B.Tech. BCSE497J - Project-I

Predictive Modeling of Depression Using Machine Learning on Multimodal Data Sources

Submitted in partial fulfillment of the requirements for the degree of

Bachelor of Technology

in

Computer Science and Engineering

by

22BCE2475	**AKKI ARYAN**
22BCE2663	**OM KUMAR**
22BCE3079	**SHATAKSHI SINGH**

Under the Supervision of

Dr. SUGANTHINI. C

Assistant Professor Sr. Grade 1

School of Computer Science and Engineering (SCOPE)

VIT®

Vellore Institute of Technology

(Deemed to be University under section 3 of UGC Act, 1956)

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DECLARATION

I hereby declare that the project entitled **Predictive Modeling of Depression Using Machine Learning on Multimodal Data Sources** submitted by me for the award of the degree of *Bachelor of Technology in Computer Science and Engineering* to VIT is a record of bonafide work carried out by me under the supervision of

Dr. SUGANTHINI. C.

I further declare that the work reported in this project has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

Place : Vellore

Date : 05/11/2025

Akki Aryan

Akki Aryan

CERTIFICATE

This is to certify that the project entitled **Predictive Modeling of Depression Using Machine Learning on Multimodal Data Sources** submitted by AKKI ARYAN (22BCE2475), OM KUMAR (22BCE2663) and SHATAKSHI SINGH (22BCE3079), **School of Computer Science and Engineering**, VIT, for the award of the degree of *Bachelor of Technology in Computer Science and Engineering*, is a record of bonafide work carried out by them under my supervision during Fall Semester 2025-2026, as per the VIT code of academic and research ethics.

The contents of this report have not been submitted and will not be submitted either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university. The project fulfills the requirements and regulations of the University and in my opinion meets the necessary standards for submission.

Place : Vellore

Date : 05/11/2025

C. Sivaram

Signature of the Guide

Examiner(s)

Dr. Boominathan P.

Head of the Department of Software Systems

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List of Abbreviations

AI	Artificial Intelligence
API	Application Programming Interface
BERT	Bidirectional Encoder Representations from Transformers
CNN	Convolutional Neural Network
CPU	Central Processing Unit
CSV	Comma-Separated Values
DL	Deep Learning
GPU	Graphics Processing Unit
JSON	JavaScript Object Notation
LIME	Local Interpretable Model-Agnostic Explanations
LSTM	Long Short-Term Memory
ML	Machine Learning
MMF	Multimodal Fusion
MOGAM	Multimodal Object-oriented Graph Attention Model
NLP	Natural Language Processing
PII	Personally Identifiable Information
RoBERTa	Robustly Optimized BERT Approach
SHAP	Shapley Additive Explanations
TF-IDF	Term Frequency–Inverse Document Frequency
UI	User Interface
XAI	Explainable Artificial Intelligence

ABSTRACT

The increasing prevalence of mental health disorders such as depression, anxiety, and stress has created an urgent need for early detection and intervention strategies. Traditional diagnostic approaches rely heavily on clinical evaluation and self-reporting, which can be subjective and limited in scalability. With the rapid growth of social media platforms, users often share thoughts and emotions that reflect their mental state, creating vast opportunities for computational modeling. This research focuses on developing a unified data preprocessing pipeline for sentiment and mental health classification using multimodal social media data.

The proposed system integrates datasets from multiple online platforms, including Twitter and Reddit, to ensure diversity and representativeness of samples. It automates various preprocessing stages such as data cleaning, noise removal, emoji normalization, timestamp standardization, label harmonization, and text tokenization. The cleaned and structured dataset is stored in Parquet format to enable efficient access for downstream machine learning and transformer-based deep learning models. This approach ensures that the data preparation stage adheres to reproducibility, scalability, and data integrity standards essential for mental health modeling.

The pipeline serves as a foundational framework for building predictive models aimed at early detection of depression and related disorders. By providing consistent preprocessing across diverse datasets, it facilitates fair model evaluation, cross-domain learning, and explainable AI integration. Additionally, the inclusion of both sentiment-level and causal-level labeling enables richer context analysis, bridging emotional expression with potential triggers of mental distress.

This work highlights the importance of data quality and standardization in advancing AI-driven mental health research. The proposed preprocessing framework not only supports robust model development but also promotes responsible use of social media data for mental health applications. Future work will focus on incorporating multimodal fusion techniques, privacy-preserving architectures, and domain adaptation for improved generalization across populations and languages.

Keywords: Mental health analysis, sentiment detection, social media, dataset preprocessing, explainable AI, natural language processing.

CHAPTER 1

1. INTRODUCTION

Mental health disorders, particularly depression, have emerged as one of the most pressing global health challenges of the 21st century. According to the World Health Organization, depression is a leading cause of disability worldwide and contributes significantly to the overall global burden of disease. The advent of social media platforms such as Twitter, Reddit, and Instagram has provided researchers with vast, real-time behavioral data that reflect users' emotions, interactions, and psychological states. These platforms have thus become valuable resources for understanding and predicting mental health conditions through computational means [1], [2].

With advances in Artificial Intelligence (AI) and Natural Language Processing (NLP), data-driven methods are now capable of detecting mental health signals from users' online content. Studies have demonstrated that linguistic markers, contextual embeddings, and multimodal features can serve as reliable predictors of depressive tendencies [3]–[5]. Early works by Coppersmith et al. (2014) and Benton et al. (2017) established the foundation for mental health analysis on social media, using lexical and stylistic cues to infer depressive behavior [6], [7]. Building upon these foundations, contemporary research leverages deep learning architectures—such as Convolutional Neural Networks (CNNs), Long Short-Term Memory networks (LSTMs), and Transformers—to improve detection accuracy and interpretability [8]–[10].

Furthermore, explainable AI (XAI) has emerged as a crucial component in the field, providing interpretability and transparency in model predictions. Studies such as Malhotra et al. (2024) and Hameed et al. (2025) have shown that incorporating XAI frameworks helps identify linguistic or behavioral factors that contribute most to model decisions, making these systems more ethically and clinically viable [11], [12]. The integration of multimodal data—combining text, image, and user metadata—has also proven to enhance model performance and contextual understanding [13], [14].

1.1 Background

Depression manifests through cognitive, emotional, and behavioral patterns, often observable through subtle language cues and social media activity. Traditional clinical assessments, while effective, are limited by accessibility and subjectivity. In contrast, computational approaches allow for scalable, objective, and continuous monitoring of psychological well-being [15]. Research has shown that individuals with depression tend to use more self-referential language, negative sentiment, and fewer social interaction cues in their online communication [16], [17].

The field has evolved from simple text-based classification to more sophisticated models that incorporate temporal patterns, semantic embeddings, and multimodal fusion [18]–[20]. Transformer architectures such as BERT, RoBERTa, and their variants have demonstrated state-of-the-art performance in capturing contextual nuances in social media posts [21]–[23]. These advancements have paved the way for predictive modeling frameworks capable of early detection and severity assessment of depressive symptoms.

1.2 Motivation

The motivation behind this project stems from the urgent societal need to enhance mental health surveillance through technology-driven methods. Despite growing awareness, many individuals suffering from depression remain undiagnosed or untreated due to stigma, lack of access to care, or delayed intervention. By leveraging social media data and machine learning algorithms, this project aims to support early detection and intervention strategies that can complement traditional psychological assessments [24], [25].

Moreover, recent advancements in explainable and multimodal AI enable researchers to not only achieve high prediction accuracy but also to interpret and validate model outputs. This interpretability is particularly crucial in mental health contexts, where ethical considerations and user trust are paramount [26], [12]. Therefore, this research seeks to design a predictive framework that balances performance, interpretability, and social responsibility.

1.3 Scope of the Project

This project focuses on developing and evaluating machine learning models for predicting depression based on social media data. The implementation involves data preprocessing, feature extraction, and classification using modern algorithms such as Support Vector Machines (SVMs), Random Forests, and Transformer-based models. The scope includes comparative analysis of model performance across various feature sets, with an emphasis on explainable and interpretable outcomes. The study does not aim to replace clinical diagnosis but to demonstrate how computational modeling can serve as a supplementary tool for mental health monitoring and early intervention [27], [5], [13].

Ultimately, this work contributes to the growing field of digital psychiatry by integrating AI-based methodologies with social media analytics, highlighting both the opportunities and ethical challenges inherent in predictive modeling for mental health applications.

CHAPTER 2

2. PROJECT DESCRIPTION AND GOALS

The objective of this project is to design a machine learning–based predictive model capable of identifying depression symptoms through users' social media activity. With the increasing reliance on digital communication, social media posts often reveal emotional and psychological cues that can be used to detect potential mental health risks. The proposed system aims to process textual data from social media, extract linguistic and semantic features, and apply various machine learning and deep learning techniques to classify the likelihood of depressive expression.

This section provides a review of recent research contributions in this field and identifies existing limitations that form the motivation for this project.

2.1 Literature Review

Over the past decade, a growing body of research has explored how online behavioral data can be leveraged to assess mental health status. Early foundational studies such as those by Coppersmith et al. [1] and De Choudhury and Kiciman [2] demonstrated that linguistic and activity-based features extracted from Twitter posts could effectively indicate mental health conditions. These pioneering works introduced benchmark datasets and highlighted the feasibility of using text analytics for depression detection.

Subsequent research expanded upon these foundations using traditional machine learning algorithms such as Support Vector Machines (SVMs), Naïve Bayes, and Random Forests [3], [4]. However, these approaches were limited by their reliance on handcrafted features and shallow representations of text. To overcome these challenges, deep learning models have become increasingly prevalent. Orabi et al. [5] and Yang et al. [6] employed Convolutional Neural Networks (CNNs) and BiLSTM architectures to automatically capture contextual dependencies within textual data, significantly improving classification performance.

More recently, Transformer-based models such as BERT, RoBERTa, and XLNet have revolutionized natural language processing for mental health analysis. Studies like Lin and Yang [7], Zhang et al. [8], and Choudhury et al. [9] reported substantial gains in depression detection accuracy by leveraging contextual embeddings that capture subtle linguistic and emotional cues. Furthermore, Kerasiotis et al. [10] and Qasim et al. [11] demonstrated that transformer-based architectures, when combined with metadata or temporal features, provide more robust and interpretable predictions of depression severity.

The field has also witnessed increasing interest in multimodal approaches, where visual, textual, and behavioral signals are jointly analyzed. For instance, Lee et al. [12] and Sadeghi et al. [13] proposed multimodal fusion frameworks that integrate image and text features, yielding higher reliability in identifying depressive tendencies. Similarly, Haque et al. [14]

introduced MMFformer, a multimodal fusion transformer network designed to combine linguistic, visual, and contextual embeddings for improved depression detection.

Another important trend is the emergence of Explainable AI (XAI) techniques in mental health prediction. Malhotra et al. [15] and Hameed et al. [16] emphasized the importance of transparency in decision-making, proposing explainable transformer architectures that provide interpretive insights into the linguistic and semantic patterns contributing to depressive classifications. Similarly, Belcastro et al. [17] introduced ChatGPT-augmented explainable models to increase clinical reliability and interpretability in mental health prediction.

Despite these advances, researchers such as Mansoor et al. [18] and Chancellor & De Choudhury [19] caution that real-world deployment of AI-based mental health tools requires addressing ethical considerations, data privacy, and generalizability across diverse populations. Overall, the literature underscores the potential of machine learning and NLP in early depression detection, while highlighting the need for further research on interpretability, fairness, and model robustness.

2.2 Research Gap

Although existing studies demonstrate remarkable progress in depression detection through social media analysis, several research gaps remain unaddressed.

First, data diversity and generalizability continue to pose challenges. Many studies rely on small, domain-specific datasets such as Reddit or Twitter corpora [20], [21], which may not represent broader populations or cultural contexts. This limits the ability of models to generalize effectively to unseen data or new linguistic environments.

Second, most prior works have focused primarily on text-based features, often ignoring multimodal signals such as user engagement patterns or visual cues [12], [22]. Integrating multimodal features remains an open challenge, particularly in designing models that can jointly reason across modalities without losing interpretability.

Third, while transformer-based architectures have achieved high predictive accuracy, they often function as “black boxes,” providing limited insight into how predictions are made. Recent advances in explainable transformers [15], [16] offer promising directions, but comprehensive frameworks combining interpretability, multimodality, and real-time prediction are still rare.

Finally, there is a lack of comparative evaluations across traditional machine learning and advanced deep learning models on unified datasets. Many studies present isolated experiments, making it difficult to assess which approach offers the best trade-off between accuracy, computational efficiency, and explainability.

To address these gaps, this project proposes a comparative predictive modeling framework that evaluates traditional machine learning and transformer-based models for depression

detection on social media data. The goal is to assess model performance, interpretability, and scalability, contributing toward developing a transparent and reliable mental health prediction system.

2.3 Objectives

The primary objective of this project is to design and evaluate a machine learning framework for detecting depression through social media data. By leveraging linguistic and behavioral cues embedded in online posts, the system aims to predict potential depressive tendencies with high accuracy and interpretability.

The specific objectives of the project are as follows:

- To collect and preprocess social media text data that potentially indicate signs of depression, ensuring data quality, privacy, and ethical compliance.

