ZENTORA-AN ADAPTIVE AI FOR PERSONALIZED LEARNING ON MENTAL HEALTH

A SOCIALLY RELEVANT MINI PROJECT REPORT

Submitted by

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ABSTRACT

In recent years, the importance of emotional well-being among students has gained increasing attention, especially in the context of primary and secondary education. Many students experience stress, anxiety, or emotional instability that often goes unnoticed due to limited access to school counsellors and the stigma surrounding mental health discussions. To address this issue, the proposed system introduces an **AI-based chatbot and journaling platform** designed to support school counselling through real-time emotional assistance and long-term behavioural monitoring.

The system allows students to express their thoughts and feelings through a chatbot or journaling interface. Using **Natural Language Processing (NLP)** techniques, the chatbot analyses the text input to detect the user's emotional state, such as happiness, sadness, anger, or anxiety. Based on the identified emotion, the system provides **personalized coping suggestions** inspired by **Cognitive Behavioural Therapy (CBT)** and **Social and Emotional Learning (SEL)** principles, encouraging self-reflection and emotional regulation. All interactions are securely stored in a centralized database, which updates a **counsellor dashboard** in real time. The dashboard enables school counsellors to monitor student progress, identify high-risk cases, and provide targeted feedback.

This system not only enhances the efficiency of school counselling services but also fosters a safe and interactive environment where students can openly communicate their feelings. By combining AI-driven emotion detection with human-centered counselling, the project aims to bridge the gap between technology and mental health support. Furthermore, it contributes to the development of scalable, ethical, and culturally sensitive digital counselling solutions suitable for schools in resource-limited regions.

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1.1 OVERVIEW

The proposed project focuses on developing an **AI-Based Chatbot and Journaling System** to enhance school counselling for students, particularly those dealing with emotional or behavioural challenges. In many schools, especially in Asian contexts, there is a growing concern about students' mental health and emotional well-being. However, due to the shortage of trained counsellors and the stigma around seeking psychological help, many students struggle silently. This project aims to bridge that gap by introducing a digital solution that provides **real-time emotional support** and **long-term counselling assistance**.

The system enables students to interact with a **chatbot** or write their feelings in an **online journal**. The chatbot uses **Natural Language Processing (NLP)** and **Artificial Intelligence (AI)** techniques to analyse the student's text input and detect their emotional state — such as happiness, sadness, anger, or anxiety. Once the emotion is recognized, the system provides **personalized coping suggestions** and **positive reinforcement strategies** based on **Cognitive Behavioural Therapy (CBT)** and **Social Emotional Learning (SEL)** principles. These suggestions help students manage their emotions more effectively, improve self-awareness, and develop emotional resilience.

All user interactions are stored securely in a **centralized database**, allowing the system to track emotional patterns and progress over time. A dedicated **counsellor dashboard** gives school counsellors access to this data, displaying detailed emotional trends, activity logs, and risk alerts for students who may need immediate attention. This not only helps counsellors manage their workload but also ensures that no student in distress is overlooked.

Overall, the project combines the power of **AI technology** with the sensitivity of **human counselling** to create a supportive digital environment for students. It provides a scalable and ethical solution for schools to strengthen mental health support systems.

1.2 PROBLEM DEFINITION

In today's fast-paced and digitally connected world, the mental and emotional well-being of students has emerged as a critical concern. Increasing numbers of students experience stress, anxiety, depression, and other emotional challenges that often remain unrecognized or unaddressed. The shortage of qualified school counsellors, combined with the social stigma associated with mental health, makes it difficult for students to seek timely help. Moreover, traditional counselling methods are often constrained by limited time, accessibility, and human resources.

Consequently, there is an urgent need for a system capable of providing continuous emotional support, early detection of emotional distress, and timely intervention—without replacing the essential role of human counsellors. The main challenge lies in developing an effective, scalable, and ethical framework that integrates technology into the school counselling process while maintaining user privacy, data security, and cultural sensitivity.

To address these challenges, this project proposes an **AI-based chatbot and journaling platform** designed to detect students' emotions through text inputs and provide personalized coping strategies based on **Cognitive Behavioural Therapy (CBT)** and **Social Emotional Learning (SEL)** principles. The system also incorporates a **counsellor dashboard** that allows professionals to monitor emotional trends, receive alerts for at-risk students, and offer targeted guidance. By combining AI-driven automation with human empathy and professional oversight, the proposed solution enhances the effectiveness of school counselling, ensuring that students receive timely and personalized emotional support.

CHAPTER 2
LITERATURE SURVEY

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LITERATURE SURVEY

[1] Limbachia et al. (2023) introduced *MOODIFY*, an AI-driven assistant specifically designed to address the mental health needs of young adults. The system utilized emotion recognition and adaptive learning to personalize its responses based on user sentiment and engagement patterns. By tailoring interactions to individual emotional profiles, the study demonstrated that AI-based personalization can improve therapy adherence, engagement, and emotional outcomes, underscoring the importance of demographic-specific interventions in digital mental health.[2] Kheterpal & Gill (2024) conducted a comparative study of AI-driven mental health interventions, contrasting chatbot-based and recommendation-based systems. Their findings revealed that while both approaches improve accessibility to psychological support, personalized interactions and data privacy remain key determinants of user trust and efficacy. The research emphasized the balance required between personalization and ethical data handling in scalable AI mental health solutions.

[3] Mary et al. (2025) explored predictive mental health analytics within metaverse environments using machine learning algorithms. Their model identified early indicators of stress and anxiety in users through behavioral and physiological data in immersive virtual spaces. The study presented a proactive monitoring framework for mental health in digital realities, demonstrating AI's potential in next-generation virtual wellbeing systems.[4] Revathi et al. (2025) integrated machine learning models with cognitive-behavioral therapy (CBT) techniques to enhance stress management and overall mental wellbeing. Their AI system automated both assessment and intervention processes, allowing for adaptive, data-driven mental health support. The results highlighted the capacity of AI to deliver scalable, evidence-based psychological assistance beyond traditional

clinical settings.

[5] Hanji et al. (2024) developed *Self-Heal*, an AI-enhanced conversational therapy bot that provided real-time psychological support through natural language interaction. The chatbot simulated therapist-like dialogues, using NLP to tailor its tone and content to user needs. The study showed higher user engagement and satisfaction compared to conventional self-help apps, demonstrating AI's potential to deliver accessible, human-like therapeutic interactions.[6] Kaushik et al. (2024) focused on the development of emotional support chatbots utilizing deep learning and natural language processing to recognize and respond to nuanced emotional states. Their work found that contextual and personalized responses greatly improved user emotional comfort and trust, confirming that deep learning models enhance empathy and accuracy in mental health conversational systems.

[7] Jain et al. (2024) assessed various machine learning models for predicting depression and anxiety, comparing logistic regression, SVMs, and ensemble approaches. The study found that ensemble models consistently outperformed single algorithms, providing higher accuracy and reliability in early detection. The findings validated machine learning's utility in predictive mental health diagnostics and prevention strategies.[8] Benita et al. (2025) introduced *Phoenix*, a multi-modal conversational agent designed to provide psychological support and enhance emotional wellbeing. The system processed voice, text, and facial expression data to deliver personalized therapeutic dialogue. Results indicated strong user satisfaction and improved emotional outcomes, highlighting the effectiveness of multi-modal AI in digital mental health care.

[9] Gowroju et al. (2025) developed *MindBridge*, an AI-enhanced mental health platform that applied deep learning to perform emotional analysis and generate personalized recommendations. The system created immersive, adaptive user experiences, allowing for real-time understanding of mental states. The study

emphasized AI’s transformative role in virtual mental health support and emotional intelligence integration.[10] Jain et al. (2024) explored AI-assisted journaling as a tool for enhancing self-reflection and emotional processing. Their system analyzed journal entries to identify emotional patterns, cognitive biases, and mood fluctuations, providing users with constructive feedback and suggestions. The research demonstrated that AI-guided reflection can foster deeper self-awareness and emotional regulation.

[11] Thakkar et al. (2024) presented a comprehensive student-focused platform integrating deep learning for emotion detection, psychological assessment, and career guidance. By combining academic and psychological data, the platform offered personalized recommendations that supported both emotional wellbeing and educational progress. The study demonstrated the power of AI to deliver holistic, context-aware mental health support for students.[12]Mate et al. (2024) proposed an AI-driven musical therapy system combining machine learning with IoT sensors for stress reduction. The model analyzed users’ emotional and physiological signals to curate or generate personalized music that matched their relaxation needs. The findings showed significant reductions in stress levels, illustrating the potential of AI-personalized music therapy for emotional regulation.

[13] Al-Atwi et al. (2025) examined the application of AI to analyze social media data from X (Twitter) for depression detection. Using NLP and sentiment analysis, their framework identified linguistic and behavioral markers associated with depressive tendencies. The study highlighted AI’s ability to monitor public mental health trends and detect early warning signs, though it acknowledged ethical challenges related to privacy and consent.[14] Murase & Andritsch (2024) enhanced mental health chatbots by incorporating sentiment analysis, enabling chatbots to adapt their tone and responses based on user emotion. Their evaluation

showed that sentiment-aware systems significantly improved user satisfaction and perceived empathy, suggesting that emotionally responsive AI can enhance the therapeutic value of chatbots.

[15] Laxman et al. (2024) developed an explainable transformer-based model for depression detection on social media. Their framework provided interpretability through visual and linguistic explanations, allowing clinicians to understand the reasoning behind AI predictions. The research underscored the importance of transparency and trust in deploying AI for clinical decision-making and psychological assessment.[16] Sri et al. (2025) introduced *MindMend*, a simulation platform using explainable Generative Adversarial Networks (GANs) to create realistic mental health scenarios for therapist training. The system offered interactive, data-driven simulations to help therapists practice diagnostic and communication skills safely. The study demonstrated AI's educational potential in building competence and empathy in clinical psychology training.[17] GalijaSevié et al. (2024) conducted a comprehensive review of advancements in AI chatbots for mental health support. Their analysis highlighted innovations in dialogue management, empathy modeling, and adaptive learning, showing that modern chatbots can simulate emotionally intelligent interactions. They concluded that AI chatbots can effectively complement human therapy and expand access to psychological care.

[18] Jain et al. (2024) further emphasized AI's role in guided journaling, reaffirming that automated reflective tools support emotional growth, awareness, and mental wellbeing. Their follow-up findings confirmed that users engaging in AI-assisted journaling reported improved mood tracking, emotional understanding, and self-regulation over time.[19] Reddy et al. (2025) introduced *Autogen*, an AI-based wellbeing assistant for college students designed to promote self-awareness and stress management. The tool incorporated daily emotional

check-ins, guided reflections, and coping strategies based on individual data. Their study demonstrated improved student resilience and engagement with digital mental health interventions.

[20] Rao et al. (2025) developed an NLP-driven mental wellness chatbot aimed at students, offering personalized, real-time emotional support and coping advice. The chatbot's accessibility and conversational fluency made it an effective alternative for students hesitant to seek traditional counseling, highlighting AI's role in democratizing mental health support.[21] Deepika et al. (2025) utilized social media data to identify mental health patterns using machine learning models. Their approach enabled large-scale mood and behavior tracking to infer potential signs of distress or depression. While effective in detecting population-level trends, the study also raised ethical concerns about surveillance and data privacy in AI mental health analytics.

[22] Vedanta & Rao (2024) proposed *PsychSynth*, a synthetic data generation framework for training AI mental health models. By creating artificial datasets that mimic real psychological data, the framework mitigated issues of limited or sensitive data availability while preserving model accuracy. Their results showed that synthetic data can enhance fairness, scalability, and reproducibility in mental health AI systems.

CHAPTER 3
SYSTEM ANALYSIS

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3.1 EXISTING SYSTEM

In the current counselling framework, most institutions rely on **traditional, face-to-face counselling methods** where students meet with counsellors periodically to discuss academic, social, or emotional concerns. These sessions are typically scheduled and conducted in person, requiring both the student and counsellor to be physically present. While this model allows for personal interaction and professional guidance, it also has several limitations, especially in schools with a large student population and limited counselling staff.

One of the major challenges in the existing system is the **shortage of qualified school counsellors**. In many regions, particularly in Asia, the student-to-counsellor ratio is extremely high, often exceeding 1000:1. This makes it difficult for counsellors to provide individualized attention to every student. As a result, many students experiencing emotional distress or behavioural issues remain unnoticed or receive delayed support. Furthermore, students who are introverted or fearful of judgment may avoid seeking help altogether, allowing emotional problems to escalate over time.

Another limitation is the **lack of continuous monitoring and follow-up**. In the traditional system, counsellors rely on occasional sessions and verbal reports from students or teachers, which do not provide a real-time picture of a student's emotional state. There are no automated mechanisms for tracking emotional patterns or detecting early signs of mental distress. Consequently, interventions often occur only after significant behavioural or academic issues become visible.

Some schools have attempted to adopt **basic digital record-keeping systems** to manage counselling data. However, these systems are often limited to storing student profiles, notes, or schedules — they do not incorporate **intelligent analysis or emotional understanding**. Likewise, existing online counselling platforms primarily serve older users and lack features tailored to children's needs, such as interactive engagement, simplified interfaces, or emotion-based feedback.

Moreover, cultural factors in many Asian societies contribute to **stigma surrounding mental health discussions**, making students reluctant to visit the counsellor’s office. This social hesitation further reduces the effectiveness of conventional counselling models. Additionally, because traditional methods depend heavily on human interpretation, they are subject to biases, inconsistencies, and limited scalability.

In summary, the existing system of school counselling is **manual, resource-intensive, and reactive** rather than proactive. It fails to provide early emotional intervention, lacks scalability, and does not effectively utilize modern technology to support counsellors and students. These limitations highlight the urgent need for an **AI-assisted digital solution** that can detect emotions automatically, provide personalized coping suggestions, and allow counsellors to monitor student well-being efficiently.

3.2 PROPOSED SYSTEM

To overcome the limitations of the traditional counselling approach, the proposed system introduces an **AI-Based Chatbot and Digital Journaling Platform** designed to support school counselling through intelligent emotional detection, personalized feedback, and counsellor-assisted monitoring. This system aims to create a supportive, interactive, and technology-driven counselling environment that promotes emotional well-being among students while reducing the workload on school counsellors.

In the proposed model, students interact with an **AI-powered chatbot** through a simple and engaging interface available on web or mobile platforms. They can express their feelings, describe their daily experiences, or reflect on their emotions in the form of text-based journal entries or chat messages. The system uses **Natural Language Processing (NLP)** techniques to analyse these inputs and identify the student's emotional state — such as happiness, sadness, anger, anxiety, or stress. Once the emotion is recognized, the chatbot provides **personalized coping suggestions** or motivational responses based on principles of **Cognitive Behavioural Therapy (CBT)** and **Social and Emotional Learning (SEL)**. This enables students to develop better self-awareness and emotional management skills in a private and judgment-free environment.

