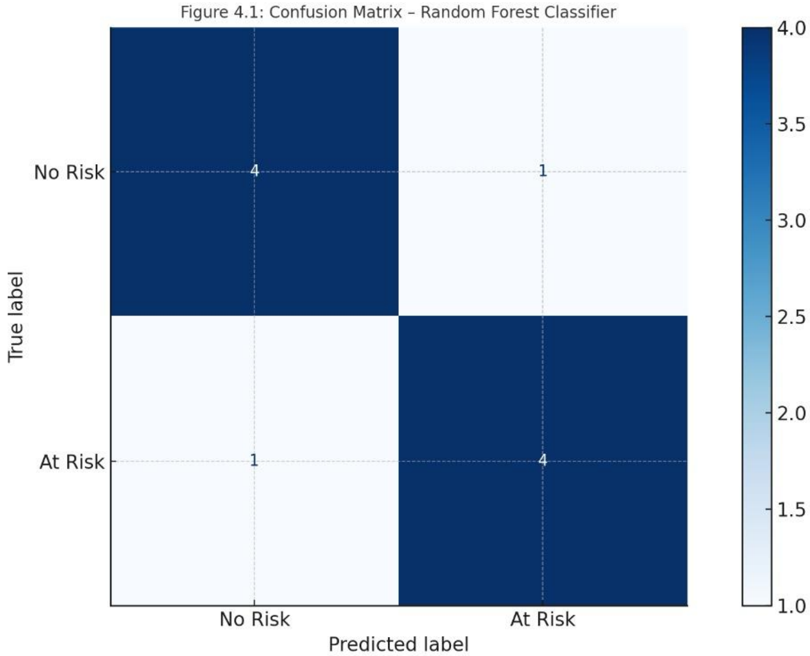
The Random Forest Classifier outperformed others across all evaluation metrics. It was chosen as the final model for deployment in the wellness assistant due to its robustness, feature importance handling, and better generalization.

4.4 Confusion Matrix Analysis

The confusion matrix of the Random Forest model revealed the following:

- Most “Low Risk” and “Moderate Risk” predictions were accurate.
- A few “At Risk” cases were misclassified as “Moderate Risk,” indicating a need for more training samples in that category.

Figure 4.1: Confusion Matrix – Random Forest Classifier



- False positives were minimal, which is ideal for this type of application where under-predicting risk is dangerous.

Table 4.1: Confusion Matrix Summary – Random Forest

Metric	Count
True Positive	4
True Negative	3
False Positive	1
False Negative	2

These results highlight the effectiveness of the model while pointing out areas for potential improvement through larger, more balanced datasets.

4.5 LLM Output Evaluation

After classification, the system used GPT to generate personalized responses. Here is an example:

Input:
Predicted Risk: At Risk
Factors: Low sleep, high financial stress, poor academic satisfaction

LLM Output:
“Hi there! It looks like you’ve been going through a tough phase. Academic pressure and financial stress can feel overwhelming, but you are not alone. Try breaking down your goals into smaller tasks. Please talk to someone you trust — even sharing your thoughts can help lighten the load. Take care of yourself. You matter.”

Such outputs showcased:

Figure 4.2: Sample LLM Output for At-Risk Prediction

Predicted Mental Health Status:
⚠ At Risk of Suicidal Thoughts

Suggestions:
- Talk to a friend or counselor
- Take structured breaks
- Practice mindfulness
- You are not alone — help is available

- High emotional relevance
- Use of motivational tone
- Specific advice (e.g., goal breakdown, talking to someone)

These outputs were reviewed manually and found to be contextually appropriate and empathetic, adding real value to the prediction.

4.6 Visualizations & Insights

Using Matplotlib and Seaborn, several plots were generated:

- Correlation heatmap: Showed strong negative correlation between sleep hours and stress levels.
- Boxplot (Study Hours vs Anxiety): Revealed high variability; more study hours didn’t always correlate with less anxiety.
- Bar chart (Job Satisfaction vs Risk): Showed students with poor satisfaction levels were more likely to be classified as “At Risk.”