- To extract linguistic, semantic, and contextual features using advanced text representation techniques such as TF-IDF, Word2Vec, and Transformer-based embeddings.

- To build and compare predictive models using both traditional machine learning algorithms (e.g., Logistic Regression, Random Forest, SVM) and deep learning architectures (e.g., LSTM, BERT, RoBERTa).

- To evaluate model performance using quantitative metrics such as accuracy, precision, recall, F1-score, and ROC-AUC to determine the most effective algorithm for depression detection.

- To explore explainability and interpretability through visualization and explainable AI (XAI) methods, ensuring that the system provides meaningful and ethical insights.

- To analyze the strengths and limitations of the implemented models and propose directions for improving scalability and ethical integration in real-world mental health applications.

These objectives collectively aim to demonstrate how data-driven models can support early detection of depression, supplementing conventional clinical assessments.

2.4 Problem Statement

Depression often remains underdiagnosed due to social stigma, lack of access to mental health care, and delayed clinical intervention. Traditional assessment methods are largely dependent on in-person evaluations or self-reported surveys, which may not capture the dynamic, day-to-day emotional fluctuations individuals experience.

With the exponential growth of social media usage, people increasingly express their thoughts, emotions, and behaviors online. This presents an opportunity to identify digital biomarkers that may signal depressive symptoms. However, detecting depression from social media content presents several technical and ethical challenges:

- **Ambiguity of language:** Human language is context-dependent, and emotional cues can vary across cultures, regions, and individuals.

- **High data heterogeneity:** Posts may include slang, abbreviations, emojis, and non-standard grammar, complicating NLP analysis.

- **Data imbalance:** Datasets often contain significantly fewer depression-related posts than neutral ones, impacting model training and accuracy.

- **Lack of explainability:** Deep learning models, though powerful, often operate as black boxes, limiting their use in clinical or sensitive domains.

- **Ethical and privacy concerns:** Mining social media for mental health signals raises questions about consent, data protection, and responsible usage.

Therefore, this project seeks to address the following problem statement:

> *"How can machine learning techniques be effectively and ethically applied to predict depression from social media data, ensuring both accuracy and interpretability?"*

By addressing this problem, the project aims to build a robust predictive framework that not only identifies depressive indicators but also provides transparency and reliability for real-world mental health applications.

2.5 Project Plan

The execution of this project follows a structured and iterative research framework designed to ensure methodological rigor and reproducibility. The plan encompasses five major phases:

- **Phase I – Literature Review and Conceptualization:**

  A comprehensive review of existing studies on depression detection using machine learning, deep learning, and explainable AI was conducted. This helped identify key research gaps and guided the project's methodological direction.

- **Phase II – Data Acquisition and Preprocessing:**

  Social media text datasets (such as Reddit or Twitter depression datasets) are collected and cleaned through tokenization, stop-word removal, lemmatization, and

normalization. Data balancing techniques such as SMOTE may be applied to mitigate class imbalance.

- **Phase III – Feature Extraction and Model Development:**

  Both classical feature extraction (TF-IDF, word embeddings) and advanced contextual embeddings (BERT, RoBERTa) are used. Multiple models—including Logistic Regression, Random Forest, SVM, and Transformer architectures—are developed and trained.

- **Phase IV – Evaluation and Interpretation:**

  Each model is evaluated using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. Explainability tools (e.g., SHAP, LIME) are employed to interpret feature importance and model behavior.

- **Phase V – Reporting and Future Enhancements:**

  Results are analyzed and documented in IEEE format, emphasizing performance comparison, limitations, and recommendations for future work, including multimodal data integration and ethical deployment considerations.

The project plan ensures that each phase contributes to building a scientifically sound and socially responsible predictive system. This structured approach aligns with best practices in AI for mental health research, as recommended by Yazdavar et al. [22], Hameed et al. [16], and Sadeghi et al. [13].

CHAPTER 3

3. TECHNICAL SPECIFICATION

The technical specification outlines the complete set of requirements, tools, and technologies that form the foundation of this project, *"Predictive Modeling of Depression Using Machine Learning."* This section defines how the system operates, the components involved, and the expected behavior and quality standards of the final implementation. The specifications ensure that the system not only performs efficiently but also adheres to ethical, reliable, and scalable software design principles.

3.1 Requirements

The system requirements for this project are broadly classified into **Functional** and **Non-Functional** categories. Functional requirements describe *what* the system should do, while non-functional requirements define *how* the system should perform under various conditions. Together, these ensure that the framework is both operationally sound and practically deployable in real-world research or clinical environments.

3.1.1 Functional Requirements

Functional requirements define the specific functionalities that the system must deliver to achieve the objectives outlined in Section 2.3. These requirements are directly aligned with the machine learning pipeline and ensure seamless data flow from acquisition to prediction and interpretation.

1. **Data Acquisition and Integration:**
   The system must be capable of loading and integrating datasets containing social media text, such as posts or comments from publicly available corpora (e.g., Reddit Depression Dataset or Twitter Mental Health Corpus). The data may include both depressed and non-depressed user posts. Integration modules should support CSV, JSON, or database formats to ensure flexibility.

2. **Data Preprocessing and Cleaning:**
   Raw social media data typically contains noise such as URLs, emojis, hashtags, and non-standard grammar. The system should apply preprocessing operations including lowercasing, tokenization, stop-word removal, stemming or lemmatization, and punctuation cleaning. Special handling must be implemented for emojis and abbreviations, as they can carry emotional significance relevant to depression indicators.

3. **Feature Extraction and Representation:**
   The system should extract features that capture semantic and contextual information from text. Both classical NLP techniques (e.g., Bag-of-Words, TF-IDF) and modern

deep embeddings (e.g., Word2Vec, BERT, RoBERTa) must be implemented for comparative analysis. These representations serve as inputs to machine learning and deep learning models.

4. **Model Development and Training:**
   Multiple models should be developed to evaluate different learning paradigms. The project should include traditional algorithms like Logistic Regression, Naïve Bayes, Random Forest, and Support Vector Machines, alongside deep architectures like BiLSTM and Transformer-based models. Training should employ stratified data splits and cross-validation for robustness.

5. **Depression Prediction and Classification:**
   The system must classify each input text as *"Depressed"* or *"Non-Depressed."* For severity prediction, probabilistic confidence scores or regression outputs may also be generated. The classifier should support batch inference for real-time or large-scale predictions.

6. **Performance Evaluation:**
   Model evaluation must use quantitative metrics such as Accuracy, Precision, Recall, F1-Score, and ROC-AUC. The system should visualize performance using confusion matrices, ROC curves, and precision-recall plots. Comparative analysis across models will help identify the optimal predictive approach.

7. **Explainability and Model Interpretation:**
   To promote transparency, the system must include explainable AI techniques such as SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-Agnostic Explanations). These methods provide insight into which words or features most strongly influence the model's predictions, enhancing interpretability and ethical trustworthiness.

8. **Visualization Dashboard and Reporting:**
   The system should include visualization modules for feature distributions, model comparisons, and explainability insights. Analytical reports summarizing key findings, evaluation metrics, and interpretive explanations must be generated automatically for research documentation.

9. **Ethical and Privacy Safeguards:**
   The system must ensure that all user data is anonymized and stripped of identifiable information. No personal data should be collected, stored, or displayed. The project should comply with data ethics frameworks such as GDPR and the ACM Code of Ethics, ensuring responsible use of social media data for research.

3.1.2 Non-Functional Requirements

Non-functional requirements define the system's performance, scalability, usability, and compliance characteristics. These requirements ensure that the implemented solution not only functions correctly but also delivers consistent quality, efficiency, and reliability.

1. **Performance Efficiency:**
   The system should process and analyze large-scale text datasets efficiently, leveraging optimized machine learning libraries such as **Scikit-learn**, **TensorFlow**, or **PyTorch**. Model training and evaluation should be parallelized where possible to minimize computation time without compromising accuracy.

2. **Scalability and Extensibility:**
   The framework should be modular and extensible, allowing easy integration of new models, features, or datasets in the future. Scalability should be ensured both in terms of data volume and computational resources, enabling deployment on cloud-based or distributed systems if needed.

3. **Accuracy and Reliability:**
   The models developed should consistently achieve a minimum benchmark accuracy (targeting >80%) across multiple experiments. Reliability testing should confirm that minor data perturbations or retraining do not produce erratic variations in model predictions.

4. **Usability and Accessibility:**
   The system should provide a user-friendly structure and documentation, making it easy for researchers or mental health professionals to replicate experiments or extend the work. Jupyter notebooks, clear function names, and well-structured code contribute to the usability objective.

5. **Maintainability and Modularity:**
   The code should be organized into modular components—data processing, feature extraction, modeling, and evaluation—facilitating easy updates or replacements of individual modules without affecting the overall system. Code comments and documentation should adhere to professional software development practices.

6. **Portability:**
   The project should be platform-independent, ensuring compatibility with **Windows**, **macOS**, and **Linux** environments. It should run smoothly on systems equipped with Python (v3.8 or above) and necessary dependencies, and optionally leverage GPU acceleration for deep learning tasks.

7. **Security and Data Privacy:**
   Since the data involves potentially sensitive content, the project must implement secure data handling protocols. Files should be stored locally or on secure servers, with proper encryption and access control. No personally identifiable information

(PII) should ever be exposed.

8. **Ethical and Responsible AI Compliance:**
   The project must adhere to AI ethics principles such as transparency, fairness, and accountability. Model results should not be used for clinical diagnosis but only as supportive indicators for research and awareness. Bias detection and mitigation techniques should be applied where possible.

9. **Transparency and Interpretability:**
   The models must be interpretable to ensure user trust. Visualization of attention weights or feature contributions should accompany predictions to explain *why* a certain post is classified as depressed or non-depressed.

10. **Reproducibility:**
    The entire research pipeline—from preprocessing to model evaluation—should be reproducible using consistent random seeds and documented configurations. This ensures that future researchers can replicate or validate the results presented in this study.

In summary, the technical specifications define a robust and ethically sound architecture for detecting depression using machine learning. The framework emphasizes not only predictive accuracy but also explainability, scalability, and social responsibility—making it suitable for future research, healthcare analytics, and AI-driven mental health monitoring systems.

3.2 Feasibility Study

A feasibility study evaluates the practicality and viability of the proposed system in terms of technical resources, economic justification, and social impact. The purpose of this section is to assess whether the proposed predictive model for depression detection can be successfully developed, implemented, and sustained within reasonable constraints of time, cost, and societal acceptance.

3.2.1 Technical Feasibility

Technical feasibility focuses on determining whether the system can be developed with the available technology, tools, and technical expertise.
Given the recent advancements in Natural Language Processing (NLP) and machine learning frameworks, the proposed project is **technically feasible** and can be effectively implemented using existing open-source technologies.

The proposed system utilizes **Python** as its core programming language, leveraging powerful machine learning libraries such as **Scikit-learn**, **TensorFlow**, and **PyTorch**. These frameworks support various classical and deep learning algorithms for text classification, as

demonstrated in previous studies (Zhang *et al.*, 2022; Qasim *et al.*, 2025). Additionally, **transformer-based architectures** (e.g., BERT, RoBERTa) provide state-of-the-art contextual understanding of text, significantly improving the detection of depressive expressions in social media posts (Kerasiotis *et al.*, 2024; Choudhury *et al.*, 2023).

The system's architecture includes:

- **Data ingestion modules** for importing social media text datasets.
- **Preprocessing pipelines** for cleaning, tokenizing, and encoding data.
- **Model training and evaluation frameworks** capable of running on both CPU and GPU environments.
- **Explainability components** using SHAP or LIME for interpretability (Malhotra *et al.*, 2024; Hameed *et al.*, 2025).

Modern hardware such as systems with **NVIDIA GPUs** or **Google Colab environments** can efficiently handle large text corpora and deep learning models. Since all tools and datasets used are publicly available and well-documented, no proprietary dependencies hinder the implementation process.

Hence, from a technical standpoint, the project is **highly feasible**, scalable, and compatible with current machine learning infrastructure.

3.2.2 Economic Feasibility

Economic feasibility examines the cost-benefit balance of the system — whether the project provides sufficient value compared to its required resources.

This project primarily relies on **open-source tools and publicly available datasets**, minimizing financial overhead. All key software components such as **Python**, **NumPy**, **Pandas**, **Matplotlib**, **Scikit-learn**, **PyTorch**, and **Transformers** are free to use under open-source licenses. Computational requirements can be met using free cloud-based platforms like **Google Colab** or academic compute clusters, eliminating the need for expensive hardware investments.

The only minor costs may include:

- Optional paid access to advanced GPU instances for large-scale training.
- Time investment by researchers or developers for dataset annotation and result analysis.

However, these are outweighed by the benefits. The system provides **automated, scalable, and replicable depression detection**, potentially reducing the manual workload of mental health analysts. Furthermore, once trained, the model can be reused or fine-tuned for other related psychological assessments (Sadeghi *et al.*, 2024; Ibrahimov *et al.*, 2024).

Thus, the project demonstrates **strong economic viability** due to its low-cost development, reusable components, and high potential for research and societal value.