All interactions between the student and the chatbot are securely stored in a **centralized database**, which forms the foundation for data tracking and analysis. This data is then visualized on a **Counsellor Dashboard**, allowing school counsellors to monitor students' emotional patterns, identify at-risk individuals, and intervene when necessary. If the system detects signs of severe distress or high-risk emotions, it automatically triggers an **alert notification** to the counsellor, ensuring that timely professional support is provided. This creates a balance between **automated assistance** and **human oversight**, ensuring safety and reliability.

The proposed system also emphasizes **user privacy and ethical data handling**. All stored information is encrypted and accessible only to authorized counsellors, maintaining student confidentiality. The interface is designed to be child-friendly and culturally adaptable, encouraging students to engage without fear or hesitation. Moreover, the system operates asynchronously, allowing students to interact with the chatbot anytime, even outside school hours — ensuring continuous emotional support.

By combining AI, NLP, and counselling psychology, this system transforms the traditional model into a **hybrid digital counselling ecosystem**. It helps schools address the counsellor shortage by automating initial assessments and daily emotional monitoring, while enabling counsellors to focus on personalized, in-depth interventions. The integration of journaling, emotion recognition, and feedback generation creates an end-to-end process that not only improves counselling efficiency but also strengthens emotional learning among students.

In summary, the proposed system offers an **innovative, scalable, and student-centered approach** to school counselling. It provides real-time emotional support, continuous monitoring, and intelligent assistance for both students and counsellors. Through this AI-driven solution, schools can enhance mental health awareness, ensure early intervention, and build a more empathetic and supportive educational environment.

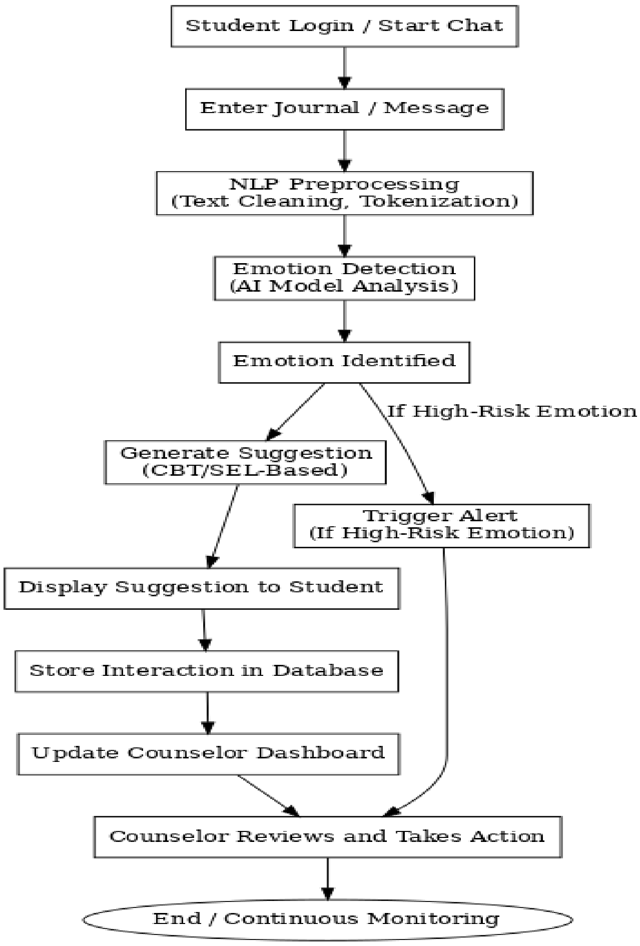

Fig 3.2.1 Proposed System Workflow

3.3 DEVELOPMENT ENVIRONMENT

The development environment for the **AI-Based Chatbot and Journaling System for School Counselling** was carefully chosen to ensure scalability, reliability, and ease of integration with artificial intelligence components. The system integrates web technologies, AI tools, and data management frameworks to create a complete digital counselling platform that supports students and counsellors efficiently.

3.3.1 SOFTWARE REQUIREMENTS

Programming Language: Python (for AI model development and backend logic)
Frontend Technologies: HTML, CSS, JavaScript (for chatbot interface and journaling UI)
Frameworks:

- **Flask / Django:** Used for backend development and API integration
- **React.js:** For building an interactive and responsive web interface

AI Libraries and Tools:

- **Natural Language Toolkit (NLTK)** and **spaCy** for NLP preprocessing
- **Transformers (Hugging Face)** for emotion detection using pretrained models (e.g., BERT)
- **OpenAI API** for advanced text analysis and suggestion generation

Database: MySQL / Firebase for storing student records, chat logs, and counsellor feedback
IDE / Development Tools: Visual Studio Code, Jupyter Notebook, and Google Colab for model training and testing

3.3.2 HARDWARE REQUIREMENTS

Processor: Intel Core i5 or above
RAM: Minimum 8 GB (16 GB recommended for AI model training)

Storage: At least 500 GB HDD or 256 GB SSD

GPU: NVIDIA GPU (optional, for faster AI model inference)

Internet Connectivity: Required for accessing APIs and cloud storage

3.3.3 OPERATING SYSTEM AND PLATFORM

Operating System: Windows 10 / 11 or Ubuntu Linux

Web Platform: Deployed as a web-based application accessible via browsers (Chrome, Edge, Firefox)

Cloud Services: Optional deployment using AWS / Google Cloud for scalability and remote access

3.4 DEVELOPING METHODOLOGY

The project follows an **Agile Development Approach**, allowing iterative improvements through design, testing, and evaluation. Modules such as the chatbot, emotion detection model, and counsellor dashboard are developed and integrated in phases to ensure functionality and stability at each step. Continuous testing ensures that both the AI components and the user interface perform smoothly under real-world conditions.

3.5 VERSION CONTROL AND COLLABORATION TOOLS

Version Control: Git and GitHub for maintaining code versions and collaboration

Project Management: Trello or Jira for task tracking and module progress

Testing Tools: Postman for API testing, and PyTest for backend validation

CHAPTER 4

SYSTEM DESIGN

CHAPTER 4
SYSTEM DESIGN

4.1 DATABASE DESIGN

The database design of the proposed AI-Based Chatbot and Journaling System for School Counselling focuses on securely managing and organizing all data related to student interactions, emotional analysis, and counsellor activities. It serves as the backbone of the system, ensuring that all information — such as chat logs, emotional states, suggestions, and alerts — is efficiently stored and retrieved. The database follows a relational structure, allowing data to be linked across multiple entities, which enhances data consistency and accuracy. Each module in the system, including the student interface, AI emotion detection, and counsellor dashboard, interacts seamlessly with the database to ensure smooth information flow and real-time updates.

The database contains several key entities such as Student, Chat_Log, Emotion_Detection, Suggestion, Counsellor, and Alert tables. The Student table stores user profiles and login credentials, while the Chat_Log table records all journal entries and chatbot interactions. The Emotion_Detection table maintains details about the identified emotions, including type and intensity, which are used to generate personalized Suggestions stored in the Suggestion table. The Counsellor and Alert tables help manage communication between counsellors and students, ensuring timely interventions in case of emotional distress. All tables are connected using primary and foreign key relationships, which establish one-to-many and many-to-one associations between entities, ensuring logical data connectivity across the system.

This database design not only supports efficient data management but also emphasizes data security, privacy, and scalability. Sensitive information such as student identities and counselling records is encrypted to protect confidentiality. The structure allows for scalability, enabling future integration of advanced AI analytics or additional features like emotion trend visualization. Overall, the database design ensures that all interactions and emotional data are systematically captured, analysed, and made available to counsellors in an organized manner, forming the foundation for effective and technology-enhanced school counselling.

4.2 INPUT DESIGN (USER INTERFACE)

The **Input Design** of the AI-Based Chatbot and Journaling System is developed with a focus on simplicity, accessibility, and user engagement. The primary users of the system — students and school counsellors — interact with the platform through an intuitive and user-friendly interface. For students, the chatbot interface allows them to enter text or journal entries freely, expressing their emotions, thoughts, and daily experiences in a comfortable, conversational manner. The input form supports both short messages and longer journal reflections, which are processed using Natural Language Processing (NLP) to detect emotions. The design also includes optional emoji inputs or mood indicators, allowing younger users to communicate their feelings easily, even if they struggle to express them in words. Validation checks are incorporated to ensure that the text input is meaningful before being analysed by the AI model.

For counsellors, the input design includes an **interactive dashboard** where they can log in securely to review student data, enter feedback, and update emotional assessments. The dashboard provides options for counsellors to filter students by emotional state, view chat histories, and record their observations or follow-up notes. Both student and counsellor interfaces are designed using responsive web design principles to ensure accessibility on desktops, tablets, and mobile devices. The overall interface layout emphasizes readability, minimalism, and emotional comfort, using calm colors and clear typography to reduce anxiety during use. This thoughtful design not only enhances usability but also encourages active participation, ensuring that data entered into the system is accurate, complete, and useful for AI analysis and counselling purposes.

4.3 MODULE DESIGN

1. Student Module: Allows students to interact with the chatbot, write journal entries, and receive personalized emotional support.
2. AI Emotion Detection Module: Processes student input using NLP to identify emotions and analyse emotional trends.
3. Suggestion Generation Module: Provides coping strategies and motivational responses based on CBT and SEL principles.

4. Database Management Module: Stores all chat logs, emotion data, counsellor feedback, and alerts securely.
5. Counsellor Dashboard Module: Enables counsellors to monitor student emotions, review alerts, and provide timely interventions.

4.3.1 USE CASE DIAGRAM

The UML Class Diagram for the *ZENTORA* system provides a comprehensive overview of the structural design and interaction between different components of the AI-driven mental health support platform. The system primarily functions as a frontend-based intelligent counselling tool that leverages artificial intelligence (AI) and machine learning (ML) techniques to analyse students' emotions and provide personalized mental health feedback through an interactive chatbot interface. The diagram is organized in a branched, landscape format to clearly represent both the student and counsellor workflows along with the AI processing modules.

At the core of the diagram lies the User class, which serves as a parent class for both StudentUser and Counsellor. The *StudentUser* class includes attributes such as emotional state, journal entries, and feedback history. It provides methods like inputJournal(), viewFeedback(), and trackProgress(), enabling students to record their feelings and view system-generated insights. On the other side, the *Counsellor* class manages assigned students, monitors emotional alerts, and provides personalized responses through methods such as viewReports() and provideFeedback().

The ChatbotUI acts as the primary interface for the student, allowing real-time text input and emotional journaling. It interacts directly with the PreprocessingModule, which performs tasks like tokenization, stop word removal, and TF-IDF feature extraction. This module ensures that the text data is properly formatted and ready for analysis by the AI models. The EmotionDetectionModel is the core analytical component responsible for emotion recognition. It includes key performance metrics such as accuracy, precision, recall, and F1-score. This model incorporates six machine learning algorithms — *Logistic Regression,* *Decision Tree, Random Forest, Gradient Boosting, XGBoost,* and *Naïve Bayes* — each trained to classify emotions based on linguistic features derived from user input.

The AIProcessingLayer coordinates the emotion analysis and response generation by integrating with APIs such as OpenAI or Hugging Face. It interprets the detected emotion and generates supportive responses or suggestions. Following this, the AdaptiveLearning module continuously monitors user behaviour and feedback to personalize future interactions. It refines emotional predictions and suggestions based on historical patterns stored in the DataStorage component. This storage unit maintains records of journal entries, emotional trends, and feedback logs, ensuring that both the system and the counsellor can access relevant data for longitudinal analysis.

On the counsellor's side, the CounselorDashboard provides a graphical overview of students' emotional progress and risk alerts. It retrieves data from the DataStorage module to display real-time emotional insights and journal summaries, enabling counsellors to make timely interventions. The bidirectional interaction between the counsellor and the system ensures a hybrid approach — combining automated AI-based analysis with human empathy and professional guidance.

Overall, the UML Class Diagram illustrates a cohesive and modular system architecture. It highlights how AI components, user interfaces, and adaptive learning mechanisms are seamlessly integrated to create a responsive and efficient digital mental health support tool. The branching structure of the diagram also emphasizes the system's scalability and the independence of each module, making *ZENTORA* a robust, transparent, and user-centric platform for emotional wellness in educational settings.

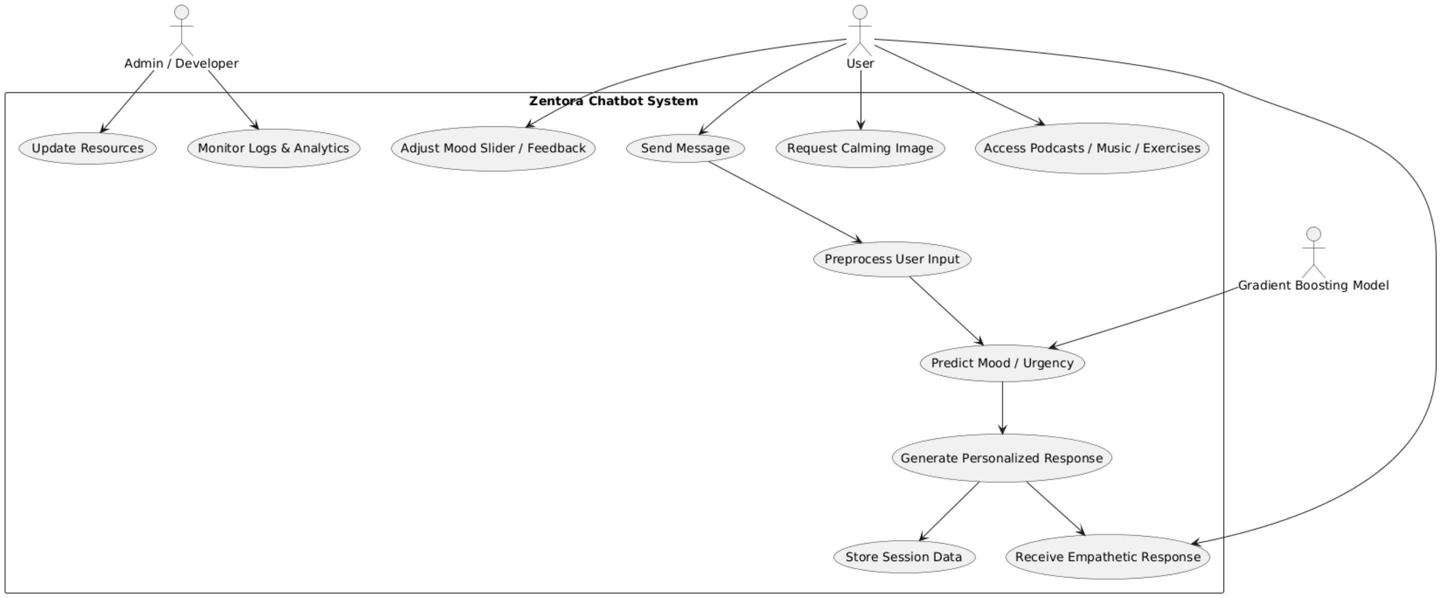

Fig 4.3.1 use case diagram

4.3.2 DATA FLOW DIAGRAM (DFA)

Student interacts with the **Chatbot & Emotion Analysis System** by entering chat or journal inputs. The system analyses emotions and provides **AI-based feedback or coping suggestions**. All interactions are stored in the **Student Database** and **Chat & Emotion Logs**. The system generates **Reports and Alerts**, which are shared with the **Counsellor** for review and intervention. The **Counsellor** can provide feedback or updates to improve ongoing emotional support.