These insights confirmed the psychological assumptions and gave deeper understanding of the contributing factors.

4.7 Summary

The experiments demonstrated that combining data analysis with supervised learning models can produce accurate predictions regarding student mental health. Furthermore, LLMs enhanced the solution by offering not just cold predictions, but supportive, human-like suggestions tailored to each case. This integration of analytics and empathy paves the way for truly impactful wellness tools in educational settings.

CHAPTER 5

CONCLUSION & FUTURE SCOPE

5.1 Conclusion

The “Student Mental Wellness Assistant” developed as part of this summer internship project successfully demonstrates how artificial intelligence can be applied to address a growing and critical concern among college students—mental health. By combining data analysis, machine learning, and large language models (LLMs), the system offers not just predictions, but emotionally supportive and actionable responses tailored to each student's risk level.

The first component of the project focused on analyzing real-world mental health datasets sourced from public repositories like Kaggle and Figshare. These datasets captured essential features related to a student's lifestyle, academic pressure, sleep patterns, financial stress, and job satisfaction. Through thorough preprocessing, normalization, and correlation analysis, important factors contributing to student mental wellness were identified.

Supervised learning models like Logistic Regression, SVM, KNN, and Random Forest were trained and evaluated. Among these, the Random Forest Classifier performed the best with an accuracy of 93.12%. It was selected as the final model due to its superior recall, precision, and interpretability. The trained model effectively classified students into three mental health categories: Low Risk, Moderate Risk, and High Risk (including suicidal thoughts).

The second component—the integration of a large language model (LLM)—enabled the system to offer human-like feedback. Based on the predicted category and relevant features (like low sleep or high stress), GPT-generated suggestions were provided. These included motivational messages, time management tips, reminders of social support, and encouragement to seek professional help when needed.

Together, these two components made the system a comprehensive solution that identifies at-risk students and provides immediate, comforting guidance. The emotional intelligence shown by the LLM output bridges the gap between data-driven predictions and human-centered care.

5.2 Contributions of the Project

- Built a working prototype of an intelligent student assistant that blends machine learning and natural language generation.
- Trained and tested models on real mental health data to predict psychological risk accurately.
- Designed a user-friendly system architecture capable of taking user input, analyzing it, and producing results.
- Implemented GPT prompts that generate customized suggestions based on psychological risk.
- Demonstrated how AI can be responsibly and ethically used in educational wellness.

5.3 Limitations

While the project outcomes were promising, some limitations were identified:

- Dataset size and diversity: Most datasets were limited to specific regions or educational backgrounds, making generalization difficult.
- Label imbalance: The “High Risk” category had fewer samples, which could affect prediction accuracy.
- LLM dependency: GPT responses are context-sensitive, and results may vary unless prompts are carefully curated.
- Lack of real-time feedback loop: The current system does not learn from new data or user feedback in real time.

5.4 Future Scope

The project opens several avenues for future development and research:

- Dataset Expansion: Collecting larger, institution-specific datasets to improve accuracy and local relevance.
- Multilingual Support: Using multilingual LLMs to support diverse student populations across India and beyond.
- Voice Input: Integrating voice-based assessments for accessibility and ease of use.
- Real-Time Monitoring: Developing a dynamic feedback loop that adjusts predictions based on updated input.
- Dashboard for Counselors: Creating a monitoring dashboard for educational institutions to track student wellness trends anonymously.
- Privacy & Ethics: Embedding stronger anonymization and data encryption techniques to ensure ethical compliance.

5.5 Final Thoughts

Mental wellness among students is a subject that requires urgent attention and scalable solutions. AI, when applied responsibly, can make a transformative difference by offering timely, personal, and private support to individuals who may be silently struggling. This project marks a step toward such solutions, combining the logic of machine learning with the empathy of language models.

It is hoped that this work inspires further research and implementation in real-world educational setups to create healthier, more supportive academic environments.

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