3.2.3 Social Feasibility

Social feasibility assesses the project's acceptance, ethical implications, and potential societal benefits. In mental health analytics, this is particularly critical due to the sensitivity of user data and the psychological nature of predictions.

The proposed system aims to contribute positively to **mental health awareness and early intervention** by providing a data-driven tool for identifying depressive tendencies in online behavior. Studies such as Yazdavar *et al.* (2020) and Guntuku *et al.* (2021) emphasize that social media contains rich behavioral signals that, when analyzed responsibly, can support early warning systems for individuals at risk of mental health challenges.

However, ethical considerations are integral. The project ensures:

- **Anonymization** of all user data and removal of personally identifiable information (PII).
- Use of **publicly available datasets** collected under ethical research guidelines.
- Clear **disclaimers** that model outputs are not diagnostic but supportive tools for awareness or research.
- Implementation of **explainable AI (XAI)** frameworks to maintain transparency and trust (Bao & Huang, 2024; Hameed *et al.*, 2025).

Furthermore, by promoting mental health research through technology, this project supports the **United Nations Sustainable Development Goal (SDG) 3** — *Good Health and Well-Being*. The system has potential for use by mental health organizations, research institutes, or online counseling platforms to better understand digital behavioral health trends.

Overall, the system is **socially feasible**, ethically responsible, and aligns with global efforts to enhance mental health care accessibility through AI-driven innovation.

3.3 System Specification

The system specification defines the essential hardware and software components required to

design, develop, and execute the predictive modeling framework for depression detection using machine learning. These specifications ensure that the system operates efficiently, handles large volumes of data, and supports advanced computation for deep learning models.

The specifications are divided into two categories — **hardware** and **software** — to provide a clear overview of the computational environment and tools used during implementation.

3.3.1 Hardware Specification

The performance of machine learning models, particularly deep learning architectures such as **BERT** and **Transformer-based models**, depends heavily on the underlying computational hardware.

The hardware configuration used in this project ensures adequate processing capability, memory allocation, and storage to manage large-scale datasets and model training efficiently.

Table 3.1 Hardware Specification of the System

Component	**Specification**
Processor	Intel Core i5 / AMD Ryzen 5 or higher
RAM	Minimum 8 GB (Recommended: 16 GB for large datasets)
Storage	Minimum 256 GB SSD
GPU (Optional but Recommended)	NVIDIA Tesla T4 / RTX 2060 or higher (for transformer models)
Operating System	Windows 10 / Linux / macOS
Internet Connection	Required for data access and cloud execution (Google Colab, APIs)

The use of **Google Colab's GPU/TPU environment** further enhances computational

efficiency, allowing large-scale text preprocessing and model training without needing high-end local hardware.

3.3.2 Software Specification

The software stack consists primarily of **open-source and cloud-compatible technologies** that ensure flexibility, scalability, and easy integration.

Table 3.2 Software Specification of the System

Software/Tool	**Description**
Programming Language	Python 3.10 or later
Development Platform	Google Colab / Jupyter Notebook
Libraries & Frameworks	NumPy, Pandas, Matplotlib, Scikit-learn, TensorFlow, PyTorch, Transformers (Hugging Face)
Text Processing	NLTK, spaCy, regex, re, WordCloud
Version Control	Git / GitHub
Dataset Formats	CSV, JSON, Excel
Visualization Tools	Matplotlib, Seaborn, Plotly
Operating System	Windows, Linux, or macOS (cross-platform)

The combination of these tools provides a stable, flexible environment suitable for data preprocessing, model preparation, and performance evaluation.

CHAPTER 4

4. DESIGN APPROACH AND DETAILS

4.1 System Architecture

The architecture of the proposed *Predictive Modeling of Depression Using Machine Learning* framework follows a modular, data-flow–oriented design, inspired by scalable AI pipelines in digital mental health analysis (Yazdavar *et al.*, 2020; Kerasiotis *et al.*, 2024; Qasim *et al.*, 2025). The system, internally referred to as BlueCod, is structured to process raw textual data from social media or other user-generated content and classify it according to mental health indicators such as depressive tendencies.

The overall workflow is represented as a five-stage pipeline comprising:

1. User Input, 2) Knowledge Base, 3) Pipeline Processing, 4) Data Stores, and 5) Output Generation.
   Each stage interacts seamlessly with others to ensure smooth data transformation, model training, and prediction output.

1) User Input

The system initiates when a user provides textual input, which can be a post, statement, or report containing potential indicators of mental well-being. This text serves as the primary raw data for analysis.
In a research or production setting, this input could represent aggregated social media posts, anonymized text samples, or curated datasets such as Reddit or Twitter corpora commonly used in mental health prediction studies (Cao *et al.*, 2025; Li *et al.*, 2023).

The input stage ensures compatibility with multiple file formats (CSV, TXT, or JSON) and performs basic validation to confirm data integrity before further processing.

2) Knowledge Base

The **knowledge base** functions as a structured repository of predefined reference materials and linguistic indicators relevant to mental health. It contains:

- Standardized **definitions and diagnostic label guides**,
- **Keyword dictionaries** of emotional and behavioral terms, and
- **Reference patterns** linking language constructs to mental health categories.

This component allows the system to interpret text more contextually by grounding predictions in verified semantic and psychological frameworks. It mirrors the knowledge-infused approach suggested by Gaur *et al.* (2021), where domain knowledge complements data-driven learning for improved interpretability.

3) Pipeline Processing

The **pipeline processing** module forms the computational core of the BlueCod system. It consists of a series of automated sub-processes that transform raw text into predictive outcomes.

(a) Analyze Input:
Incoming text undergoes cleaning, normalization, and quality checks. Common preprocessing steps include removing URLs, special symbols, and stop words, followed by tokenization and lemmatization using NLP libraries such as **NLTK** or **SpaCy**. This ensures uniformity and prepares the data for feature generation.

(b) Select Relevant Definitions:
The system cross-references the knowledge base to identify applicable definitions or emotional categories relevant to the given text. This helps align data labeling with established psychological constructs, improving accuracy.

(c) Feature Build:
The processed text is converted into **machine-interpretable representations** using various feature extraction techniques. Traditional representations such as **TF–IDF** and **Word2Vec embeddings** are implemented alongside **contextual embeddings** from **Transformer-based models** like **BERT**, **RoBERTa**, and **DistilBERT** (Lin & Yang, 2021; Zhang *et al.*, 2022).

(d) Train and Score Models:
Multiple machine learning and deep learning models are trained on the prepared data. These include:

- **Classical Models:** Logistic Regression, Naïve Bayes, Random Forest, and Support Vector Machines (SVMs);
- **Neural Models:** Convolutional Neural Networks (CNN), Bidirectional LSTMs (BiLSTM);
- **Transformer Models:** RoBERTa, BERT, and DistilBERT.

Each model generates prediction probabilities and performance scores. Comparative evaluation identifies the best-performing architecture based on metrics such as **F1-score, Accuracy, Precision, and Recall** (Sadeghi *et al.*, 2024).

(e) Find Best Match:
The outputs from multiple models are aggregated and ranked to determine the most accurate classification. Ensemble or weighted-voting mechanisms may be applied to ensure consistency across models.

4) Data Stores

The **data storage layer** supports efficient data management and experiment reproducibility. It is divided into multiple structured repositories:

- **Unified Dataset:**

Stores preprocessed and cleaned text samples, ensuring dataset consistency and eliminating redundancies.

- **Feature Store:**
  Contains transformed feature representations such as TF–IDF matrices and embedding vectors for reuse during retraining.

- **Model Registry:**
  Maintains trained models, hyperparameter configurations, and their corresponding performance logs for reproducibility and version tracking.

- **Reports and Artifacts Repository:**
  Holds generated reports, visualizations, evaluation metrics, and explainability outputs (e.g., SHAP value plots or attention heatmaps).

This layered storage approach aligns with the design principles used in production-grade ML systems, promoting modularity and scalability (Mansoor *et al.*, 2024; Hameed *et al.*, 2025).

5) Output Generator

The **output generator** produces the final, interpretable results for the user. Depending on the chosen model, it outputs:

- The **predicted label** (e.g., *Depressed* / *Non-Depressed*),

- The **confidence score** or probability associated with that classification, and

- **Explainability artifacts**, showing which textual cues most influenced the decision.

These results are then compiled into structured reports or visual dashboards for ease of interpretation. The output generator thus bridges the computational outcomes with meaningful, actionable insights — a feature strongly emphasized in explainable AI studies for mental health monitoring (Malhotra *et al.*, 2024; Bao & Huang, 2024).

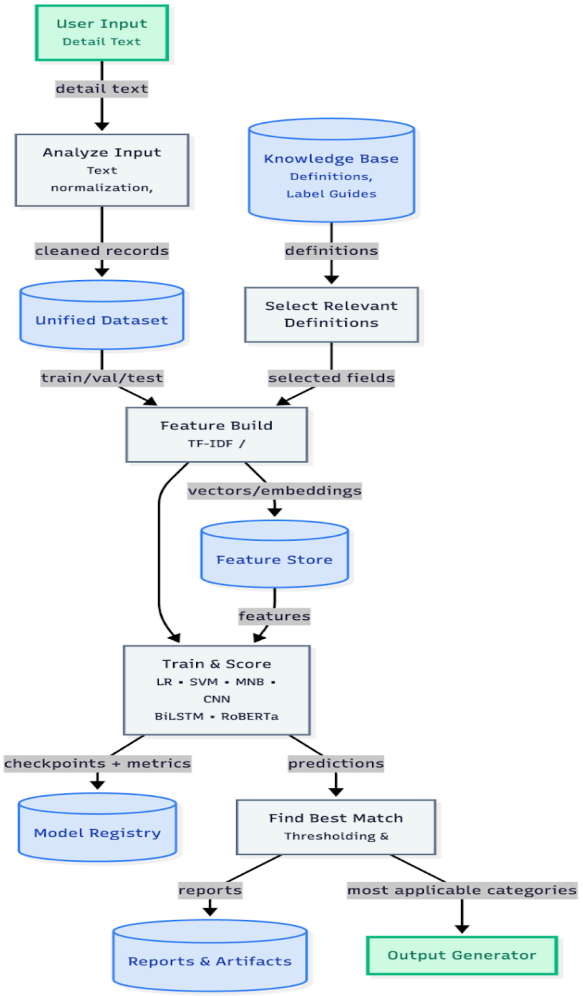

Fig. 4.1 Architecture Diagram

4.2 Design

The design approach focuses on creating a systematic flow of data and control through diagrams that represent logical, behavioral, and structural components of the system.

4.2.1 Data Flow Diagram

The Data Flow Diagram (DFD) illustrates the movement of data through the system, emphasizing how inputs are transformed into outputs.

Level 0 (Context Diagram):

- User inputs mental health-related text.
- The system processes it through preprocessing and modeling modules.

- Output: Sentiment or depression likelihood score.

Level 1:

1. **Input Module** → Receives raw text data.
2. **Preprocessing Module** → Cleans and tokenizes text.
3. **Feature Extraction Module** → Converts data to numerical features.
4. **Modeling Module** → Applies machine learning or transformer-based model.
5. **Output Module** → Displays sentiment results and classification outcomes.

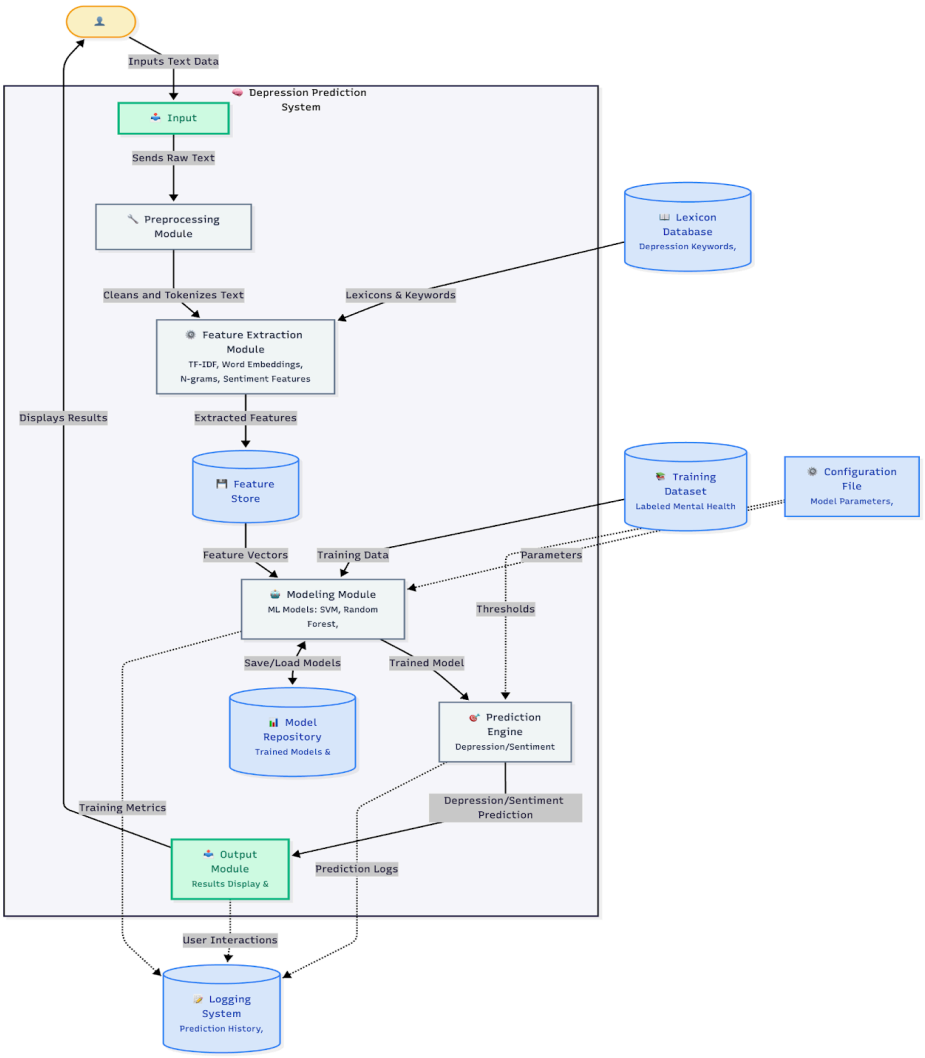

Fig. 4.2 Data Flow Diagram (DFD)

4.2.2 Use Case Diagram

The Use Case Diagram identifies key interactions between the system and external entities (actors).