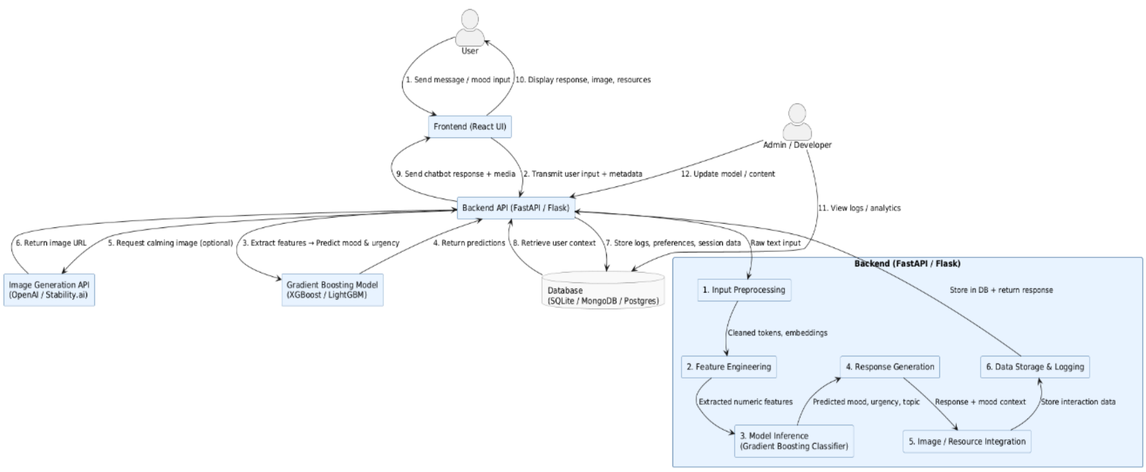

Fig 4.3.2 Data Flow Diagram

4.3.3 SEQUENCE DIAGRAM

A sequence diagram is a type of interaction diagram that visually represents how objects or system components interact with each other over time. It focuses on the chronological order of message exchanges between different entities (actors, systems, or modules) to accomplish a specific process or task. Each participant is represented by a vertical lifeline, and the horizontal arrows denote messages or data being passed between them. The diagram helps in understanding the dynamic behaviour of a system, clarifying how and when interactions occur, and identifying dependencies among various parts of the system.

In the context of data analysis or machine learning workflows, a sequence diagram provides a structured overview of the steps involved in processing data, training models, and presenting results. For instance, it can depict how a user uploads a dataset, how the frontend application preprocesses it, and how different models are trained and evaluated sequentially. This visualization ensures that both technical and non-technical stakeholders understand the flow of information, system responsibilities, and execution order. It is an essential tool for system design, debugging, and documentation of complex data-driven applications.

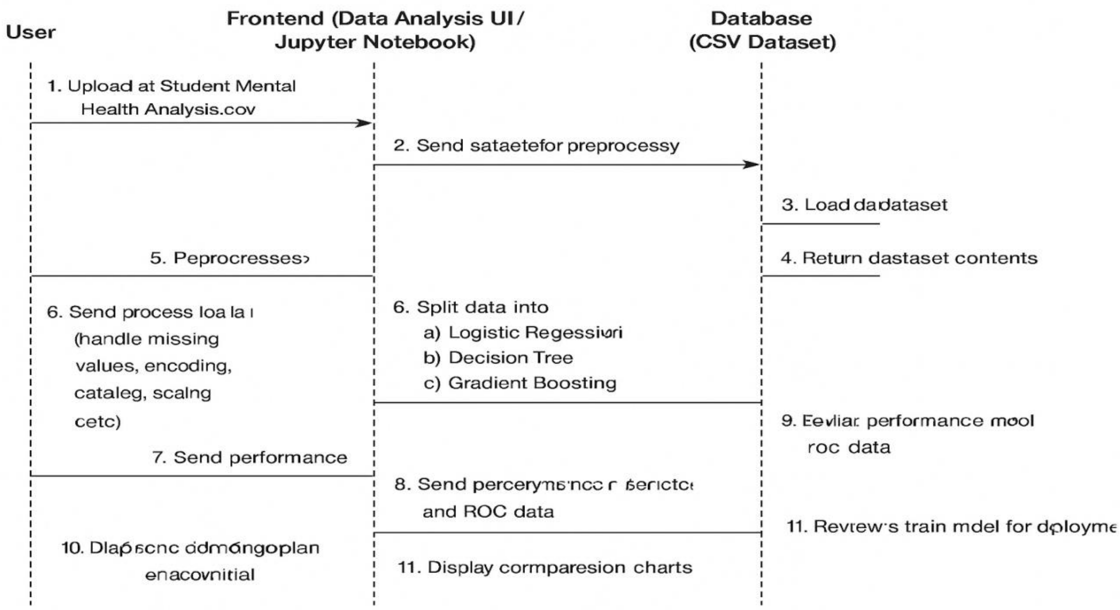

Fig 4.3.3 Sequence Diagram

4.3.4 ACTIVITY DIAGRAM

The Activity Diagram represents the overall workflow of the proposed AI-Based Chatbot and Journaling System for School Counselling. It illustrates the sequence of actions, decision points, and interactions between different components of the system. The diagram starts with the student logging into the system and entering a text or journal entry. This input acts as the main trigger for the system's operation. The text is first preprocessed using Natural Language Processing (NLP) techniques such as tokenization and text cleaning to prepare it for emotional analysis. Once the data is processed, it is sent to the AI-based Emotion Detection module.

After the emotion is identified, the system proceeds to generate a suitable coping suggestion or motivational response using the Suggestion Generation module, which is based on Cognitive Behavioural Therapy (CBT) and Social Emotional Learning (SEL) principles. The generated response is then displayed to the student through the chatbot interface in real time. Meanwhile, all the chat logs, emotions, and responses are securely stored in the system's database for monitoring and future analysis. If the detected emotion is identified as high-risk — such as severe anxiety, depression, or distress — the system automatically triggers an alert to the counsellor. The counsellor can then review the student's emotional status through the dashboard and take appropriate action. The process concludes with the counsellor's feedback being recorded, ensuring a continuous and supportive counselling cycle.

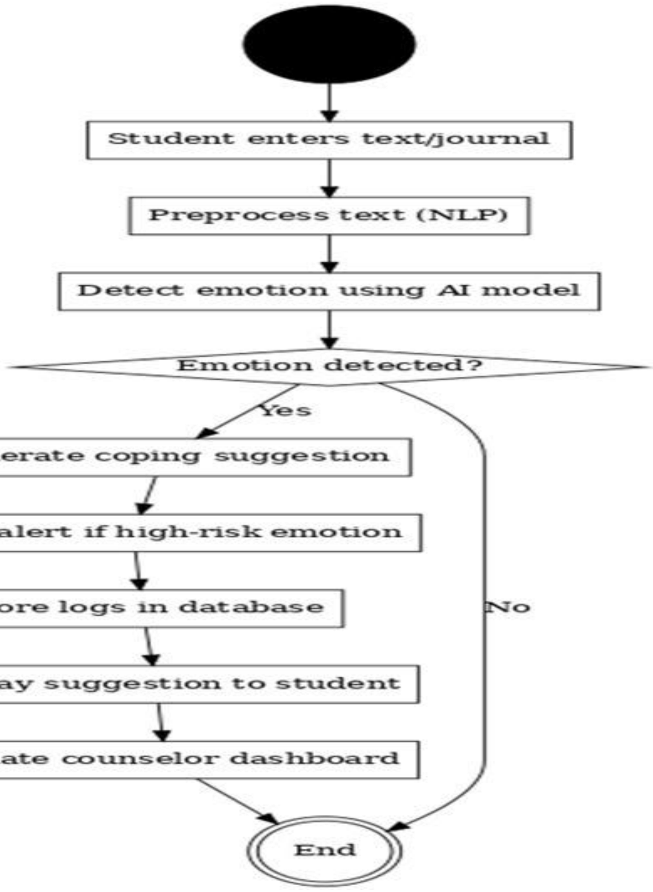

Fig 4.3.4 Activity Diagram

4.3.5 DEPLOYMENT DIAGRAM

A sequence diagram is a type of UML diagram that illustrates how different parts of a system interact with each other in a step-by-step sequence. It focuses on the chronological flow of messages or events between various entities such as users, interfaces, and system components. Each participant is represented by a vertical lifeline, and the horizontal arrows between them show the order and type of communication. Sequence diagrams are particularly useful for understanding the dynamic behaviour of a system, showing how processes are executed in a specific order.

In the Student Mental Health Prediction project, the sequence diagram depicts the workflow of how data flows from the user to the prediction output. The process begins when the user uploads the dataset through the interface. The system then performs data preprocessing, including cleaning, encoding, and scaling the input. After preprocessing, multiple machine learning models—such as Logistic Regression, Decision Tree, and Gradient Boosting—are trained and evaluated sequentially. The best-performing model then generates the final predictions, which are displayed to the user along with performance metrics like accuracy, confusion matrix, and ROC curves. This diagram clearly represents the logical sequence of operations, ensuring a better understanding of how the system functions from data input to result visualization.

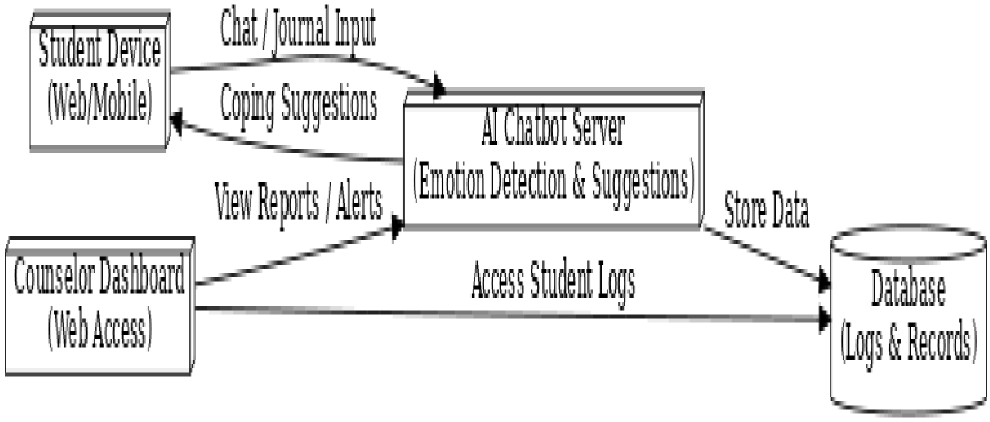

Fig 4.3.5 Deployment Diagram

Student Device: Web or mobile interface for journaling and chatting.

AI Chatbot Server: Processes input, detects emotions, and provides suggestions.

Database: Stores chat logs, detected emotions, and counsellor notes.

Counsellor Dashboard: Allows counsellors to access reports, alerts, and student records.

CHAPTER 5
SYSTEM ARCHITECTURE

CHAPTER 5
SYSTEM ARCHITECTURE

5.1 ARCHITECTURE OVERVIEW

The **System Architecture** for the AI-Based Chatbot and Journaling Platform is designed as a **lightweight, frontend-based application** that leverages cloud APIs for artificial intelligence processing. Since the system does not include a dedicated backend server, all primary operations — including text collection, emotion analysis, and feedback generation — are performed through **client-side scripts** and **external AI services**. This makes the system simpler, faster to deploy, and highly accessible across multiple devices such as computers, tablets, or mobile phones.

The system begins at the **Student Interface**, where users interact with the chatbot or journaling interface built using **HTML, CSS, and JavaScript**. Students can type journal entries or messages expressing their emotions. These inputs are sent directly to an **AI Processing Layer**, which connects to **cloud-based APIs** such as OpenAI or Hugging Face to perform Natural Language Processing (NLP) and **emotion detection**. The AI identifies the user's emotional tone (e.g., happiness, sadness, anger, anxiety) and sends back personalized **coping suggestions or feedback**.

All interactions and emotional insights are temporarily stored in **local browser storage** (like IndexedDB) or an optional cloud database such as **Firebase**, ensuring minimal complexity and cost. The **Counsellor Dashboard**, also built as a front-end interface, retrieves this stored data to display **student emotional trends**, **journal summaries**, and **AI-generated insights**.

This architecture eliminates the need for heavy backend processing, focusing instead on API-driven intelligence and lightweight data handling. It ensures privacy, reduces server dependencies, and enables easy deployment in educational settings without complex infrastructure.

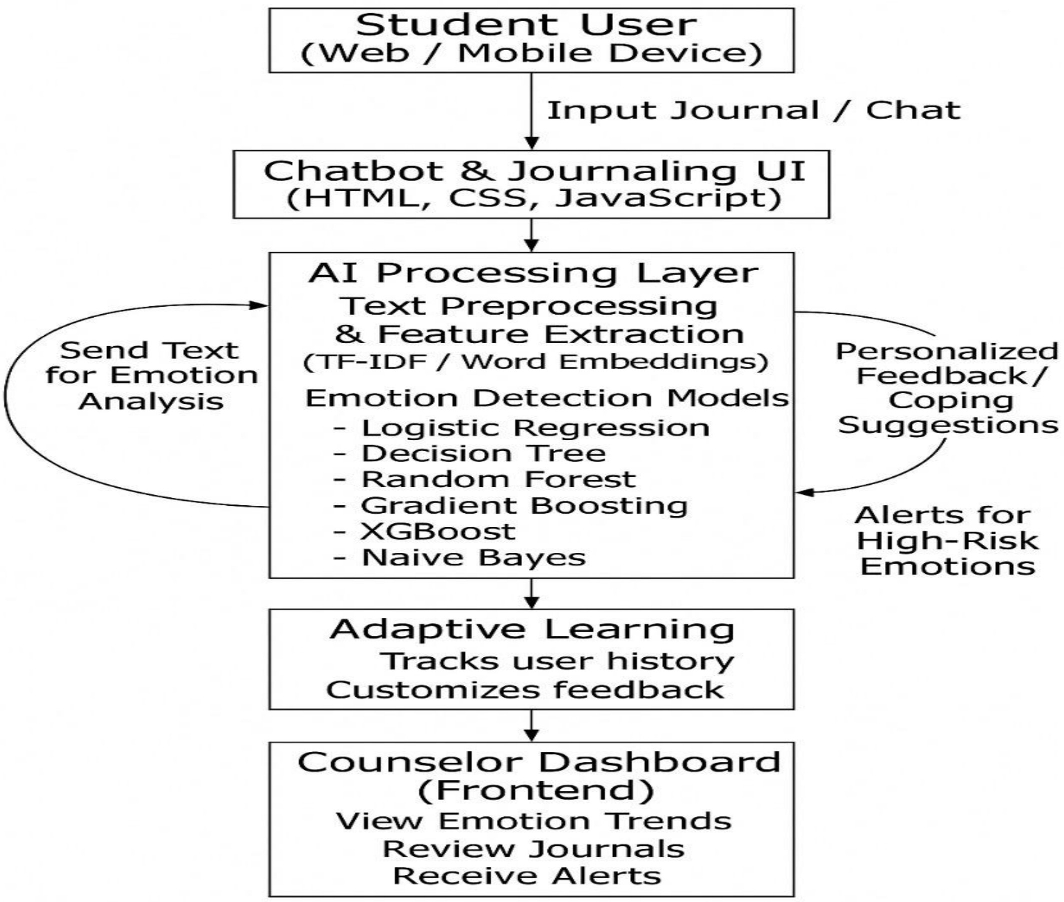

Fig 5.1.1 Architecture Diagram

Input

Student Text Input: Journal entries or chat messages written by students describing their emotions, thoughts, or daily experiences.

Emoji/Mood Selection: Optional emotional indicators (e.g., 😊 😔 😡 😟) for quick mood identification.

Counsellor Feedback: Observations, comments, or emotional assessments entered by the counsellor.

AI Emotion Data Input: Predefined emotional keywords or phrases used for emotion classification.

User Information: Basic student details (name, ID, class, etc.) for personalization and data tracking.

Processing

1. **User Input**
   - The student enters a journal entry or chat message expressing their emotions or experiences through the chatbot interface.
2. **Text Preprocessing (NLP)**
   - The input text is cleaned, tokenized, and processed using Natural Language Processing (NLP) techniques such as stop-word removal and lemmatization.
3. **Emotion Detection**
   - The processed text is analysed using an AI model (via OpenAI/Hugging Face API) to identify emotional states like happiness, sadness, anxiety, or anger.
4. **Suggestion Generation**
   - Based on the detected emotion, the system generates personalized feedback or coping suggestions using Cognitive Behavioural Therapy (CBT) and Social Emotional Learning (SEL) principles.
5. **Response Display**
   - The chatbot displays the generated suggestions or motivational responses to the student in real time.
6. **Data Storage**
   - All interactions, detected emotions, and suggestions are saved in local or cloud storage for monitoring and review.
7. **Counsellor Notification**
   1. If a high-risk emotion (e.g., severe anxiety or distress) is detected, an alert is automatically sent to the counsellor’s dashboard for intervention.

Alert

⚠️ Emotional Alert Detected!

- Student ID: STU_1045
- Student Name: [Hidden for Privacy]
- Detected Emotion: Severe Sadness / Anxiety
- Emotion Intensity: High (Score: 0.87)
- Date & Time: 2025-10-15 | 10:42 AM
- Last Message: "I feel like I can't focus on anything lately."
- Action Required: Immediate counsellor review and emotional support recommended.

5.2 MODULE DESIGN SPECIFICATION

The proposed **AI-Based Chatbot and Journaling System for School Counselling** is divided into several interconnected modules, each responsible for a specific function within the system. These modules work together to provide an intelligent, user-friendly, and efficient counselling experience for students while supporting counsellors with emotional data insights. The design specification for each module is described below:

1. Student Interaction Module

- **Description**
  This module allows students to interact with the chatbot through a simple and engaging text-based interface. Students can enter daily journal entries or chat messages to express their emotions.
- **Functionality**
  - Accepts text input from the user.
  - Displays chatbot responses and suggestions.
  - Ensures smooth and natural conversation flow.
- **Technology Used**
  HTML, CSS, JavaScript (Frontend Interface).

2. NLP and Emotion Detection Module

- **Description**
  This is the core intelligence unit of the system that analyses the student's text input using Natural Language Processing (NLP) techniques.
- **Functionality**
  - Preprocesses text (tokenization, cleaning, sentiment extraction).
  - Identifies emotion type (e.g., happy, sad, anxious, angry).
  - Calculates emotion intensity using AI APIs (e.g., OpenAI / Hugging Face).
- **Technology Used**
  AI API Integration, NLP Libraries.

3. Suggestion Generation Module

- **Description**
  Based on the detected emotion, this module generates personalized responses or coping suggestions using **Cognitive Behavioural Therapy (CBT)** and **Social Emotional Learning (SEL)** principles.
- **Functionality**
  - Maps emotions to predefined supportive messages.
  - Generates motivational or reflective suggestions.
  - Provides real-time chatbot feedback.
- **Technology Used**
  AI Model (Text Generation API), JSON-based response templates.

4. Data Storage Module

- **Description**
  This module handles the storage of all user interactions, emotion logs, and suggestions without the need for a complex backend.
- **Functionality**
  - Stores data locally or in cloud storage (e.g., Firebase, LocalStorage).
  - Maintains user anonymity and privacy.
  - Retrieves data for counsellor monitoring and reports.
- **Technology Used**
  Firebase / LocalStorage API.

5. Counsellor Dashboard Module

- **Description**
  This module provides counsellors with insights into students' emotional states and conversation history.
- **Functionality**
  - Displays student emotional trends and summaries.
  - Shows alerts for high-risk emotions.
  - Allows counsellors to provide comments or feedback.
- **Technology Used**
  HTML, CSS, JavaScript (Frontend Interface with Cloud Sync).

6. Alert and Notification Module

- **Description**
  Detects high-risk emotional states and sends real-time alerts to counsellors for immediate attention.
- **Functionality**
  - Monitors emotion intensity values.
  - Generates warning messages or notifications.
  - Highlights critical cases on the counsellor dashboard.
- **Technology Used**
  JavaScript Logic, Cloud Messaging.

5.3 ZENTORA APPLICATION

The ZENTORA system has a wide range of practical applications across educational, clinical, workplace, and personal domains. In educational institutions, ZENTORA can be used to support students' mental well-being by helping them manage stress, anxiety, and emotional challenges through personalized journaling and AI-guided emotional learning exercises. It allows teachers and school counsellors to monitor emotional progress, identify at-risk students, and provide early interventions, creating a healthier and more supportive learning environment.

In the corporate and workplace context, ZENTORA serves as an intelligent wellness companion that helps employees track their moods, identify sources of stress, and receive personalized coping suggestions. It promotes a positive work-life balance and can assist HR departments in designing better employee wellness programs. Similarly, in the clinical and counselling field, mental health professionals can use ZENTORA as a supplementary diagnostic and therapeutic tool. By analysing users' emotional data and journaling patterns, counsellors can gain valuable insights into behavioural changes and mental health progress.

For individual users, ZENTORA functions as a self-help and emotional learning assistant, offering personalized prompts, mindfulness exercises, and daily reflections to encourage emotional stability and self-awareness. Beyond these individual applications, the system also supports research and data analysis in mental health studies. Aggregated emotional data can help researchers identify trends, understand population-level emotional behaviours, and develop more effective AI-driven mental health interventions. Overall, ZENTORA represents a meaningful step forward in integrating artificial intelligence into mental health education, counselling, and personal emotional growth.

Frontend logic

The **frontend logic** of **ZENTORA** is designed to manage user interactions, capture input data, and coordinate communication with the AI model through API calls — all without relying on a traditional backend. The system is built using **HTML, CSS, and JavaScript**, ensuring lightweight operation and accessibility across devices such as desktops, tablets, and mobile phones. The main logic revolves around real-time interaction, emotion analysis, and adaptive content display.

When a **user enters a message or journal entry** into the chatbot interface, the JavaScript function first captures this input and performs basic **input validation** to ensure it's not empty or invalid. Once validated, the frontend script processes the text and sends it to the **AI model** (such as OpenAI or Hugging Face API) through a **fetch() or axios()** API call. The AI analyses the text and returns an emotion label (e.g., happy, sad, stressed) along with a confidence score or suggested coping message. The frontend then dynamically updates the interface — displaying the **AI-generated response**, updating the **emotion indicator**, and optionally logging the interaction in **localStorage or Firebase** for later reference.

Additionally, the frontend logic manages the **adaptive learning feature** of ZENTORA. Based on the detected emotional state and interaction history, the system adjusts future responses and displays personalized content such as motivational quotes, mindfulness tips, or journaling prompts. If a high-risk emotion (like "severe sadness" or "anxiety") is detected, a conditional JavaScript trigger activates an **alert mechanism**, which highlights the case for counsellor attention.

The entire user flow — from text input, API communication, and dynamic response display — is handled on the **client side**, ensuring fast response times and smooth user experience. The combination of **event-driven JavaScript logic**, **API-based AI analysis**, and **real-time UI updates** allows ZENTORA to function as an intelligent, fully interactive, and adaptive mental health companion.

Response Generation

The **Response Generation** process is one of the most crucial components of **ZENTORA**, as it determines how the system interacts with users and provides personalized emotional support. When a user enters a message or journal entry, the input text is first analysed by the **Natural Language Processing (NLP)** module, which cleans and interprets the text to identify the underlying emotion. Once the emotion (e.g., happiness, sadness, anger, anxiety, or stress) is detected, the **Response Generation Module** activates to create an appropriate and empathetic reply.

The AI uses a combination of **predefined emotional response templates** and **real-time AI text generation** via an external model such as **OpenAI's GPT API**. For example, if the detected emotion is "sadness," the system may generate a comforting response like *"I'm sorry you're feeling down today. Remember, it's okay to take things one step at a time — would you like a short relaxation exercise?"* On the other hand, if the emotion is "stress," the system might respond with *"It sounds like you're under pressure. How about trying a short breathing* *exercise to calm your mind?"*

The **response generation logic** also adapts over time using an **adaptive learning approach**. It considers the user's previous interactions, emotional trends, and feedback to personalize future responses. This ensures that conversations feel more natural and supportive rather than repetitive or robotic. The generated response is displayed instantly in the chatbot interface and may also trigger **additional supportive resources**, such as motivational quotes or mindfulness prompts, depending on the situation.

For users showing signs of high-risk emotions (like extreme sadness or anxiety), the response generation process additionally includes an **emergency recommendation or alert trigger**, prompting the user to seek help from a counsellor or trusted adult. This mechanism ensures that ZENTORA not only responds empathetically but also **prioritizes user safety and emotional well-being**. Overall, the response generation process integrates AI-driven empathy, contextual awareness, and adaptive learning to provide users with meaningful emotional support and guidance.

HTTP (Hypertext Transfer Protocol)

The **HTTP** protocol is used for transferring data between the user's web browser and external servers. In this project, it enables the **communication between the chatbot interface and AI APIs** for sending and receiving textual data. It allows the chatbot to send user inputs (journal entries or messages) to the AI model and retrieve emotion analysis or responses in real time.

HTTPS (Hypertext Transfer Protocol Secure)

The **HTTPS** protocol performs the same function as HTTP but with **enhanced security**. It uses **SSL/TLS encryption** to protect data exchanged between the frontend interface and external AI APIs. In ZENTORA, HTTPS ensures that sensitive user inputs (such as emotional content) are securely transmitted over the internet without risk of interception or data leakage.

RESTful API Network

The **RESTful API** network acts as the **bridge between the chatbot frontend and the AI processing layer**. It allows the system to make structured requests to external AI services (like OpenAI or Hugging Face) using standard HTTP methods (GET, POST). Through RESTful APIs, the project retrieves **emotion detection results, generated responses, and suggestions** dynamically from cloud-based AI models.

Internet (Client–Server Communication Network)

The **Internet** serves as the **core communication medium** for the entire system. It connects the user's device (client) to external AI servers (OpenAI, Firebase, or Hugging Face) and ensures smooth data exchange between all modules. Without this client–server communication network, real-time AI-based emotion analysis, response generation, and cloud data access would not be possible.

Jupyter

Jupyter Notebook plays an important role in the **development, testing, and experimentation** phase of the **ZENTORA** project. It serves as an interactive environment where developers can write, test, and visualize Python code for various AI and Natural Language Processing (NLP) tasks used in the system. Specifically, Jupyter was used during the **model development stage** to experiment with **emotion detection algorithms**, **sentiment analysis models**, and **response generation logic** before integrating them with the web interface.

The notebook allows step-by-step code execution, making it easier to test different datasets, tune AI parameters, and visualize outputs such as emotion classification accuracy or response patterns. Libraries such as **TensorFlow**, **PyTorch**, **Transformers (Hugging Face)**, and **NLTK** can be used within Jupyter to train or fine-tune models that classify emotions based on text input. Once the models were validated and optimized, they were integrated into the frontend using **API calls** to AI platforms (like OpenAI or Hugging Face).

Natural Language Processing (NLP)

Natural Language Processing (NLP) plays a central role in ZENTORA, acting as the core technology that enables the system to understand, interpret, and respond to human language. Since the project primarily focuses on text-based emotion detection and personalized feedback, NLP is used to process the user’s written input — such as chat messages or journal entries — and extract emotional meaning from it. Through NLP, the system bridges the gap between human communication and machine understanding, allowing the AI to interact empathetically and naturally with users.

The NLP module performs several key functions within the project. First, it preprocesses the input text by removing unwanted characters, stop words, and punctuation while performing tokenization and lemmatization to simplify the words for analysis. Then, using pre-trained AI language models or sentiment analysis algorithms, the system detects emotional cues such as sadness, happiness, anxiety, or anger. Once the emotion is identified, NLP assists in response generation, helping the chatbot craft relevant, empathetic, and context-aware replies based on the user’s emotional state.