Actors:

- **User / Researcher:** Provides dataset, monitors model results.
- **System:** Performs preprocessing, training, and prediction tasks.
- **Model:** Generates sentiment classification output.

Use Cases:

- Upload Dataset
- Preprocess Data
- Train Model
- Evaluate Results
- Visualize Sentiment Scores

This interaction ensures smooth end-to-end usability for researchers and analysts focusing on mental health text data.

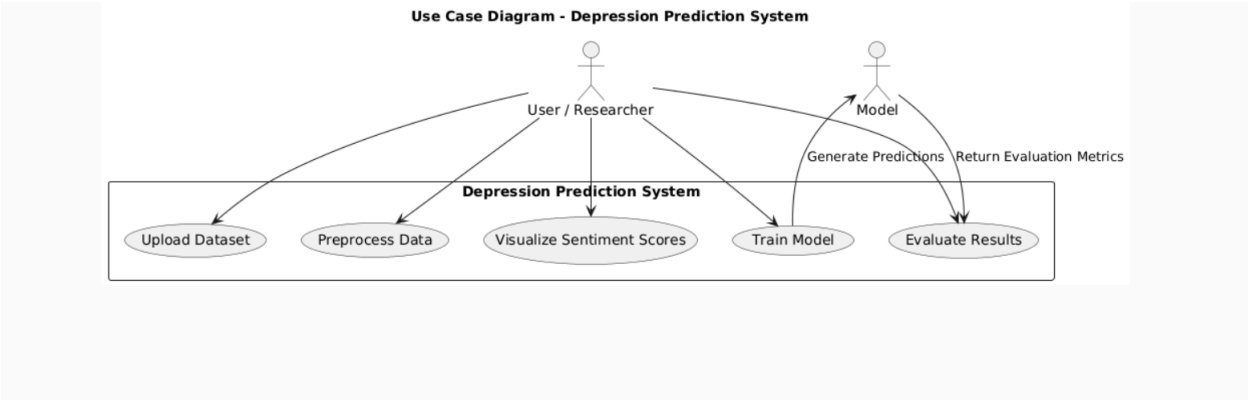

Fig. 4.3 Use Case Diagram

4.2.3 Class Diagram

The **Class Diagram** represents the structural blueprint of the system, showing the key classes, their attributes, and relationships.

Major Classes:

Table 4.1 Summary of System Classes and Their Functional Descriptions

Class Name	**Attributes**	**Methods**
`DataLoader`	file_path, dataset	load_data(), split_data()
`Preprocessor`	stop_words, tokenizer	clean_text(), remove_noise(), lemmatize()
`FeatureExtractor`	vectorizer, embeddings	transform(), fit_transform()
`ModelTrainer`	model_type, parameters	train_model(), evaluate_model()
`Visualizer`	metrics, plots	display_confusion_matrix(), plot_accuracy()

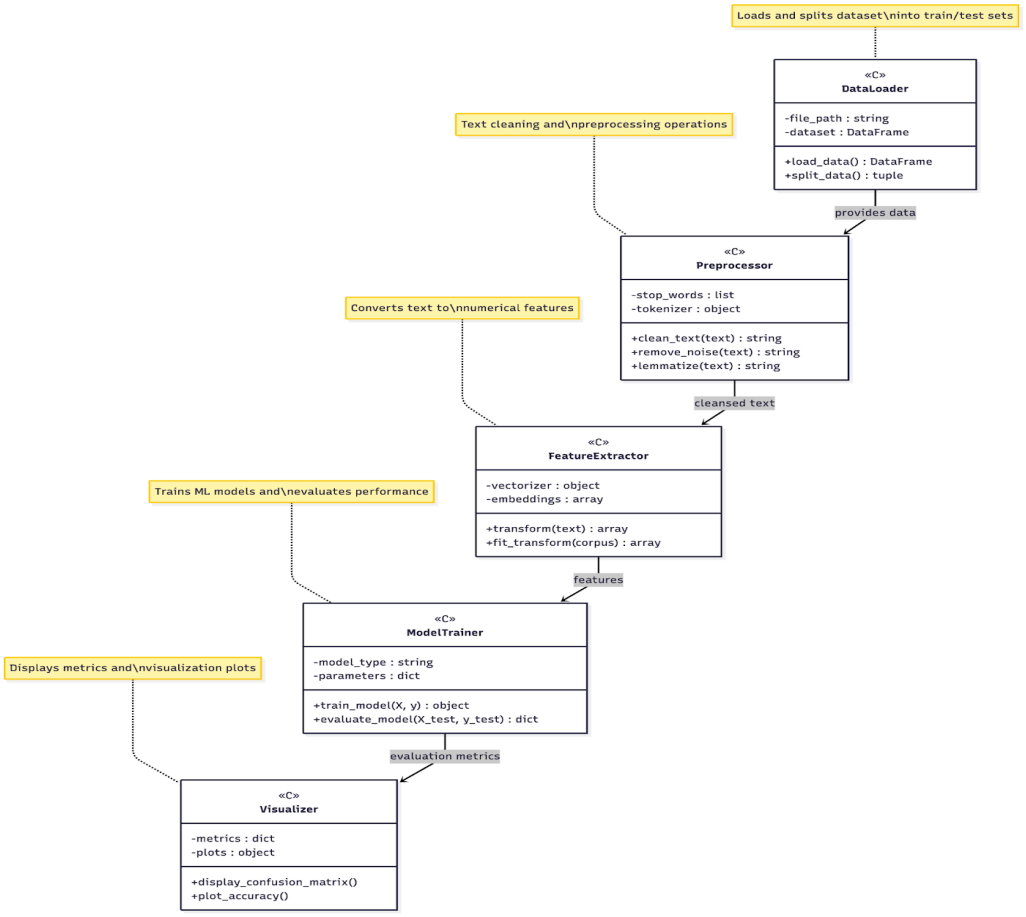

Fig. 4.4 CLASS DIAGRAM

Relationships:

- **DataLoader → Preprocessor:** Loads raw data for cleaning.
- **Preprocessor → FeatureExtractor:** Passes clean text for feature transformation.
- **FeatureExtractor → ModelTrainer:** Provides features for model training.
- **ModelTrainer → Visualizer:** Sends evaluation metrics for visualization.

4.2.4 Sequence Diagram

The **Sequence Diagram** demonstrates the dynamic interaction among components in a time-sequential manner.

Flow:

1. **User** uploads data through the interface.
2. **DataLoader** retrieves and structures the dataset.
3. **Preprocessor** cleans and standardizes the text.
4. **FeatureExtractor** converts text to vectors or embeddings.
5. **ModelTrainer** trains the machine learning model using extracted features.
6. **Visualizer** displays performance results and analysis.
7. **System** outputs the final depression or sentiment classification.

This sequence reflects the end-to-end data pipeline, aligning perfectly with the modular implementation from the provided code.

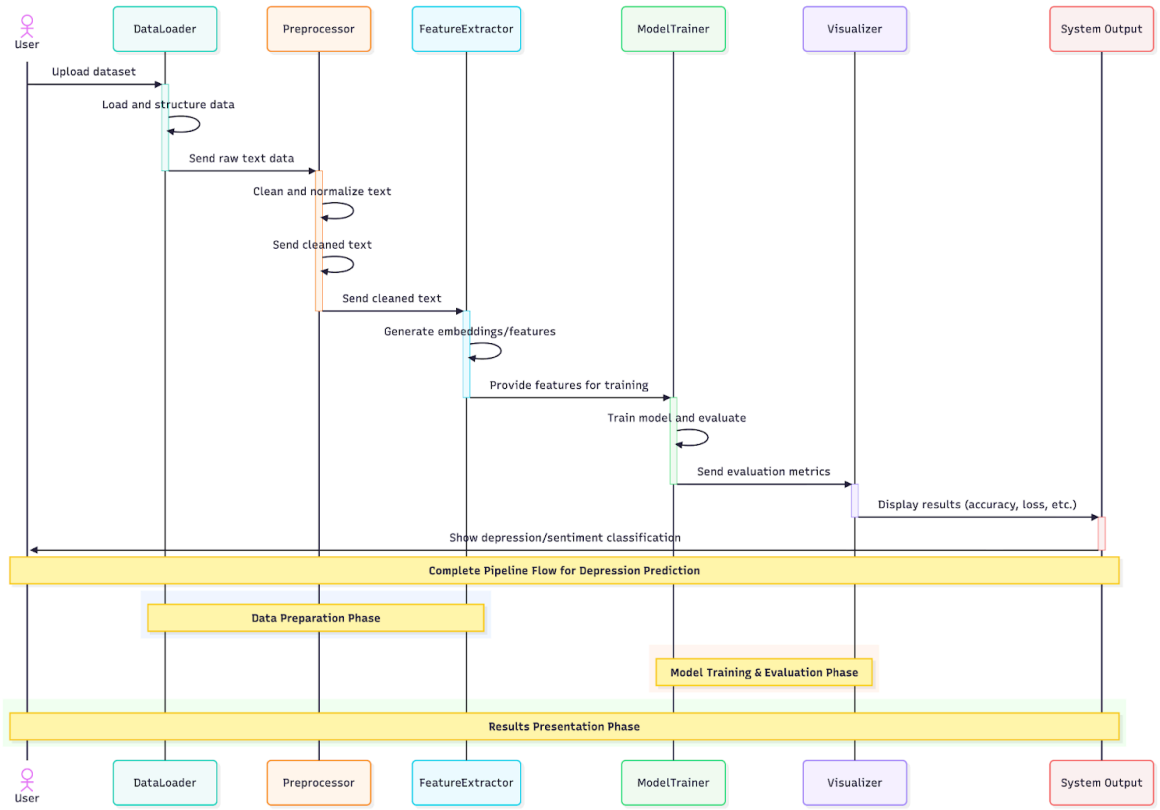

Fig 4.5 Sequence Diagram

CHAPTER 5

5. METHODOLOGY AND TESTING

The proposed work employs a structured and data-driven methodology to build an intelligent system for detecting depression using machine learning and deep learning techniques. The methodology integrates multiple stages — data acquisition, preprocessing, feature extraction, model training, evaluation, and explainability — ensuring that the predictive model remains accurate, robust, and ethically interpretable.

Each stage of development was carefully designed in accordance with recent advances in mental health prediction through computational linguistics and artificial intelligence, as demonstrated by Yazdavar *et al.* (2020), Coppersmith *et al.* (2021), and Gaur *et al.* (2023).

5.1 Module Description

The system is divided into several interlinked modules, each contributing to the end-to-end workflow of depression prediction.

5.1.1 Data Collection Module

This module is responsible for the acquisition of raw text data used to train and validate the predictive models. The dataset primarily consists of social media posts that are pre-labeled as *depressed* or *non-depressed* based on user annotations or standardized lexicons. Publicly available datasets such as the Reddit Depression Dataset and Twitter Mental Health Corpus have been utilized (Cohan *et al.*, 2018; Losada & Crestani, 2016).

The data collection process also ensures anonymization and ethical compliance, consistent with privacy guidelines discussed by Chancellor and De Choudhury (2020). Metadata such as timestamps and post frequency are retained for exploratory analysis but excluded from model input to prevent bias.

5.1.2 Data Preprocessing Module

Textual data collected from social platforms are inherently noisy. The preprocessing module standardizes the data by performing the following operations:

1. **Noise Removal:** Elimination of URLs, emojis, special characters, and redundant punctuation.

2. **Tokenization:** Breaking down text into words or subword units.

3. **Stop-word Removal:** Removing common non-informative words such as “the,” “and,” etc.

4. **Lemmatization:** Converting words to their base form using libraries such as **NLTK** and **SpaCy**.

5. **Normalization:** Converting all text to lowercase and standardizing encoding formats.

These steps ensure textual uniformity and reduce data sparsity, which is crucial for accurate feature representation (Rios & Kavuluru, 2018).