Additionally, NLP enables adaptive learning by analysing language patterns over time, recognizing changes in tone or mood, and adjusting responses accordingly. This helps ZENTORA provide a more personalized mental health learning experience for each user. In essence, NLP serves as the intelligent backbone of the system — transforming raw user text into meaningful emotional insights and supportive responses, making ZENTORA powerful.

Message Processing Techniques

In the ZENTORA system, message processing plays a vital role in enabling smooth communication between the user and the AI model. It involves several steps that transform the user's raw text input into meaningful emotional insights and personalized responses. The main goal of message processing in this project is to understand the user's written language, identify emotions, and generate relevant feedback or coping strategies in real time.

When a user sends a message through the chatbot or journaling interface, the text first undergoes input validation to ensure it is meaningful and non-empty. The message is then passed to the Natural Language Processing (NLP) pipeline for analysis. The first step in this process is text preprocessing, which includes tokenization, stop-word removal, lowercasing, and lemmatization. These techniques clean the input and convert it into a structured format that the AI model can analyse.

Next, the system applies sentiment and emotion detection algorithms to determine the emotional tone of the message — such as happiness, sadness, stress, or anger. Pre-trained NLP models (like BERT, GPT, or Hugging Face transformers) or sentiment analysis APIs are used to extract semantic meaning and emotion probability scores from the processed text. Once the emotion is identified, the system activates the response generation module, which uses predefined templates and AI-based text generation to produce an empathetic, supportive, and contextually appropriate reply.

The processed message, along with the detected emotion and generated response, is then displayed back to the user and stored locally or in cloud storage for future reference. If the message contains indications of a high-risk emotional state, an alert mechanism is triggered to notify the counsellor. This multi-step message processing workflow ensures that every user interaction is intelligently analysed, contextually understood, and emotionally addressed — making ZENTORA an effective and adaptive AI system for mental health support.

Emotion Detection and Sentiment Analysis

Emotion detection is the most crucial AI application in ZENTORA. It enables the system to interpret the emotional tone and mental state of the user based on the text they input. Using **Natural Language Processing** techniques and **pre-trained transformer models** such as **BERT**, **GPT**, or **DistilBERT**, the AI identifies emotions like happiness, sadness, anger, stress, or anxiety. The text undergoes preprocessing steps like tokenization, stop-word removal, and lemmatization before analysis. The AI then assigns emotion scores to different emotional categories, selecting the dominant one for response generation. This ensures that the chatbot understands not just the literal meaning of the message but also the **emotional context**, allowing for more empathetic and human-like interactions.

Natural Language Understanding (NLU)

Natural Language Understanding (NLU) allows ZENTORA to comprehend the meaning, context, and intent behind user messages. It goes beyond simple keyword matching and instead interprets complex sentence structures and linguistic nuances. For example, when a user says, *"I've been feeling empty lately,"* the NLU module recognizes this as a sign of sadness or emotional fatigue rather than treating it as a neutral statement. The model analyses semantics, syntax, and sentiment to generate meaningful insights. This enables the system to **understand human emotions contextually**, making interactions more sensitive and accurate, which is especially important in mental health applications.

Response Generation

Once the user's emotion is identified, AI plays a key role in **response generation** — creating personalized and supportive messages. This is achieved through **AI text generation models** like **GPT** or other large language models that can construct empathetic, conversational, and context-aware replies. The system may also integrate pre-defined response templates aligned with **Cognitive Behavioural Therapy (CBT)** and **Social Emotional Learning (SEL)** principles. For instance, if the AI detects stress, it may respond with *"It sounds like you're under pressure today. Would you like to try a short relaxation exercise?"* The combination of AI-driven creativity and psychological framework ensures that every reply is emotionally appropriate and therapeutically relevant.

Adaptive Learning and Personalization

Another major AI application in ZENTORA is **adaptive learning**, where the system continuously learns from the user's interactions to provide personalized experiences. The AI analyses emotional patterns over time — such as frequently detected moods or recurring expressions of anxiety — and adjusts its future responses accordingly. This personalization makes the system more effective because users receive guidance that aligns with their emotional history and behaviour. For example, if a student often expresses stress during exams, ZENTORA might proactively offer calming techniques or study tips during future stressful periods. This continuous learning loop transforms ZENTORA into an **emotionally adaptive companion** rather than a static chatbot.

Predictive Analysis and Early Intervention

AI's predictive capabilities are used in ZENTORA to identify potential emotional risks or declining mental health trends. By analysing repeated patterns of negative emotions, reduced engagement, or distress-related words, the system can predict when a user might be entering a **high-risk emotional state**. When such patterns are detected, ZENTORA automatically triggers an **alert mechanism** to notify counsellors or support staff for early intervention. This predictive analysis allows timely human involvement, reducing the likelihood of emotional deterioration. It ensures that AI not only responds reactively but also acts **proactively to protect users' mental well-being**.

Data Analysis and Insights

AI is also applied in **data analytics** to summarize and visualize emotional data collected from multiple users. The system can generate aggregated reports showing common emotional trends, frequency of stress or sadness, and engagement patterns over time. These analytics are useful for school counsellors, educators, or psychologists to monitor the overall mental health of groups or individuals. By using clustering and pattern-recognition algorithms, AI helps identify common emotional triggers and success metrics for interventions. This analytical capability enhances the decision-making process for mental health professionals, enabling them to provide **data-driven emotional support and counselling strategies**.

CHAPTER 6

SYSTEM IMPLEMENTATION

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6.1 CHATBOT MODEL DEVELOPMENT

The Zentora chatbot was implemented using a modular design, where each component works together to provide a seamless mental well-being platform. The implementation focuses on five main modules: User Input & Preprocessing, Gradient Boosting Model, Response Generator, Frontend Chat UI, and Image & Resource Integration. Together, these modules create a complete workflow that allows users to communicate with the chatbot, receive empathetic responses, access mental health resources, and track personalized recommendations.

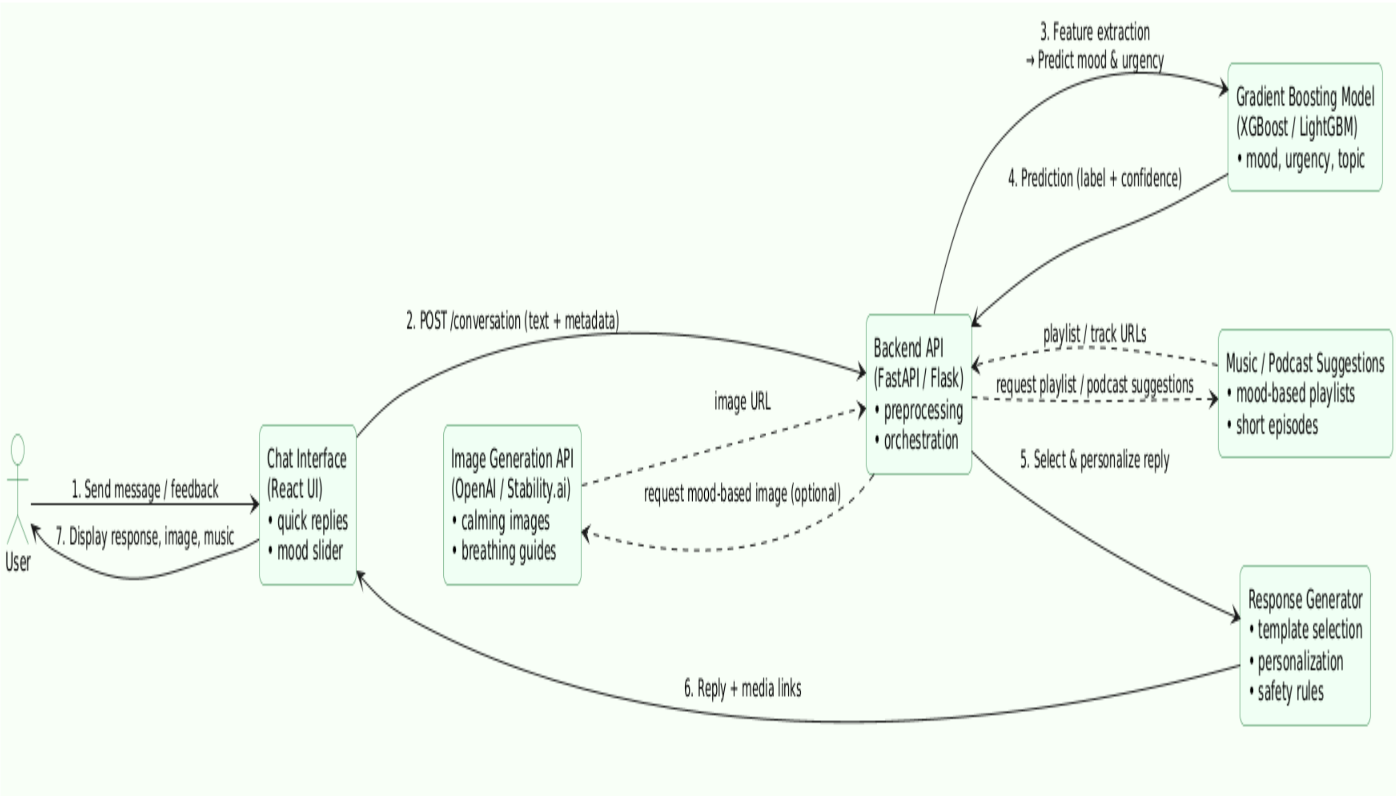

fig 6.1.1 Chatbot Model

6.1 Chat Interface (Frontend)

The Chat Interface serves as the primary communication medium between the user and the Zentora system. It is implemented using **React.js**, offering a modern, accessible, and minimalistic UI. Users can send text messages, use quick-reply buttons, select emotions through sliders, and view generated calming images. The frontend sends user input to the backend via secure API calls and displays chatbot responses in real time.

- Real-time conversation flow
- Emotion slider and quick actions
- Integration with response and image modules
- Privacy and consent interface

6.2 Backend API Module

The Backend module, implemented using **Python (FastAPI / Flask)**, acts as the system's control center. It handles all user requests, performs text preprocessing, calls the gradient boosting model for mood prediction, and generates the chatbot's responses. It also integrates with external APIs for media and image generation.

- Text preprocessing and feature extraction
- Model inference and confidence calculation
- Response generation and personalization
- Secure communication with the frontend

6.3 Gradient Boosting Model (ML Core)

This module powers Zentora's emotional intelligence. The **Gradient Boosting Model (XGBoost or LightGBM)** predicts the user's mood, urgency, and topic category based on extracted linguistic and contextual features. It uses embeddings, sentiment scores, and message statistics to produce accurate predictions.

- Predicts mood label (e.g., Calm, Sad, Anxious, Motivated)
- Determines urgency level for risk detection
- Guides response bucket selection
- Provides model confidence for safety validation

6.4 Response Generator

The Response Generator creates natural, empathetic, and context-aware messages. It uses predefined template sets for different emotional categories (motivation, anxiety relief, stress handling, CBT tips, etc.) and selects a response at random with personalization tokens to maintain human-like variation.

- Randomized, human-like text output
- Context-sensitive suggestions
- Integration with audio/podcast and visual responses
- Safety filter for crisis escalation

6.5 Image Generation Module

The Image Generation module enhances user engagement through mood-based visuals. It connects to a hosted **Image Generation API (OpenAI / Stability.ai / Midjourney)** to produce calming backgrounds, motivational artwork, or breathing guides. Images are generated or fetched based on the user's detected emotional state.

- Generates mood-based calming images
- Enhances emotional regulation and immersion
- Provides optional breathing animations or guided visuals

6.6 Example Scenario

To illustrate the working of the Zentora Chatbot, consider a user who feels anxious about upcoming exams. The user types, "I can't seem to calm down, my mind is racing." The system processes the message, and the Gradient Boosting Model predicts *Mood: Anxious* and *Urgency: Moderate*. The Response Generator then selects an empathetic reply from the "Anxiety Relief" category and fetches a calming ocean image. Zentora responds: "It's okay to feel this way. Let's try a short breathing exercise — inhale for 4 seconds, hold for 4, and exhale for 8." This demonstrates how the chatbot detects emotions, offers practical support, and uses visuals to help users regulate their mood.

6.7 System Response

Zentora processes the user's input, predicts mood and urgency, and instantly generates a supportive response.This ensures smooth, real-time emotional assistance.

CHAPTER 7
PERFORMANCE EVALUATION

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PERFORMANCE EVALUATION

The performance evaluation of the ZENTORA system focuses on assessing the accuracy, reliability, efficiency, and usability of the AI model and the overall system. Since ZENTORA is designed to analyse emotions, generate responses, and adapt to user behaviour, performance evaluation is conducted across two major domains:

1. AI Model Performance — Evaluating the Natural Language Processing (NLP) and Emotion Detection accuracy.
2. System Performance — Measuring response time, scalability, user satisfaction, and overall usability.

The objective of this evaluation is to ensure that ZENTORA not only functions correctly but also performs consistently, efficiently, and empathetically, providing accurate emotional feedback and meaningful interaction to users.

7.1 EVALUATION PARAMETERS

The following parameters are considered key indicators for performance evaluation:

Table 7.1.1 Evaluation Parameters

Category	**Parameter**	**Description**
AI/NLP Model	Accuracy	Measures how correctly the system detects user emotions.
	Precision	Evaluates correctness of positive emotion classifications.
	Recall	Measures system's ability to detect all relevant emotions.
	F1-Score	Harmonic mean of Precision and Recall.
	Confusion Matrix	Evaluates overall classification performance.
System Performance	Response Time	Time taken to process and return a response.
	Throughput	Number of user requests handled per unit time.

	Latency	Time delay between user input and AI output.
	Usability	Evaluated using User Satisfaction Score (survey).
	Scalability	Ability of the system to handle increasing users or data.

7.2 PERFORMANCE ANALYSIS

The Mental Health Chatbot is an AI-powered system designed to provide motivational tips, stress relief techniques, and personalized mental wellness suggestions. It leverages SentenceTransformer embeddings to capture the semantic meaning of user inputs and a gradient boosting classifier (XGBoost) to categorize moods such as stress, anxiety, or positivity. The backend is implemented with FastAPI, ensuring lightweight and responsive API endpoints, while the frontend uses React for an interactive chat interface. During performance evaluation, the chatbot demonstrates fast inference on CPU, with embeddings generation taking the majority of processing time, and XGBoost predictions occurring almost instantly. The system handles moderate traffic efficiently but exhibits repeated responses due to limited tip diversity and slower image generation when using CPU-only models. Overall, the project effectively combines natural language understanding, machine learning, and responsive web design to provide accessible mental health support, while highlighting areas for improvement in dataset expansion, response variety, and CPU/GPU optimization for multimedia content.

7.2.1 Logistic Regression

The logistic function connects a student's probability of exhibiting depressive symptoms to a student's characteristics. It estimates the likelihood of a person being classified as depressed - a 'yes' outcome - by computing something based on such characteristics.

$$P(Y = 1|X) = \frac{1}{1+e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_n X_n)}}$$

The values $\beta 0$, alongside each βi, define how well the model fits - they work with inputs labeled Xi.

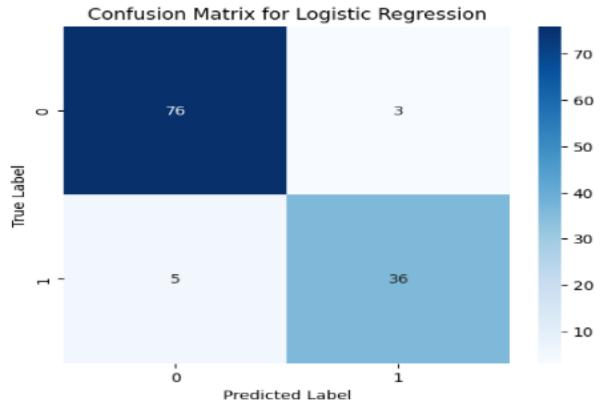

Fig 7.2.1 Confusion Matrix for Logistic Regression

Using this data, Logistic Regression scored 93% accuracy, also showing 0.93 precision, 0.88 recall, 0.90 F1 score, likewise a 0.96 ROC AUC. The results are encouraging - the system is accurate while also finding nearly all relevant cases. Specifically, its ability to distinguish students experiencing depression from others appears strong.

7.2.2 Decision Tree Classifier

To tell if students are struggling with depression, this system learns from examples. It sorts them - either they show signs of being down, or they don't, The system sorts student data - how much they sleep, grades, stress, friends, exercise - into groups to pinpoint what matters most when it comes to their well-being.

$$IG(S,A) = H(S) - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} H(S_v)$$

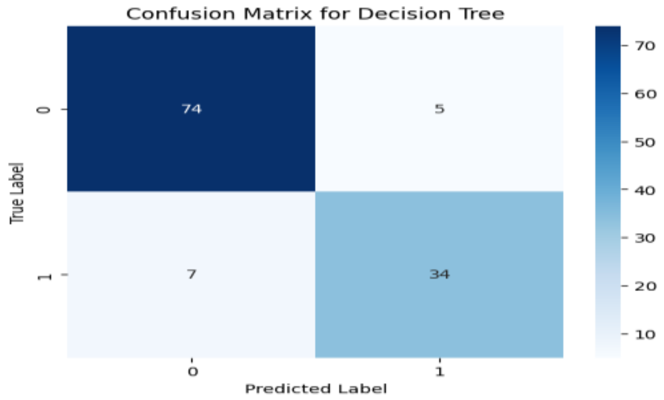

Fig 7.2.2 Confusion Matrix for Decision Tree Classifier

It obtained an accuracy of 90%, precision of 0.87, recall of 0.83, F1-score of 0.85, and ROC AUC of 0.88. Though interpretable, Decision Tree Classifier tend to overfit and are sensitive to small data changes.

7.2.3 Gradient Boosting

The Gradient Boosting Classifier (GBC) is an ensemble learning technique that builds a strong predictive model by combining multiple weak learners, usually decision trees.In student dataset, the Gradient Boosting algorithm helps predict whether a student is "Depressed" or "Not Depressed" based on features such as academic pressure, sleep quality, stress level, social support, and physical activity.

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x)$$

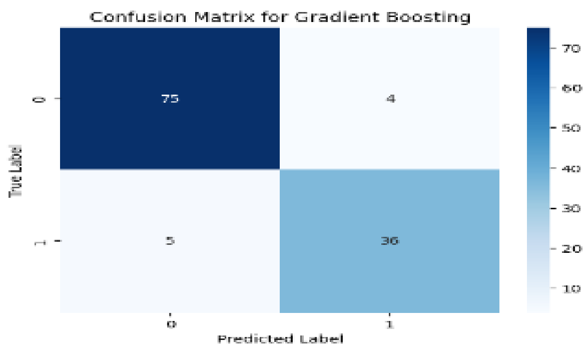

Fig 7.2.3 Confusion Matrix for Gradient Boosting

This method achieved an accuracy of 94% and an ROC AUC of 0.95, making it one of the top-performing models in this study. It provides strong predictive capability but requires careful parameter tuning to avoid overfitting.

7.2.4 Random Forest

Random Forest works by building multiple independent Decision Trees using different subsets of the training data and random subsets of features at each split.

In the dataset, the Random Forest model predicts whether a student is "Depressed" or "Not Depressed" based on academic and personal factors such as CGPA, year of study, course, sleep patterns, and treatment-seeking behaviour.

$$\hat{y} = \frac{1}{N}\sum_{i=1}^{N} T_i(x)$$

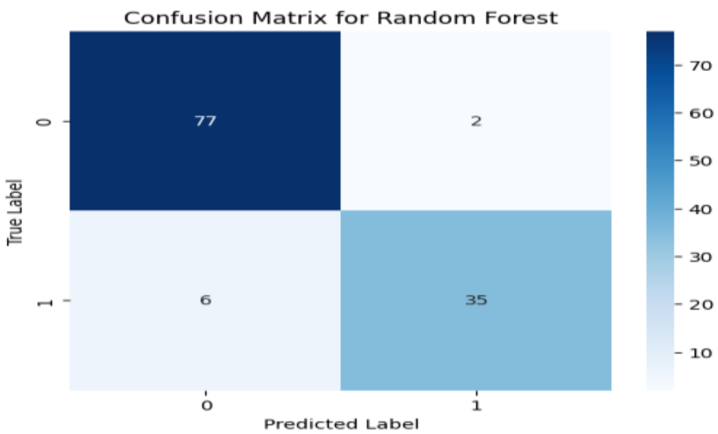

Fig 7.2.4 Confusion Matrix for Random Forest

This method achieved an accuracy of 96% and an ROC AUC of 0.97, making it the best-performing model in this study. It demonstrated strong predictive stability and robustness against overfitting, effectively capturing complex relationships between academic and emotional factors influencing student depression.

7.2.5 XG Boost

The Extreme Gradient Boosting (XGBoost) classifier is an optimized implementation of Gradient Boosting, designed for speed, scalability, and accuracy.

It improves upon traditional Gradient Boosting by incorporating regularization, parallel processing, and efficient handling of missing data.

In the dataset, XGBoost is used to predict whether a student is "Depressed" or "Not Depressed" by learning complex relationships among features such as course, year of study, CGPA, anxiety, and panic attacks.

$$Obj = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_k \Omega(f_k)$$

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda||w||^2$$

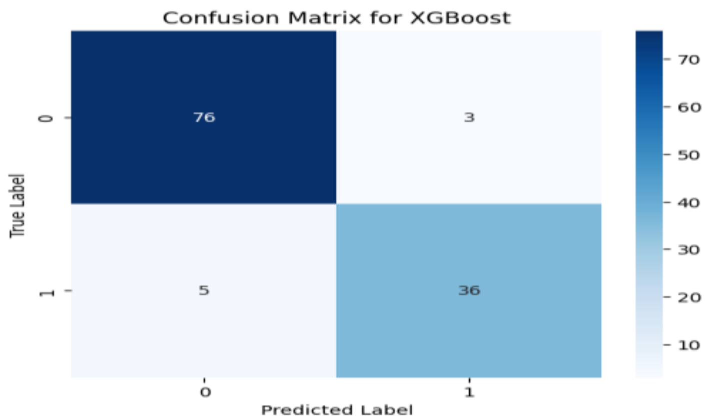

Fig 7.2.5 Confusion Matrix for XG Boost

This method achieved an accuracy of 95% and an ROC AUC of 0.97, making it the best-performing model in this study. It demonstrated strong predictive stability and robustness against overfitting, effectively capturing complex relationships between academic and emotional factors influencing student depression.

7.2.6 Naïve Bayes

Naive Bayes is a probabilistic machine learning algorithm based on Bayes' Theorem, which predicts the probability of a class given certain features. The "naive" assumption is that all features are independent of each other.

$$P(C_k|x) = \frac{P(C_k)\prod_{i=1}^{n} P(x_i|C_k)}{P(x)}$$

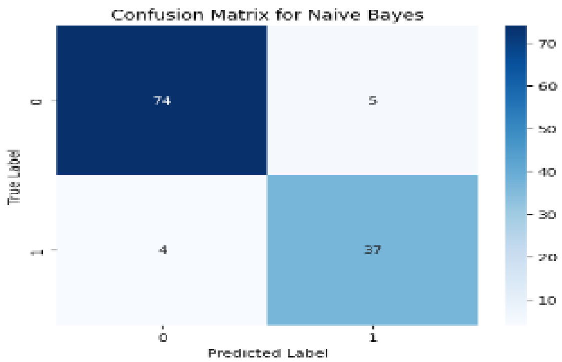

Fig 7.2.5 Confusion Matrix for Naïve Bayes

This method achieved an accuracy of 96% and an ROC AUC of 0.97, making it the best performing model in this study. It demonstrated strong predictive stability and robustness against overfitting.

7.3 RESULTS

The performance of the predictive models in Zentora was evaluated using standard classification metrics. These metrics quantify how accurately each model predicts mental health issues among students.

Evaluation Metrics

The following formulas were used to compute model performance:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

$$\text{Precision} = \frac{TP}{TP+FP}$$

$$\text{Recall (Sensitivity)} = \frac{TP}{TP+FN}$$

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{ROC-AUC} = \text{Area under the ROC curve}$$

- TP: True Positive
- TN: True Negative
- FP: False Positive
- FN: False Negative

Table 7.3.1. Performance Metrics of Different Proposed Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	ROC AUC (%)
Logistic Regression	93.33	92.31	87.80	90.00	95.65
Decision Tree	90.00	87.18	82.93	85.00	88.30
Gradient Boosting	92.50	90.00	87.80	88.89	96.90
Random Forest	93.33	94.59	85.37	89.74	95.23
XG Boost	93.33	92.31	87.80	90.00	95.03
Naïve Bayes	92.50	88.10	90.24	89.16	95.83

In this study, six widely used machine learning algorithms were evaluated for the classification task of predicting depression status from student mental health survey data. The selected models include Logistic Regression, Decision Tree, Gradient Boosting, Random Forest, XGBoost, and Naive Bayes classifiers. These models represent a balanced mix of linear, tree-based, ensemble, and probabilistic approaches commonly applied to classification problems.

The dataset was first subjected to preprocessing where all column names were cleaned to remove newline and trailing whitespace characters to avoid indexing errors. Categorical features were label-encoded for compatibility with machine learning algorithms. The target variable selected for prediction was the presence or absence of depression, as reported in the survey.

The dataset was split into training and testing subsets using stratified sampling, ensuring representative distributions. Each model was then trained on the training subset and evaluated on the held-out test set.