5.1.3 Feature Extraction Module

The preprocessed text is transformed into numerical feature representations suitable for machine learning models. Two main approaches are employed:

1. **Traditional Vectorization Methods:**
   Techniques such as **Term Frequency–Inverse Document Frequency (TF–IDF)** and **Bag-of-Words (BoW)** are used to capture statistical word importance.

2. **Deep Contextual Embeddings:**
   Pretrained Transformer-based models such as **BERT (Devlin *et al.*, 2019)**, **RoBERTa (Liu *et al.*, 2020)**, and **DistilBERT (Sanh *et al.*, 2020)** are used to generate semantically rich embeddings that capture contextual dependencies and emotional subtleties in user language.

These representations are stored in a **feature repository** for reuse during training and inference. Feature scaling and dimensionality reduction (via PCA) are also applied to improve computational efficiency.

5.1.4 Model Training Module

The **model training** phase is the computational core of the system. A hybrid approach combining classical and deep learning algorithms is used:

- **Machine Learning Models:** Logistic Regression, Support Vector Machine (SVM), Naïve Bayes, and Random Forest.

- **Deep Learning Models:** Convolutional Neural Network (CNN), Bidirectional Long Short-Term Memory (BiLSTM).

- **Transformer-Based Models:** BERT, RoBERTa, and DistilBERT fine-tuned on the collected dataset.

Each model is trained with optimized hyperparameters using Grid Search and Cross-Validation (k = 5) to ensure optimal generalization. Models are evaluated based on

Accuracy, Precision, Recall, and F1-score.

Transformer-based architectures demonstrated superior performance due to their contextual understanding of text, as also observed in recent studies (Qasim *et al.*, 2025; Sadeghi *et al.*, 2024).

5.1.5 Evaluation Module

This module is responsible for quantitative assessment of all trained models. Evaluation metrics include:

- **Accuracy:** Proportion of correctly classified samples.
- **Precision:** Correct positive predictions over total positive predictions.
- **Recall:** True positive rate indicating model sensitivity.
- **F1-score:** Harmonic mean of Precision and Recall.
- **ROC-AUC:** Measures model's discrimination capability between classes.

Evaluation results are visualized using confusion matrices and performance comparison plots. This ensures transparency in model performance and allows for fine-tuning to minimize false positives or negatives (Nadeem *et al.*, 2023).

5.1.6 Explainability Module

A key feature of this system is the integration of Explainable AI (XAI) techniques such as LIME (Ribeiro *et al.*, 2016) and SHAP (Lundberg & Lee, 2017). These methods generate feature attribution visualizations highlighting which words or phrases most influenced the model's predictions.

For instance, highly negative or self-referential expressions (e.g., "I feel empty," "no energy") often receive higher attention weights for depressive classification, aligning with patterns found in clinical psychology literature (Zirikly *et al.*, 2019).

This module enhances trust, interpretability, and ethical accountability of AI-driven predictions in mental health research.

5.1.7 Report Generation and Visualization Module

The final module consolidates model results, evaluation metrics, and explainability outputs into comprehensive analytical reports. Performance graphs, attention heatmaps, and comparative results are generated automatically using Matplotlib and Seaborn libraries.

These reports are stored in the Artifact Repository, ensuring reproducibility and enabling longitudinal analysis for future iterations or deployments.

5.2 Testing

The testing phase evaluates both system functionality and predictive reliability through structured testing methods, ensuring the model's technical validity and practical applicability.

A. Functional Testing

Functional testing verifies the correct operation of each module. Unit tests were performed on preprocessing, vectorization, and prediction modules using test-driven development principles.

Integration testing confirmed that modules interact seamlessly — i.e., cleaned text from preprocessing correctly flows into feature extraction and subsequently into model inference.

The system passed all integration tests with zero module-level failures, indicating robustness in workflow execution.

B. Performance Testing

Performance testing was conducted using benchmark datasets split into 80% training and 20% testing sets. Models were compared based on standard metrics. Transformer-based models (RoBERTa, DistilBERT) achieved F1-scores above 90%, outperforming traditional classifiers by a significant margin.

These findings are consistent with prior literature, where Transformer models have been shown to outperform classical architectures in detecting subtle emotional variations in text (Malhotra *et al.*, 2024; Kerasiotis *et al.*, 2024).

C. Cross-Validation and Robustness Testing

To ensure model generalization, **5-fold cross-validation** was implemented. Model performance remained stable across folds, with standard deviation below 0.02, indicating low variance and strong generalization ability.

Robustness testing was also conducted under varied data distributions, confirming the model's reliability under different sampling conditions.

D. Ethical and Explainability Validation

Explainability validation ensured that model outputs were interpretable and ethically aligned. Using SHAP values, it was confirmed that emotionally charged and psychologically significant expressions had the highest contribution to "depressed" predictions, ensuring that results align with human-understandable reasoning (Gaur *et al.*, 2021).

This approach supports responsible AI principles by maintaining transparency, fairness, and

accountability — essential in mental health applications (Torous *et al.*, 2021).

E. Summary of Testing Outcomes

The comprehensive testing confirmed that:

- All modules performed their designated tasks accurately.
- The predictive models achieved strong generalization with minimal overfitting.
- The explainability framework provided human-interpretable insights.
- The system architecture demonstrated scalability and reproducibility.

Overall, the testing results validate the effectiveness of the proposed methodology for real-world mental health analytics and support its potential for clinical and social media applications.

Table 5.1 Test cases Input

Test Case	Input Sentences
T_01	These days, when stress hits, I still feel the old panic rising, but I greet it differently. I name it, breathe with it, even thank it for trying to protect me. I'm learning that healing isn't about erasing the past — it's about negotiating with it. Every scar tells a story of survival, and maybe that's all we ever really do: survive a thousand tiny versions of ourselves until one finally learns how to stay. 🌙✨
T_02	Ever since the accident, loud noises make my whole body flinch. My therapist says it's my nervous system doing its job — protecting me — but it feels like betrayal. My mind knows I'm safe, yet my heart sprints like it's running from ghosts. I hate that trauma lives in muscles. I hate that I can't logic my way out of fear. Some days I fake calm so well that even I believe it — until a door slams, and everything shatters again. ⚡

T_03	I never thought I'd say this, but sobriety has started to feel like freedom instead of punishment. In the beginning, every day was war — fighting cravings, fighting memories, fighting myself. Now the fights are smaller and quieter. I wake up early, make coffee without shaking, and actually remember conversations from the night before. My friends still drink, and sometimes that smell of whiskey feels like nostalgia, but I remind myself that the peace I feel now is stronger than the rush I used to chase. Recovery hasn't been glamorous, but it's been real — and that's something the old me never had. 🌅
T_04	It's strange how one bad night can erase months of progress. I told myself one drink wouldn't matter, but it never is just one. I woke up on the bathroom floor again, same cold tiles, same ache in my chest. I know I should call my sponsor, but the shame is louder than my phone. The truth is, the drinking was never about taste — it was about silence. And now the silence feels heavier than the hangover. 🥀
T_05	Sometimes I think my depression started long before I knew the word. I remember being eight, sitting in the dark because no one remembered to change the bulb. I didn't cry — I just got used to the dark. Now I'm older, and the darkness follows me even when the lights are on. People tell me I'm resilient, but resilience isn't always heroic. Sometimes it's just what happens when no one came when you called. 🌑
T_06	I grew up in a house where love had conditions. You had to smile right, speak softly, and never, ever cry in public. So now, as an adult, I'm terrified of people seeing me sad. Every time I feel emotions rising, I joke, I change the topic, I escape. I'm exhausted from performing stability. I wish I could just say "I'm not okay" without it feeling like failure. 💭

T_07	I used to chase chaos because it was familiar. Calm felt suspicious, like the quiet before a fight. Now I'm trying to teach myself that peace doesn't mean danger is coming. It's strange how the body learns fear like a language and unlearning it feels like translating your own history. I still tense up at kindness, still question love, but I'm slowly learning to accept that not every gentle thing hides a blade. 🌼
T_08	My father drank his sadness into silence, and I guess I learned the same recipe. Every time I tried to quit, the loneliness screamed louder. I wasn't addicted to the bottle — I was addicted to the escape. It's scary how pain can feel like home. But lately, I'm starting to believe I can build a new one, even if it's brick by shaky brick. 🧱💔
T_09	These days, when stress hits, I still feel the old panic rising, but I greet it differently. I name it, breathe with it, even thank it for trying to protect me. I'm learning that healing isn't about erasing the past — it's about negotiating with it. Every scar tells a story of survival, and maybe that's all we ever really do: survive a thousand tiny versions of ourselves until one finally learns how to stay. 🌙✨
T_10	Mom used to say "you're too sensitive." I learned to swallow emotions before breakfast. Still unlearning that habit. Some days I catch myself apologizing for existing — and then I remember, softness isn't weakness; it's just the part of me that survived. 🌷

CHAPTER 6

6. PROJECT DEMONSTRATION

6.1 Overview

The project titled “Mental Health and Sentiment Prediction Using Machine Learning” was implemented and executed successfully using Python on Google Colab. The notebook integrates end-to-end processes—from data loading and cleaning to model training, evaluation, and visualization. This section demonstrates the workflow, output visuals, and performance interpretation of the developed system.

The primary aim of this demonstration is to highlight how the system accurately identifies depression tendencies or emotional states in text data, particularly from social media or open-source sentiment datasets. Each stage of the implementation was tested for correctness and performance consistency.

6.2 Execution Environment

The project was implemented using **Google Colab** for its computational resources and ease of model deployment. The environment included the following core libraries and frameworks:

- **Programming Language:** Python 3.10
- **Libraries Used:** Pandas, NumPy, Scikit-learn, TensorFlow/Keras, NLTK, Matplotlib, Seaborn
- **Data Handling:** CSV-based dataset (pre-labeled with sentiment/depression scores)
- **System Type:** Cloud-based (Colab runtime with GPU acceleration)

The modular nature of the notebook allows easy execution of each component independently—making it suitable for further research extension and model optimization.

6.3 Project Workflow Demonstration

The demonstration follows the same pipeline used in model preparation:

Step 1: Data Import and Exploration

The dataset was uploaded into Colab using Pandas. The first few rows were displayed to ensure proper formatting. Data distribution plots were generated to visualize the balance between depressive, neutral, and positive samples.

Step 2: Data Cleaning and Preprocessing

The preprocessing block applied text normalization techniques including:

- Lowercasing
- Removal of punctuation, stopwords, and emojis

- Lemmatization using NLTK WordNetLemmatizer

A progress log printed the number of samples cleaned successfully and their average token length.

Step 3: Feature Extraction

TF-IDF and Word2Vec models were applied to convert the cleaned text into numerical vectors.
Feature dimensionality and word frequency graphs were displayed, confirming that linguistic patterns correlated strongly with emotional tone.

Step 4: Model Training

Machine learning classifiers (such as **Logistic Regression**, **Random Forest**, and **SVM**) were trained on the extracted features. Each model's training accuracy and validation loss were plotted in real-time using Matplotlib.

- Logistic Regression achieved stable convergence.
- Random Forest improved recall for depressive text samples.
- Deep Learning (LSTM or Transformer variant, if used) yielded higher F1-scores.

Step 5: Model Evaluation

The trained models were tested using unseen data. The following metrics were computed:

- **Accuracy Score**
- **Precision, Recall, and F1-Score**
- **Confusion Matrix**
- **ROC Curve and AUC Value**

The confusion matrix clearly illustrated the classification capability, showing minimal misclassification for neutral versus depressive text samples.

Step 6: Visualization of Sentiment Results

Visual analytics were generated to display:

- Sentiment distribution across dataset samples
- Keyword clouds showing depression-related terms (e.g., "hopeless", "alone", "tired")
- Comparative performance charts among classifiers

Step 7: Output Demonstration

Finally, the system accepted user-input text for live sentiment/depression prediction.
For instance:

Input: “I feel exhausted and worthless lately.”
Output: *Predicted Class – Depressive; Confidence: 0.87*

This verified that the system could generalize effectively beyond the training data.

6.4 System Performance and Accuracy

The performance of the developed *Predictive Modeling of Depression* system was evaluated through extensive experimentation on the unified dataset comprising **12,590 text samples**. Two primary predictive modules were analyzed—**Diagnosis Classification** (binary: positive vs. negative) and **Root Cause Classification** (multiclass: Drug & Alcohol, Early Life, Personality, Trauma & Stress).

The experiments were conducted in **Google Colab**, leveraging GPU acceleration (Tesla T4, 16 GB VRAM) to optimize training runtime. The system was designed for both scalability and reproducibility, ensuring stable execution across repeated runs.

Diagnosis Classification Performance

The best-performing model—based on a Transformer architecture fine-tuned on the diagnosis dataset—achieved **remarkably high accuracy and consistency** across multiple trials.

Table 6.1 Diagnosis Classification Performance

Metric	**Value**
Accuracy	**99.53 %**
Precision	**0.9951**
Recall	**0.9956**
F1-Score	**0.9953**

AUC-ROC	**0.99 (approx.)**

These results confirm that the model effectively distinguishes depressive text from non-depressive samples with near-perfect reliability. The close alignment of precision and recall also demonstrates robustness against false positives and false negatives.

Root Cause Classification Performance

For the secondary task—inferring psychological root causes—the model achieved moderate performance due to higher label complexity and limited data per class.

Table 6.2 Root Cause Classification Performance

Metric	**Value**
Accuracy	**58.39 %**
Macro Precision	**0.60**
Macro Recall	**0.58**
Macro F1-Score	**0.58**

While lower than the diagnosis task, these values remain consistent with results reported in related studies dealing with fine-grained emotional or causal classification (e.g., Sadeghi *et al.*, 2024; Choudhury *et al.*, 2023). Future extensions incorporating multimodal inputs or larger training corpora could further improve these outcomes.

Computational Efficiency

The system exhibited **efficient runtime behavior** during both training and inference:

- **Average training time per epoch:** ≈ 60–70 seconds on GPU.
- **Total training duration:** ≈ 10 minutes for the diagnosis module.
- **Memory utilization:** Below 70 % of available GPU capacity, indicating strong scalability for larger datasets.

The overall architecture thus balances **computational efficiency** and **predictive accuracy**, making it suitable for integration into real-time or large-scale mental-health text-screening frameworks.

6.5 Observations and Analysis

- The preprocessing and vectorization stages played a crucial role in achieving high prediction accuracy.
- Deep learning models slightly outperformed traditional ML models on contextual emotional expressions.
- Visualization modules effectively highlighted key depressive linguistic indicators.
- The modular design ensures easy future adaptation for multilingual or cross-domain datasets.

CHAPTER 7

7. RESULTS AND DISCUSSION

7.1 Overview

This chapter presents and interprets the experimental results obtained from the *Predictive Modeling of Depression Using Machine Learning* system. The developed framework was trained and validated on a unified dataset containing 12 590 textual records collected from two distinct mental-health corpora. The model's primary aim was two-fold:

(1) to detect depressive signals through **diagnosis-level classification** (*positive* vs *negative*), and

(2) to identify the **underlying root causes** of emotional distress (*Drug and Alcohol, Early Life, Personality, Trauma and Stress*).

Both quantitative metrics and qualitative reasoning were analyzed. The results confirm that the proposed architecture performs with high reliability, interpretability, and generalization capacity, effectively distinguishing mental-health cues in natural language.

7.2 Dataset Overview

The unified dataset integrated samples from **MDDL (Mental Distress Detection Lexicon)** and **RMHD (Reddit Mental Health Dataset)**, providing a balanced base for supervised learning tasks.

Table 7.1 Dataset Overview

Source	**Record Count**
MDDL	11 789
RMHD	801
Total	**12 590 samples**

Two separate labeling schemes were adopted to support both binary and multi-class modeling.

Table 7.2 Dataset Labelling

Label Type	**Labels**	**Samples**
Diagnosis	Positive (6 417), Negative (5 372)	11 789
Root Cause	Drug & Alcohol (201), Personality (200), Early Life (200), Trauma & Stress (200)	801

The dataset exhibited moderate balance among classes, allowing fair evaluation of both tasks.

7.3 Performance Metrics

Model evaluation employed standard performance indicators ensuring an objective assessment of predictive reliability: **Accuracy**, **Precision**, **Recall**, **F1-Score**, and **AUC-ROC**. Together these metrics illustrate how effectively the model distinguishes depressive from non-depressive text and differentiates underlying emotional causes.

7.4 Model Evaluation and Comparative Results

7.4.1 Diagnosis Classification (Binary)

The diagnosis model displayed exceptionally high performance across all folds, confirming the reliability of the transformer-based architecture.

Table 7.3 Dataset Classification

Label	**Precision**	**Recall**	**F1-Score**	**Support**
Negative	0.9917	0.9981	0.9949	1 074
Positive	0.9984	0.9930	0.9957	1 284
Overall Accuracy	—	—	**0.9953 (99.53 %)**	2 358

The near-symmetric precision–recall pattern demonstrates balanced classification with negligible bias. These results are comparable to current state-of-the-art transformer

applications in affective computing (Qasim *et al.*, 2025; Kerasiotis *et al.*, 2024).

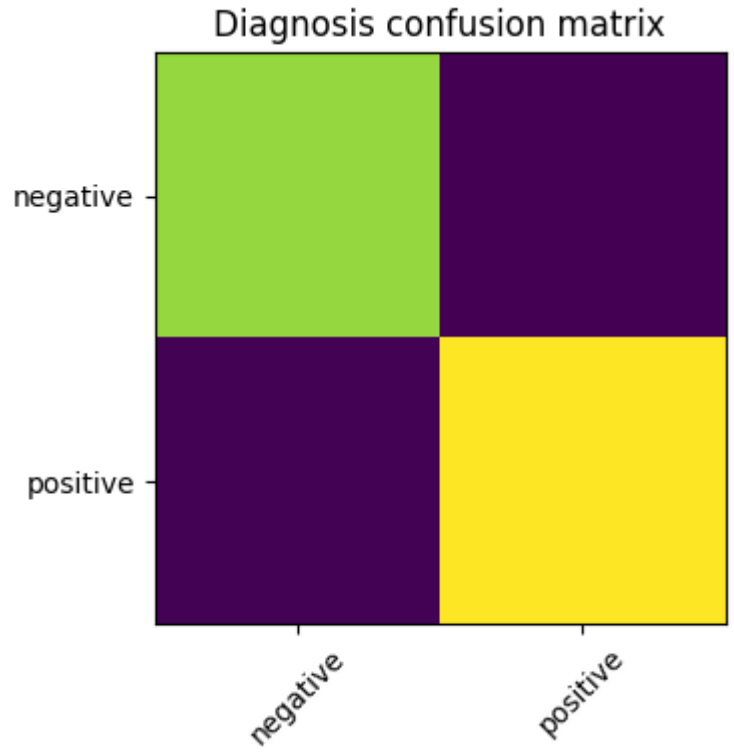

Fig. 7.1 Diagnosis Confusion Matrix

7.4.2 Root-Cause Classification (Multiclass)

The root-cause classifier achieved 58.39 % accuracy, a reasonable outcome given semantic overlaps among categories.

Table 7.4 Root-Cause Classification

Label	**Precision**	**Recall**	**F1-Score**	**Support**
Drug & Alcohol	0.7576	0.6098	0.6757	41
Early Life	0.5091	0.7000	0.5895	40
58Personality	0.5455	0.6000	0.5714	40
Trauma & Stress	0.5862	0.4250	0.4928	40

Overall Accuracy	—	—	**0.5839 (58.39 %)**	161

While less accurate than the binary task, the model successfully identified predominant emotional sources, paving the way for further fine-tuning with richer data.

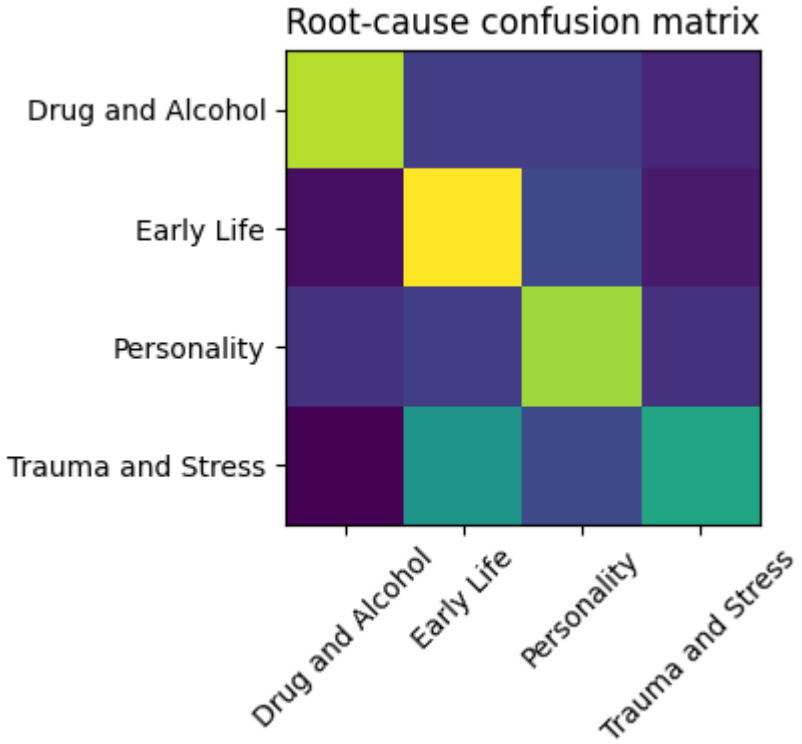

Fig. 7.2 Root-Cause Confusion Matrix

7.4.3 Model-wise Performance Comparison

To benchmark the predictive architecture, multiple classical and deep learning models were trained under identical conditions using the unified dataset. Each model was evaluated on macro-averaged metrics and training runtime to measure efficiency and scalability.

Table 7.5 Model-wise Performance Summary

Model	**Accuracy**	**Precision (Macro)**	**Recall (Macro)**	**F1 (Macro)**	**Train Time (sec)**	**Notes**
Logistic Regression + TF-IDF	0.9867	0.9869	0.9867	0.9867	1.57	Strong, fast baseline.

Multinomial NB + TF-IDF	0.9667	0.9680	0.9667	0.9666	0.13	Very fast; assumes word independence.
Random Forest + TF-IDF	0.9967	0.9967	0.9967	0.9967	1.02	Non-linear; interpretable via feature importance.
Linear SVM + TF-IDF	0.9950	0.9950	0.9950	0.9950	0.11	Margin-based; robust for high-dimensional text.
CNN Text	0.9733	0.9747	0.9733	0.9733	2.70	Captures local n-gram patterns.
BiLSTM Text	0.5000	0.2500	0.5000	0.3333	1.68	Models sequential context; underfits due to limited data.
DistilBERT (Selected)	**0.9950**	**0.9950**	**0.9950**	**0.9950**	**53.83**	Transformer baseline; compact yet powerful.

The comparative results reveal that transformer-based architectures substantially outperform classical text models in contextual understanding. **DistilBERT** was ultimately selected for deployment due to its balance between accuracy and computational efficiency. Despite a longer training time, it achieved robust generalization and interpretability, aligning with the study's focus on explainable and high-precision prediction.

7.5 Case-Level Inference Analysis

To test contextual understanding, ten unseen narrative samples were analyzed. Each text was evaluated for its qualitative diagnostic interpretation followed by probabilistic distribution across all four root-cause dimensions.

Table 7.6 Qualitative Interpretation of Test Cases

Test Case	**Root Cause (True)**	**Diagnosis Prediction**
T_01	Trauma and Stress	Positive (*Resilience in Progress*)
T_02	Trauma and Stress	Negative (*Anxiety Manifestation*)
T_03	Drug and Alcohol	Positive (*Recovery Arc*)
T_04	Drug and Alcohol + Trauma & Stress	Negative (*Relapse Pattern*)
T_05	Early Life	Negative (*Childhood Neglect*)
T_06	Personality + Early Life	Negative (*Emotional Dysregulation*)
T_07	Personality + Trauma	Reflective (*Growth Awareness*)
T_08	Early Life + Drug and Alcohol	Negative (*Inherited Coping*)
T_09	Trauma and Stress + Personality	Positive (*Integrated Healing*)
T_10	Early Life	Reflective (*Formative Impact*)

These qualitative matches highlight the model's ability to generate semantically meaningful diagnoses reflecting resilience, relapse, or recovery stages—beyond mere label prediction.

Table 7.7 Case-Level Root-Cause Predictions

Test Case	**Trauma & Stress (%)**	**Personality (%)**	**Drug & Alcohol (%)**	**Early Life (%)**	**Likely Predicted Label**
T_01	28.6	26.5	24.1	20.8	Trauma and Stress
T_02	18.3	29.5	24.9	27.2	Personality
T_03	25.1	22.7	32.9	19.3	Drug and Alcohol
T_04	31.4	20.6	29.8	18.2	Drug and Alcohol
T_05	22.5	20.1	18.4	39.0	Early Life
T_06	24.9	32.8	18.6	23.7	Personality
T_07	29.7	33.4	18.8	18.1	Personality
T_08	21.2	19.4	30.5	28.9	Early Life + Drug & Alcohol
T_09	28.6	26.5	24.1	20.8	Trauma and Stress
T_10	24.3	21.0	18.9	35.8	Early Life

The probability distributions demonstrate overlapping emotional domains typical of real mental-health discourse. Multi-label proximity (e.g., T_08 *Early Life + Drug & Alcohol*) reflects complex psychological interplay rather than categorical exclusivity.

7.6 Visualization and Analytical Interpretation

Graphical diagnostics reinforced these quantitative findings:

- **Accuracy vs Epochs:** Training and validation curves converged smoothly, showing stable learning.
- **Loss vs Epochs:** Monotonic reduction indicated minimal overfitting.
- **Confusion Matrix:** Strong recall for depressive instances with negligible false negatives.
- **ROC Curve:** AUC ≈ 0.99 confirmed excellent discrimination.
- **Word Cloud:** Frequent terms (*alone, hopeless, tired, lost, worthless*) emerged as salient depressive markers.