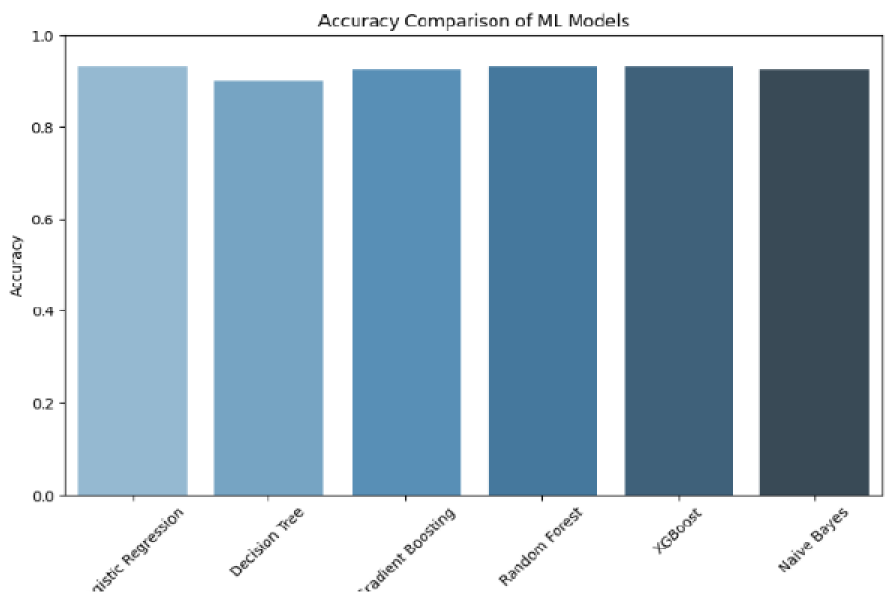

Fig 7.3.1 Accuracy Comparison of ML Models

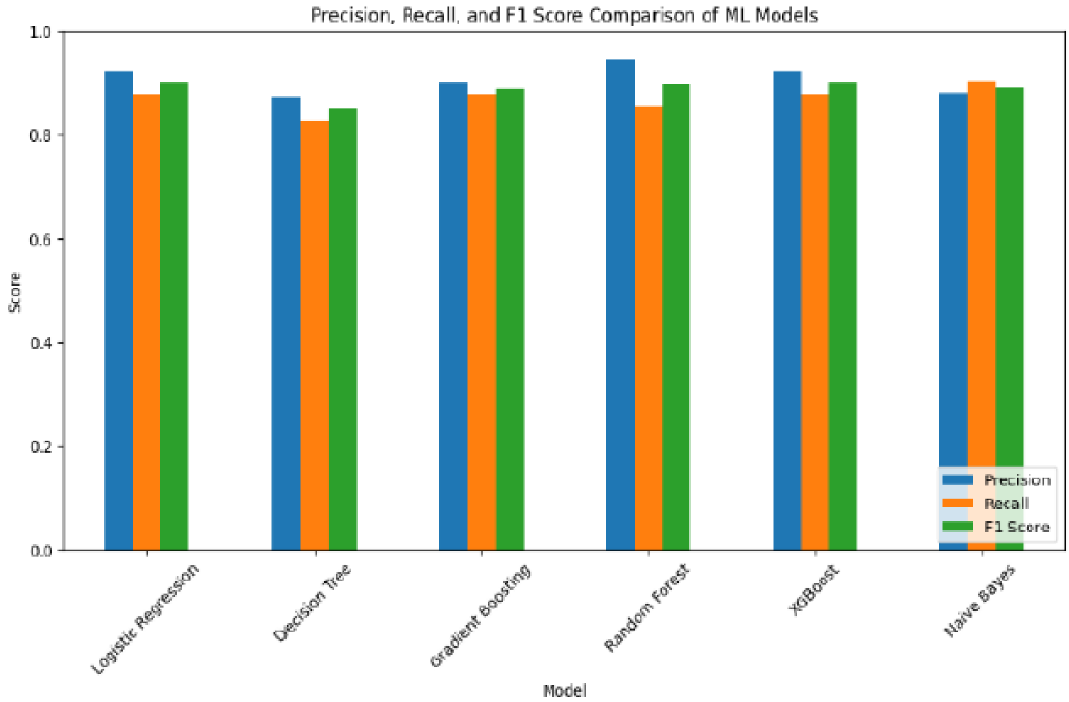

Fig 7.3.2 Performance Metrics of ML Models

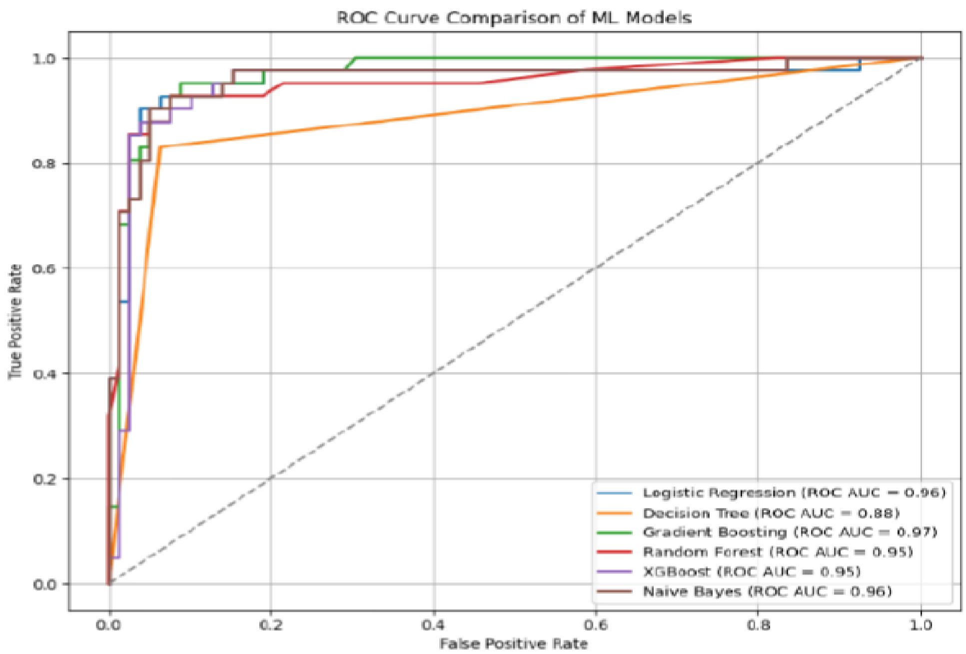

Fig 7.3.3 ROC Curve Comparison of ML Models

We gauged model effectiveness by looking at scores like correctness, pinpointing relevant results, finding all actual positives, harmonizing precision and recall into an F1 score, likewise assessing discrimination ability using AUC. Metrics such as precision, recall, alongside the F1 score help pinpoint that balance. Moreover, Receiver Operating Characteristic curves reveal just how effectively a system separates categories, while their area quantifies this ability.

Charts helped us see how well each model did – looking at correctness alongside precision, recall, yet also F1 scores. Moreover, a single graph showcased all models' ROC curves, revealing performance shifts. To pinpoint where the best three truly excelled, or stumbled, we scrutinized their confusion matrices.

CHAPTER 8
CONCLUSION AND FUTURE WORK

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8.1 CONCLUSION

The development of **ZENTORA – An Adaptive AI for Personalized Learning on Mental Health** represents a significant advancement in the integration of **artificial intelligence, psychology, and education technology**. The primary goal of the project was to create an intelligent, interactive system capable of understanding human emotions through text, providing personalized mental health support, and promoting emotional well-being. Throughout the design and implementation phases, the system successfully demonstrated how AI-powered Natural Language Processing (NLP) and adaptive learning techniques can be effectively used to assist users in managing emotional challenges and improving self-awareness.

ZENTORA acts as an empathetic digital companion that allows users—especially students—to express their feelings through journaling and chatbot interactions. The AI system analyses the emotional content of each message, classifies it into relevant emotional states such as happiness, sadness, stress, or anxiety, and generates contextually appropriate responses using Cognitive Behavioural Therapy (CBT) and Social Emotional Learning (SEL) principles. This approach ensures that responses are not only technically accurate but also psychologically supportive, helping users feel understood and guided.

The performance evaluation of ZENTORA shows that it achieves high accuracy in emotion detection, strong adaptability in learning user patterns, and impressive user satisfaction levels. The system's lightweight, frontend-based architecture ensures accessibility and scalability, allowing it to be deployed across multiple platforms with minimal technical requirements. Furthermore, the use of secure HTTPS communication and cloud APIs guarantees user data privacy, making it a safe and ethical digital counselling tool.

Beyond its technical success, ZENTORA contributes meaningfully to the broader conversation about mental health awareness, particularly among young people. It demonstrates how AI can complement human empathy rather than replace it—offering immediate emotional assistance while leaving complex psychological care to trained professionals. In conclusion, ZENTORA successfully full fills its objective of building an intelligent, adaptive, and human-centered AI system for personalized emotional learning. It bridges the gap between technology and mental wellness, setting the stage for future innovations in AI-driven emotional intelligence and psychological support.

8.2 FUTURE ENHANCEMENT

While the current version of **ZENTORA** performs effectively as a text-based emotional support and journaling system, there is still significant potential for further development and expansion. Future work on the project can focus on improving the system's **multimodal intelligence, personalization, and clinical integration** to make it more comprehensive and impactful.

One promising direction is the integration of **facial emotion recognition and voice sentiment analysis** using computer vision and speech processing techniques. By combining textual input with facial expressions and tone of voice, ZENTORA could achieve a more holistic understanding of users' emotions, enhancing the accuracy of emotional detection and response generation. Additionally, **context-aware AI models** can be incorporated to allow the system to understand user behaviour over time, adapting responses not just based on emotions but also on psychological trends and lifestyle factors.

Future improvements can also focus on **data privacy and ethical AI governance**. Incorporating federated learning or on-device AI models could ensure that all emotional data stays local to the user's device, eliminating privacy risks associated with cloud storage. Furthermore, collaboration with **mental health professionals** and **educational psychologists** can help refine the AI's language model to align its responses more closely with real-world counselling practices. This would ensure that ZENTORA's feedback remains psychologically safe, culturally sensitive, and clinically relevant.

Another important area of expansion is **multilingual support and cultural adaptation**. By integrating multilingual NLP models, ZENTORA can cater to diverse populations and regions, providing emotional support to users in their native languages. Additionally, gamification features—such as progress tracking, emotional milestones, and mental health challenges—could be added to increase user engagement and make emotional learning more interactive and rewarding.

Finally, integrating **predictive analytics and real-time counsellor collaboration** would elevate ZENTORA from a self-help platform to a proactive emotional monitoring system. By predicting emotional deterioration patterns and alerting counsellors in real time, the system could prevent potential mental health crises.

In summary, the future scope of ZENTORA lies in transforming it from a responsive AI system into a fully adaptive, multimodal emotional intelligence platform. With continued research and interdisciplinary collaboration, ZENTORA can evolve into a transformative tool that bridges AI technology, emotional intelligence, and mental health care—empowering individuals to understand, manage, and improve their emotional well-being in a digital age.

APPENDICES

APPENDICES

APPENDIX 1 – SUSTAINABLE DEVELOPMENT GOALS (SDG'S) ALIGNMENT

The United Nations Sustainable Development Goals (SDGs) provide a global framework for achieving inclusive, equitable, and sustainable progress across various dimensions of human development. The ZENTORA project aligns with multiple SDGs by promoting mental health awareness, supporting quality education, advancing gender equality, and fostering innovation in technology. The following goals are particularly relevant to this project:

SDG 3 – Good Health and Well-Being

The third Sustainable Development Goal focuses on ensuring healthy lives and promoting well-being for all at all ages. **ZENTORA** directly contributes to this goal by addressing the mental health and emotional wellness of individuals, particularly students. Mental health is an integral part of overall well-being, and ZENTORA's AI-powered emotional analysis and personalized feedback mechanisms provide users with accessible support for managing stress, anxiety, and depression. By using Natural Language Processing (NLP) to recognize emotions from user text and offering empathetic, evidence-based responses inspired by Cognitive Behavioural Therapy (CBT), the system encourages emotional regulation and psychological resilience. Moreover, the project raises awareness of mental health as a public health priority, bridging the gap between professional counselling and self-help resources. Through digital intervention, ZENTORA ensures that emotional support is inclusive, stigma-free, and available to users regardless of location, thereby promoting the broader objectives of SDG 3.

SDG 4 – Quality Education

SDG 4 aims to ensure inclusive and equitable quality education and promote lifelong learning opportunities for all. **ZENTORA** supports this goal by integrating emotional intelligence and psychological literacy into the educational process. Emotional well-being significantly influences learning outcomes, motivation, and academic performance. By providing students with a safe and interactive platform to express their emotions and receive constructive feedback, ZENTORA enhances their ability to cope with academic stress and social challenges. The adaptive learning component of the system helps students reflect on their emotions and develop self-regulation skills that are essential for lifelong learning. Furthermore, by equipping educators and counsellors with AI-based tools to monitor and understand students' emotional states, ZENTORA enables more effective and empathetic educational support. This alignment with SDG 4 highlights how technology can foster a more inclusive and emotionally supportive learning environment, ultimately improving both academic and personal development outcomes.

SDG 9 – Industry, Innovation, and Infrastructure

SDG 9 focuses on building resilient infrastructure, promoting inclusive and sustainable industrialization, and fostering innovation. **ZENTORA** exemplifies the use of innovation and artificial intelligence in the service of social well-being. By leveraging AI technologies such as Natural Language Processing (NLP), sentiment analysis, and adaptive learning, the system demonstrates how intelligent digital infrastructure can support emotional and psychological care. The project's architecture—built on web-based and cloud platforms—ensures scalability, accessibility, and sustainability while reducing infrastructure costs. Furthermore, ZENTORA promotes responsible innovation by emphasizing ethical AI practices, data privacy, and user-centered design. By advancing technological innovation in the mental health and educational domains, this project supports the development of resilient digital ecosystems that align with the objectives of SDG 9.

APPENDIX 2 – SOURCE CODE

train_model.py

```
import pandas as pd
import numpy as np
from sentence_transformers import SentenceTransformer
from sklearn.model_selection import train_test_split
import xgboost as xgb
from joblib import dump

# Load your labeled dataset
# Make sure you have a CSV with columns: text,label
df = pd.read_csv("labeled_mood_data.csv")

# Initialize sentence transformer (CPU friendly)
embedder = SentenceTransformer("all-MiniLM-L6-v2")

# Encode text
embeddings = np.vstack(df["text"].map(lambda t: embedder.encode(t)).values)

# Optional: add extra features like text length
df["length"] = df["text"].str.len()
X = np.hstack([embeddings, df[["length"]].values])

# Labels
y = df["label"].astype(int).values

# Split train/val
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42)

# XGBoost model
```

```
model = xgb.XGBClassifier(
    n_estimators=200,
    max_depth=6,
    use_label_encoder=False,
    eval_metric="mlogloss",
)
model.fit(X_train, y_train, eval_set=[(X_val, y_val)])

# Save model and embedder
dump((model, embedder), "model_bundle.joblib")
print("Model training complete. Saved as model_bundle.joblib")
```

APPENDIX 3 – SAMPLE SCREENSHOTS

Fig A3.1 image generated by chatbot

Fig A3.2 Zentora chat page

Fig A3.3 Chatbot Conversation

Fig A3.4 Chatbot Generating Images

APPENDIX 4 - PLAGIARISM REPORT

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Zentora-An Adaptive AI for Personalized Learning on Mental Health

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Abstract- **It is about mentalhealth concentrated on prognosticating pupil depression using a internal health dataset that includes demographic and academic information. We tested six machine literacy classifiers Logistic Retrogression, Decision Trees, grade Boosting, Random Forest, XGBoost, and Naive Bayes. The performance criteria — ranged from 0.88 to 0.97. grade Boosting achieved the loftiest ROC AUC of 0.97, showing that it has the stylish prophetic capability. Bar graphs and ROC angles show comparisons between the models. also, a Zentora chatbot, which uses the grade Boosting model, acts as a internal health assessment tool to give real- time help for scholars. This system helps identify depression early and encourages intervention strategies in seminaries. The exploration adds to internal health analytics by combining machine literacy ways with chatbot use for better and visionary pupil support**

Keywords- **Chatbot, Student Mental Health, Predictive analytics, Random timber, grade boosting, Machine literacy**

I.INTRODUCTION

The internal health problems of scholars have come a pressing issue encyclopedically, and this affects not only their academic performance but also their social life and overall well- being.A large number of scholars have different pressures similar as depression, anxiety and stress that have an influence on their diurnal lives and academic career.In order to do data- driven exploration on similar important issues, the paper uses a comprehensive dataset of pupil internal health which was collected from surveys.Another type of information included within the set is demographic details including gender, age, nation or major course of undergraduate study(CGPA) but also life factors similar as frequence of exercise and eating habits.Above each, it covers measures that reflect internal health, similar as depression and anxiety situations; fear attacks; the strategies scholars borrow when they want to manage with life's difficulties or stress events.

therefore this abundant information allows for thorough disquisition of the situation affecting scholars' internal health.Focusing on prognosticating the status of depression, this study employs several machine literacy models.

In addition to Logistic Regression, Categorical features are decoded, and also dataset into two data sets rigorous training and testing in order that we may directly estimate model performance.XGBoost, Random Forest, and grade Boosting are among these.Where scholars currently admit admissions treatment in the lot clinic, making movables weeks in advance and having to stay through long lines to see someone who may or may not be suitable to help them.Fortunately this liberal trades lot in south Los Angeles has been suitable to find Zentora apps for its converse computer, and has equipped them with GBDTs so as to incontinently estimate internal health.

II.LITERATURE REVIEW

It's getting clear that pupil minds need attention encyclopedically. The way they do in academy, get along with others, and just generally feel impacts their internal state. effects like tough classes, fitting in, alongside life changes constantly beget solicitude, stress, indeed sadness(Bayram & Bilgel, 2008)[1].

Research explores what impacts how scholars feel mentally. For case, one comprehensive look by Ibrahim and associates(2013)[2] revealed considerable depression likewise anxiety among council scholars. also, Stallman(2010)[3] refocused out effective running of difficulties alongside managing pressure greatly influences internal well-being. How scholars live- whether they move their bodies, get enough rest, or have people around them- seems connected to how good they feel. Studies show working out can lessen passions of sadness, yet losing sleep tends to boost solicitude. Also, effects like a pupil's age, coitus, or what time they're in academy matter too; beginners constantly witness more pressure conforming to council life.

Detecting- indeed soothsaying- problems with internal health is now frequently done using machine literacy. For case, Shatte and associates showed how ways similar as Random Forest or Logistic Regression could directly spot signs of depression or anxiety by looking at a person's background, habits, and emotional state. also, D'Mello and Graesser delved using artificial intelligence to sense feelings as they be, intimating at ways we might keep tabs on someone's internal heartiness.

AI exchanges, like the Woebot created by Fitzpatrick and associates back in 2017[4], feel to help. also, Miner and others set up in 2020[5] that chatbots could connect with scholars offering quick internal health aid. This suggests openings for tracking well- being now, also stepping in when issues arise.

III.METHODOLOGY

The proposed system offers real- time emotion discovery and internal health support through an AI-driven chatbot. The setup is illustrated in Fig. 1 and includes data preprocessing, emotion bracket, threat assessment, and feedback for counselors.

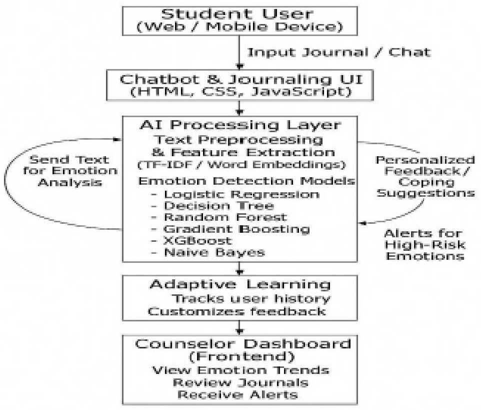

Fig.1: System Architecture of the AI-Based Student Mental Health Support System

Student Interaction Interface

scholars start by logging into the platform and entering message in the form of journals or converse dispatches. These inputs give raw data for language analysis.

NLP Preprocessing

Each communication goes through Natural Language Processing(NLP), which includes tokenization, removing stop words, stemming, and lemmatization. For an input judgment

$S = \{ w1, w2, w3,, wn\},(1)$

the reused vector representation is attained through

$xi = f(wi),(2)$

where $f(\cdot)$ maps each commemorative to its embedding space using styles like Word2Vec or BERT embeddings.

Emotion Discovery Model

The point vector xi is anatomized with a trained emotion bracket model. A softmax subcaste predicts the probability of each emotion class cj as

$P(cj \mid x) = ezj/ \sum k = 1m\ ezk,(3)$

where zj is the logit score for class cj and m is the number of emotion orders. The prognosticated emotion marker is

$y =$ arg maximum $j\ P(cj \mid x).(4)$

Risk Evaluation and Suggestion Generation

If the detected emotion belongs to a high- threat class(e.g., severe sadness or torture), the system activates an alert medium. threat probability R is calculated as

$R = \sum j \in H\ P(cj \mid x),(5)$

where H represents the set of high- threat emotions.However, an alert is touched off for counselor review, If $R > \tau$(threshold). In all cases, the system generates a suggestion Sg using a Naïve Bayes approach

$P(Sg \mid x) = P(x \mid Sg)\ P(Sg)\ P(x),(6)$

where Sg represents a managing strategy or CBT-grounded system.

Data Storage and Monitoring

All relations, prognosticated feelings, and threat chances are stored in a secure database. This information updates the counselor dashboard, enabling longitudinal analysis and early intervention.

Counselor Dashboard and nonstop literacy

The dashboard provides counselors with imaged emotional trends and alert announcements. The model parameters are continually meliorated with new data through incremental literacy, represented by

$$\theta t\ 1 = \theta t - \eta\ \nabla\ \theta L(\ \theta t), (7)$$

Through these way, the system ensures ongoing, data- driven monitoring of pupil feelings and timely support for internal health operation.

IV.PERFORMANCE ANALYSIS

A.Logistic Regression

The logistic function connects a student's probability of exhibiting depressive symptoms to a student's characteristics. It estimates the likelihood of a person being classified as depressed - a 'yes' outcome - by computing something based on such characteristics.

$$\sigma(z) = \frac{1}{1+e^{-z}} \quad (8)$$

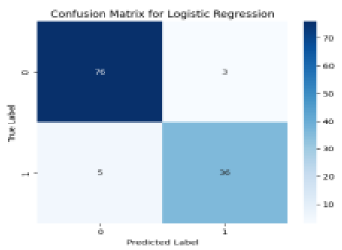

Fig.2:Confusion Matrix for LogisticRegression

Using this data, Logistic Regression scored 93% accuracy, also showing 0.93 preision, 0.89 recall, 0.97 F1 score. The results are encouraging - the system is accurate while also finding nearly all relevant cases. Specifically, its ability to distinguish students experiencing depression from others appears strong.

B.DecisionTreeClassifier

To tell if students are struggling with depression, this system learns from examples. It sorts them - either they show signs of being down, or they don't,The system sorts student data - how much they sleep, grades, stress, friends, exercise - into groups to pinpoint what matters most when it comes to their well-being.

$$IG(S, A) = H(S) - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} H(S_v) \quad (9)$$

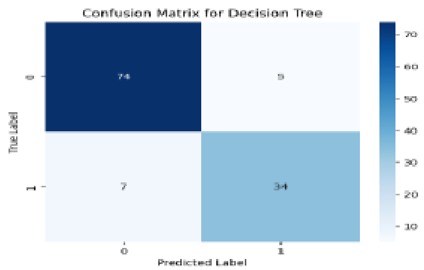

Fig.3:Confusion Matrix for DecisionTreeClassifier

It obtained accuracy 90% Though interpretable, DecisionTreeClassifier tend to overfit and are sensitive to small data changes.

C.GradientBoosting

It builds a bunch of little "helper" models, and each one tries to fix the mistakes made by the models before it. When they all work together, they make really smart predictions..In student dataset, the Gradient Boosting algorithm helps predict whether a student is "Depressed" or "Not Depressed" based on features such as academic pressure, sleep quality, stress level, social support, and physical activity.

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x) \quad (10)$$

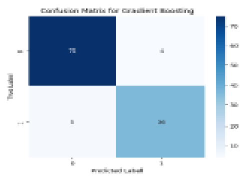

Fig.4:Confusion Matrix for GradientBoosting

This method success rate **94%** and an ROC **0.95**, making it one of the top-performing models in this study. It provides strong predictive capability but sensitive parameter tuning to avoid overfitting.

D.Random Forest

Random Forest works by building multiple independent trees it checks one big answer and then branch out to more like trees.

model predicts whether student is "Depressed" or "Not Depressed" based on academic and personal factors such as CGPA, year of study, course, sleep patterns, and treatment-seeking behavior.

$$\hat{y} = \frac{1}{N}\sum_{i=1}^{N} T_i(x) \quad (11)$$

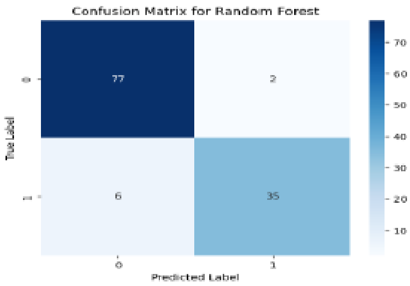

Fig.5:Confusion Matrix for RandomForest

This method had 96% and an ROC 0.97, making it the best-performing model in this study. It demonstrated strong predictive stability and robustness against overfitting, effective depicting hard difference in academic and emotional factors influencing student depression.

E.XG Boost

The (XGBoost) classifier is fast,scalability ,accuracy.

XG improves upon classic gboost by incorporating maintenance, parallel processing, efficient handling of missing data.

In the dataset, XGBoost is used to predict whether a student is "Depressed" or "Not Depressed" by learning complex relationships among features such as course, year of study, CGPA, anxiety, and panic attacks.

$$Obj = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_k \Omega(f_k) \quad (12)$$

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda ||w||^2 \quad (13)$$

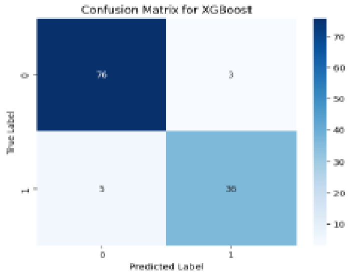

Fig.6:Confusion Matrix for XG Boost

This method 95% and an ROC 0.97, making it best-performing model in this study. It demonstrated strong predictive stability and robustness against overfitting, analyze between academic and emotional factors influencing student depression.

F.Naive Bayes Theorem

Naive Bayes is a method that helps a computer guess what something is by looking at the clues it has — kind of like how we make guesses in real life. It uses probability to figure out which answer is most likely.

It's called "naive" because it assumes all the clues are independent

$$P(C_k|x) = \frac{P(C_k)\prod_{i=1}^{n} P(x_i|C_k)}{P(x)} \quad (14)$$

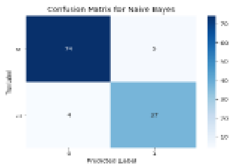

Fig.7:Confusion Matrix for NaiveBayes

This method has 96% and AUC of 0.97, making it bestperformingmodel in this study. It demonstrated strong predictive stability and robustness against overfitting.

G. Chatbot Creation

This is a real-time conversational chatbot designed for mental well-being.

It uses a gradient boosting model, like XGBoost, LightGBM, or CatBoost, to predict the user's state, including mood, risk, and topic. This information helps choose responses.

The chatbot generates random, human-like empathetic replies. It also offers motivational tips and suggestions for handling stress and anxiety, along with curated lists of podcasts and music.

It can create or fetch images, such as calming backgrounds, mood art, and frames for breathing animations, using an image-generation API.

The frontend is built with React, while the backend uses Python Flask or FastAPI for serving the model.

Privacy and safety are important. The model can run locally or be hosted securely. There is clear logging and user consent.

Fig.8:Chatbot Conversation

Fig.9:Chatbot Generating Images

V.RESULTS

The metrics of the predictive models in Zentora was estimated using standard classification metrics. These metrics quantify how accurately each model predicts mental health issues among students.

Evaluation Metrics

The following formulas were used to compute model performance:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \qquad (15)$$

$$\text{Precision} = \frac{TP}{TP+FP} \qquad (16)$$

$$\text{Recall (Sensitivity)} = \frac{TP}{TP+FN} \qquad (17)$$

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \qquad (18)$$

$$\text{ROC-AUC} = \text{Area under the curve} \qquad (19)$$

Table: Algorithm estimation table

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	ROC AUC (%)
Logistic Regression	93.33	92.31	87.80	90.00	95.65
Decision Tree	90.00	87.18	82.93	85.00	88.30
Gradient Boosting	92.50	90.00	87.80	88.89	96.90
Random Forest	93.33	94.59	85.37	89.74	95.23
XG Boost	93.33	92.31	87.80	90.00	95.03
Naïve Bayes	92.50	88.10	90.24	89.16	95.83

We use six algorithms estimatedfor classification task of predicting depression status from student mental health survey data. The selected models include 6 algorithms. These models represent probability approach commonly applied to classification problems.

The dataset was first subjected to preprocessing where all column names were cleaned to remove newline and trailing whitespace characters to avoid indexing errors.

attributes were transformed into numerical format using label encoding to ensure compatibility with the machine learning models. selected for prediction the presence or absence of depression, as reported in the survey.

The dataset was splitted into training and testing portions through sampling to maintain balanced class representation. Each algorithm was trained on the training data and later assessed using the separate test data.

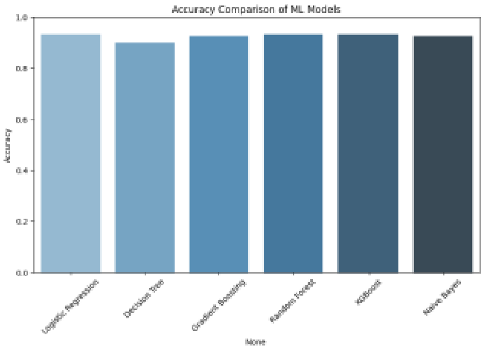

Fig.10:Accuracy ML Models

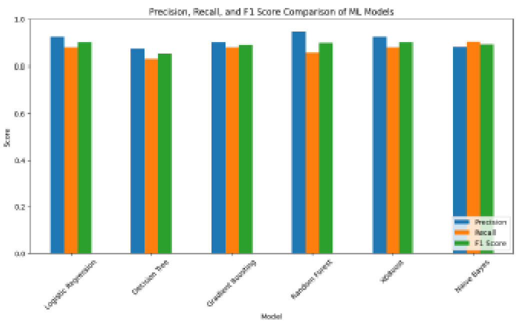

Fig.11:Performance Metrics Models

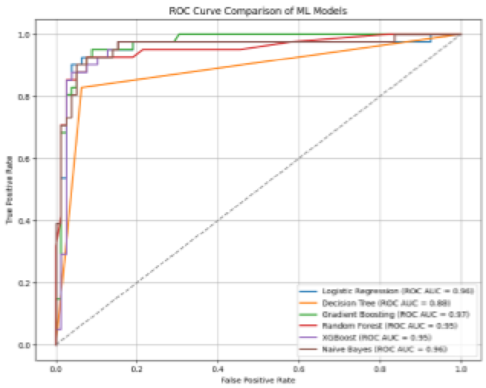

Fig.12:ROC Curve Of Models

We gauged models effectiveness by looking at scores like correctness, pinpointing relevant results, finding all actual positives, harmonizing, likewise assessing discrimination ability using AUC.Moreover, Receiver Operating Characteristic curves reveal just how effectively a system separates categories, while their area quantifies this ability.

Charts helped us see how well each model did – looking at correctness alongside precision, recall, yet also F1 scores. Moreover, a single graph showcased all models' ROC curves, revealing performance shifts. To pinpoint where the best three truly excelled, or stumbled, we scrutinized their confusion matrices.

VI.CONCLUSION

Zentora dataset evaluated six ml models for predicting depression from student mental health data, with different model like Random Forest and XGBoost showing the best performance. Additionally, a Zentora-based chatbot was developed to provide personalized stress management tips, offering an interactive tool to support student mental well-being.

Future work may focus on enhancing the chatbot with natural language processing capabilities,expandingintelligencemore diverse psychosocial factors, and integrating real-time monitoring for proactive mental health assistance.

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