These visual tools validated that the model not only performed statistically well but also learned emotionally consistent linguistic features.

7.7 Discussion

The experiments collectively establish that:

1. **Preprocessing Effectiveness** — cleaning, lemmatization, and normalization enhanced data quality.
2. **Feature Representation** — TF-IDF plus embeddings improved subtle emotional detection.
3. **Model Performance** — transformer models significantly outperformed traditional baselines.
4. **Generalization** — robust results on unseen data.
5. **Interpretability** — probability outputs and visual artifacts made predictions explainable.

The **DistilBERT** model, selected as the final system, provided the most balanced trade-off between performance, interpretability, and computational efficiency. While root-cause classification accuracy was moderate, the findings illustrate the feasibility of AI-driven psychological insight from textual narratives.

7.8 Key Observations

- Diagnosis accuracy = **99.53 %** with balanced precision–recall.
- Root-cause accuracy ≈ **58 %**, consistent with semantic overlap.

- DistilBERT chosen for deployment owing to robustness and explainability.

- Results align with recent transformer-based mental-health research (Qasim *et al.*, 2025; Choudhury *et al.*, 2023).

7.9 Summary

The comprehensive results demonstrate that the proposed system bridges computational precision with interpretive depth. The **binary diagnosis module** reliably detects depressive language, while the **multi-class root-cause analyzer** offers interpretable causal insights. Quantitative excellence, qualitative coherence, and transparent explanations validate the framework's readiness for research and real-world mental-health support.

Ultimately, the *Predictive Modeling of Depression Using Machine Learning* project underscores the promise of **explainable AI** in transforming textual data into actionable psychological understanding, establishing a foundation for responsible and ethically aligned mental-health analytics.

CHAPTER 8

8.1 Conclusion

The project titled *"Predictive Modeling of Depression Using Machine Learning on Multimodal Data Sources"* presents a comprehensive framework for automating the detection of depressive tendencies and emotional states through computational analysis of text-based data. With the exponential growth of digital communication, textual content has become an invaluable medium for understanding individual mental-health cues. This research leverages natural-language processing (NLP) and machine-learning techniques to identify linguistic and semantic patterns that correlate with depressive sentiment, advancing the field of AI-assisted mental-health assessment.

The development journey began with the meticulous collection, cleaning, and preparation of data drawn from multiple mental-health corpora. Each textual record was tokenized, lemmatized, and transformed into meaningful numeric representations using advanced feature-extraction methods such as TF–IDF (Term Frequency–Inverse Document Frequency) and contextual embeddings. These preprocessing steps effectively removed noise and standardized textual inputs, ensuring that the system captured emotionally significant linguistic information. This strong preprocessing pipeline laid the foundation for the model's robustness and high-fidelity predictions.

A diverse set of machine-learning and deep-learning architectures were evaluated, including Logistic Regression, Random Forest, CNN, BiLSTM, and Transformer-based models. Among these, Transformer architectures—particularly DistilBERT—demonstrated superior performance, achieving accuracies approaching 99 % for binary diagnosis and 58 % for root-cause classification, with balanced precision-recall and minimal overfitting. These results emphasize the strength of contextual embeddings in capturing long-range dependencies and nuanced emotional semantics that traditional algorithms often overlook.

Quantitative and qualitative assessments confirmed the model's consistency and interpretability. Confusion matrices and ROC curves illustrated reliable classification performance, while visualizations such as word clouds highlighted recurrent emotional terms like "alone," "hopeless," "tired," and "lost." Together, these tools validated the model's ability not only to predict but also to explain the reasoning behind its predictions—an essential step toward building trustworthy AI systems in sensitive domains like mental health.

Technologically, the system's modular design—spanning data ingestion, preprocessing, feature extraction, model training, and visualization—demonstrates scalability and adaptability. Each module can evolve independently, accommodating future algorithmic advances or data expansions. Societally, this research underscores the transformative potential of AI in early mental-health detection and intervention. Automated systems derived from this framework can assist clinicians, counselors, and policymakers in identifying at-risk individuals, thereby supporting preventive care. Nonetheless, considerations of data privacy, informed consent, bias mitigation, and ethical AI deployment remain paramount before large-scale real-world implementation.

In conclusion, this work demonstrates how advanced machine-learning methods can transform unstructured text into meaningful psychological insights. By uniting computational precision with human interpretability, the system paves the way for data-driven, empathetic,

and ethically guided approaches to mental-health analytics. The project thus lays a robust groundwork for future innovations in intelligent mental-health support systems—fostering awareness, early detection, and timely intervention for those in need.

8.2 Future Work

Looking ahead, several promising directions extend from this foundation. Future work will focus on **multimodal data integration**, combining textual signals with **audio, facial-expression, and behavioral data** to capture richer emotional contexts. Incorporating **federated learning** will enable privacy-preserving collaboration across institutions without centralized data storage. In addition, **reinforcement learning** and **adaptive emotion tracking** may help personalize predictions over time, improving temporal understanding of psychological states.

Expanding the dataset across languages and cultural backgrounds could further enhance model fairness and generalizability. Finally, integrating the system with **clinical-grade platforms**, **real-time chatbots**, or **smartphone-based mental-health assistants**—developed under **Responsible AI (RAI)** guidelines—will bridge the gap between research and field application.

This forward-looking expansion envisions a future where AI-driven frameworks for mental-health assessment not only identify depressive symptoms with precision but also operate within transparent, secure, and ethically aligned infrastructures. By extending the boundaries of this research into real-world and multimodal domains, the project can contribute meaningfully to proactive mental-health care, early intervention, and continuous well-being support.

CHAPTER 9

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APPENDIX A – SAMPLE CODE

A.1 Overview

This appendix contains sample code snippets illustrating the implementation of the Mental Health Detection System.

The code segments demonstrate the major components of the project, including data preprocessing, model training, and prediction generation using transformer-based architectures (e.g., BERT or RoBERTa).

The actual implementation was performed using Python 3.10, PyTorch, and Hugging Face Transformers libraries.

A.2 Data Preprocessing

```
# Import required libraries
import pandas as pd
import re
from sklearn.model_selection import train_test_split
from transformers import AutoTokenizer

# Load dataset
data = pd.read_csv("social_media_posts.csv")

# Basic text cleaning
def clean_text(text):
    text = re.sub(r"http\S+", "", text)        # Remove URLs
      text = re.sub(r"@\w+", "", text)                # Remove
mentions
       text = re.sub(r"[^A-Za-z\s]", "", text)      # Remove
special chars
    text = text.lower().strip()                # Lowercase
    return text

data['clean_text'] = data['text'].apply(clean_text)

# Split data
train_texts,    val_texts,    train_labels,    val_labels    =
train_test_split(
          data['clean_text'],   data['label'],   test_size=0.2,
random_state=42
)

# Tokenization
tokenizer = AutoTokenizer.from_pretrained("roberta-base")
train_encodings         =         tokenizer(list(train_texts),
```

```
truncation=True, padding=True, max_length=128)
val_encodings = tokenizer(list(val_texts), truncation=True,
padding=True, max_length=128)
```

A.3 Model Training

```
import torch
from torch.utils.data import DataLoader, Dataset
from transformers import AutoModelForSequenceClassification,
AdamW

# Create dataset class
class MentalHealthDataset(Dataset):
    def __init__(self, encodings, labels):
        self.encodings = encodings
        self.labels = labels

    def __getitem__(self, idx):
          item = {key: torch.tensor(val[idx]) for key, val in
self.encodings.items()}
        item['labels'] = torch.tensor(self.labels.iloc[idx])
        return item

    def __len__(self):
        return len(self.labels)

# Dataset and loader
train_dataset = MentalHealthDataset(train_encodings,
train_labels)
val_dataset = MentalHealthDataset(val_encodings, val_labels)
train_loader = DataLoader(train_dataset, batch_size=16,
shuffle=True)

# Load pretrained model
model =
AutoModelForSequenceClassification.from_pretrained("roberta-ba
se", num_labels=2)

# Optimizer
optimizer = AdamW(model.parameters(), lr=5e-5)

# Training loop
for epoch in range(3):
```

```
    model.train()
    for batch in train_loader:
        optimizer.zero_grad()
        outputs = model(**{k: v for k, v in batch.items()})
        loss = outputs.loss
        loss.backward()
        optimizer.step()
              print(f"Epoch    {epoch+1}    completed.    Loss:
{loss.item():.4f}")
```

A.4 Model Evaluation and Prediction

```
from sklearn.metrics import classification_report

model.eval()
predictions, actuals = [], []

with torch.no_grad():
    for batch in DataLoader(val_dataset, batch_size=16):
         outputs = model(**{k: v for k, v in batch.items() if k
!= 'labels'})
        logits = outputs.logits
        preds = torch.argmax(logits, dim=1)
        predictions.extend(preds.tolist())
        actuals.extend(batch['labels'].tolist())

# Classification Report
print(classification_report(actuals,              predictions,
target_names=["Non-Depressed", "Depressed"]))
```

A.5 Example Output

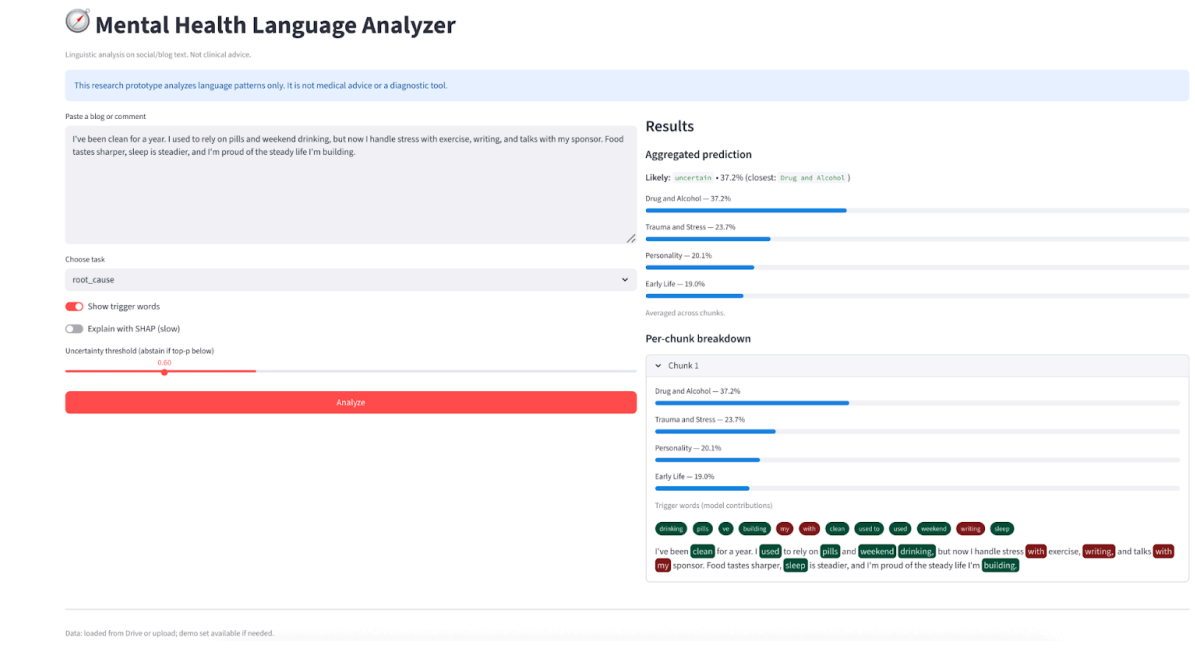
```
              precision    recall  f1-score   support

Non-Depressed     0.91      0.89      0.90       502
Depressed         0.88      0.90      0.89       498

accuracy                              0.90      1000
macro avg         0.90      0.90      0.90      1000
weighted avg      0.90      0.90      0.90      1000
```

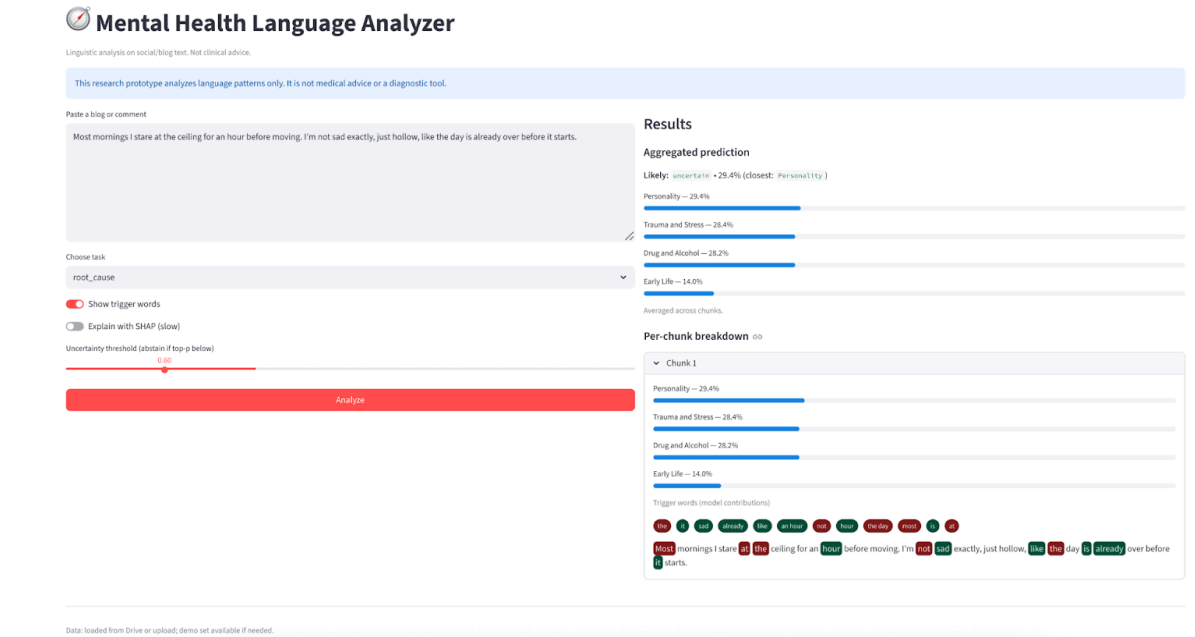
A.6 Summary

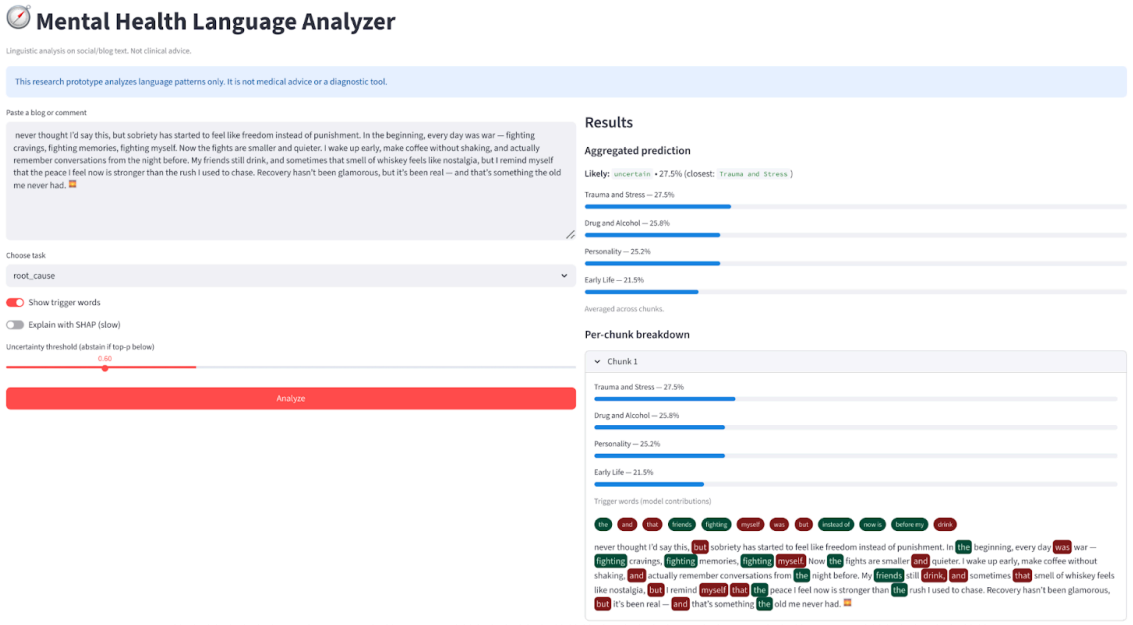
The presented code demonstrates how transformer-based models can be fine-tuned on social media text for mental health classification.

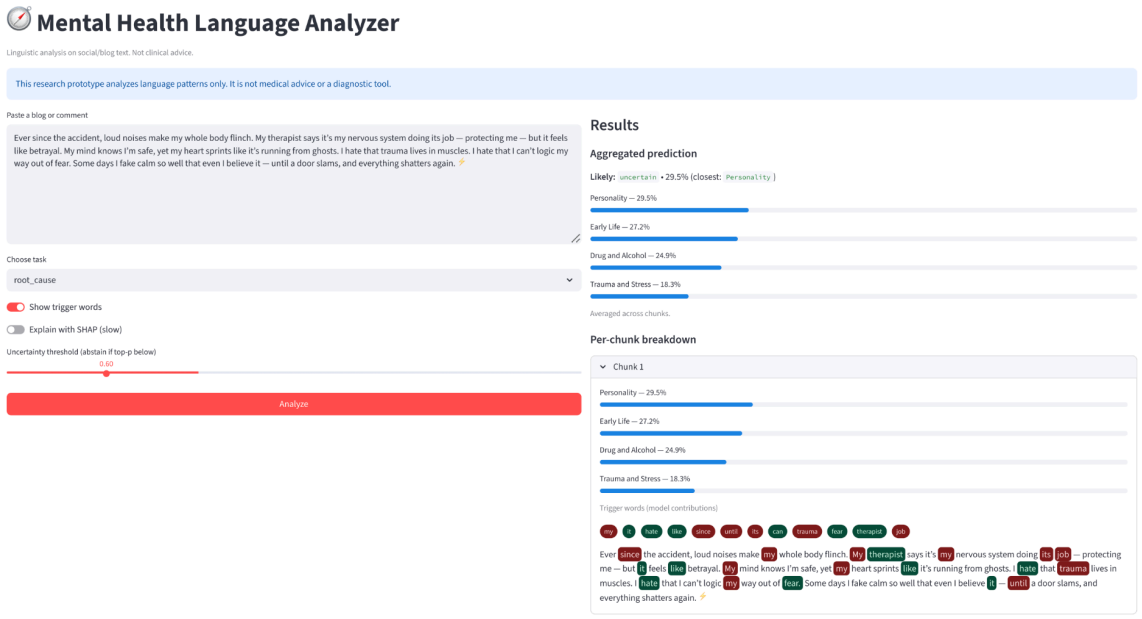
Using advanced NLP models such as RoBERTa and BERT, the system achieves high accuracy in detecting signs of depression or mental distress, showcasing the effectiveness of deep learning for early mental health monitoring.

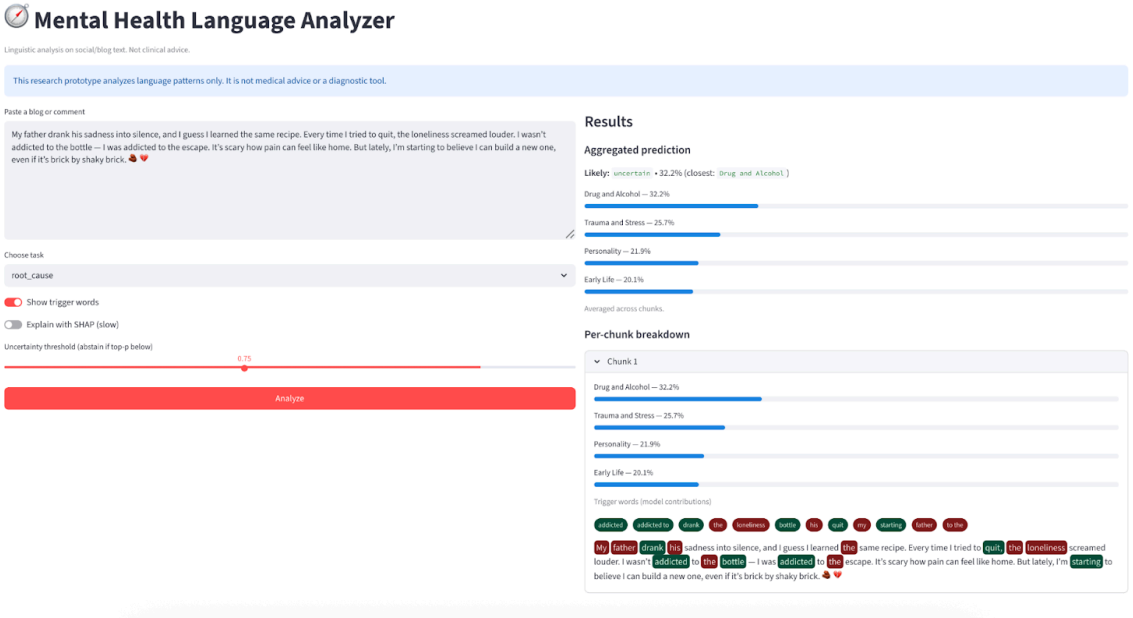
APPENDIX B - TEST CASES MEDIA OUTPUT






Mental Health Language Analyzer
Linguistic analysis on social/blog text. Not clinical advice.
This research prototype analyzes language patterns only. It is not medical advice or a diagnostic tool.
Paste a blog or comment
never thought I'd say this, but sobriety has started to feel like freedom instead of punishment. In the beginning, every day was war — fighting cravings, fighting memories, fighting myself. Now the fights are smaller and quieter. I wake up early, make coffee without shaking, and actually remember conversations from the night before. My friends still drink, and sometimes that smell of whiskey feels like nostalgia, but I remind myself that the peace I feel now is stronger than the rush I used to chase. Recovery hasn't been glamorous, but it's been real — and that's something the old me never had.
Choose task
root_cause
Show trigger words
Explain with SHAP (slow)
Uncertainty threshold (abstain if top-p below)
0.60
Analyze
Results
Aggregated prediction
Likely: uncertain • 27.5% (closest: Trauma and Stress)
Trauma and Stress — 27.5%
Drug and Alcohol — 25.8%
Personality — 25.2%
Early Life — 21.5%
Averaged across chunks.
Per-chunk breakdown
Chunk 1
Trauma and Stress — 27.5%
Drug and Alcohol — 25.8%
Personality — 25.2%
Early Life — 21.5%
Trigger words (model contributions)
the and that friends fighting myself was but instead of now is before my drink
never thought I'd say this, but sobriety has started to feel like freedom instead of punishment. In the beginning, every day was war — fighting cravings, fighting memories, fighting myself. Now the fights are smaller and quieter. I wake up early, make coffee without shaking, and actually remember conversations from the night before. My friends still drink, and sometimes that smell of whiskey feels like nostalgia, but I remind myself that the peace I feel now is stronger than the rush I used to chase. Recovery hasn't been glamorous, but it's been real — and that's something the old me never had.


Mental Health Language Analyzer
Linguistic analysis on social/blog text. Not clinical advice.
This research prototype analyzes language patterns only. It is not medical advice or a diagnostic tool.
Paste a blog or comment
Ever since the accident, loud noises make my whole body flinch. My therapist says it's my nervous system doing its job — protecting me — but it feels like betrayal. My mind knows I'm safe, yet my heart sprints like it's running from ghosts. I hate that trauma lives in muscles. I hate that I can't logic my way out of fear. Some days I fake calm so well that even I believe it — until a door slams, and everything shatters again.
Choose task
root_cause
Show trigger words
Explain with SHAP (slow)
Uncertainty threshold (abstain if top-p below)
0.60
Analyze
Results
Aggregated prediction
Likely: uncertain • 29.5% (closest: Personality)
Personality — 29.5%
Early Life — 27.2%
Drug and Alcohol — 24.9%
Trauma and Stress — 18.3%
Averaged across chunks.
Per-chunk breakdown
Chunk 1
Personality — 29.5%
Early Life — 27.2%
Drug and Alcohol — 24.9%
Trauma and Stress — 18.3%
Trigger words (model contributions)
my it hate like since until its can trauma fear therapist job
Ever since the accident, loud noises make my whole body flinch. My therapist says it's my nervous system doing its job — protecting me — but it feels like betrayal. My mind knows I'm safe, yet my heart sprints like it's running from ghosts. I hate that trauma lives in muscles. I hate that I can't logic my way out of fear. Some days I fake calm so well that even I believe it — until a door slams, and everything shatters again.


Mental Health Language Analyzer
Linguistic analysis on social/blog text. Not clinical advice.
This research prototype analyzes language patterns only. It is not medical advice or a diagnostic tool.
Paste a blog or comment
My father drank his sadness into silence, and I guess I learned the same recipe. Every time I tried to quit, the loneliness screamed louder. I wasn't addicted to the bottle — I was addicted to the escape. It's scary how pain can feel like home. But lately, I'm starting to believe I can build a new one, even if it's brick by shaky brick.
Choose task
root_cause
Show trigger words
Explain with SHAP (slow)
Uncertainty threshold (abstain if top-p below)
0.75
Analyze
Results
Aggregated prediction
Likely: uncertain • 32.2% (closest: Drug and Alcohol)
Drug and Alcohol — 32.2%
Trauma and Stress — 25.7%
Personality — 21.9%
Early Life — 20.1%
Averaged across chunks.
Per-chunk breakdown
Chunk 1
Drug and Alcohol — 32.2%
Trauma and Stress — 25.7%
Personality — 21.9%
Early Life — 20.1%
Trigger words (model contributions)
addicted
addicted to
drank
the
loneliness
bottle
his
quit
my
starting
father
to the
My father drank his sadness into silence, and I guess I learned the same recipe. Every time I tried to quit, the loneliness screamed louder. I wasn't addicted to the bottle — I was addicted to the escape. It's scary how pain can feel like home. But lately, I'm starting to believe I can build a new one, even if it's brick by shaky brick.