Multimodal AI Framework for Social Media Based Mental Disorder Detection and Personalized Wellbeing Insights

Submitted by

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Submitted for the partial fulfillment for the degree of Bachelor of Technology in Computer Science and Engineering

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CERTIFICATE

This is to certify that the project entitled "Multimodal AI Framework for Social Media Based Mental Disorder Detection and Personalized Wellbeing Insights" prepared by SOUMYADEEP NANDY *(13000121033)*, PRITHWISH SARKAR *(13000121037)*, SAGNIK MUKHOPADHYAY *(13000121040)* and ARKAPRATIM GHOSH *(13000121058)* of B.Tech (Computer Science & Engineering), Final Year, has been done according to the regulations of the Degree of Bachelor of Technology in Computer Science & Engineering. The candidates have fulfilled the requirements for the submission of the project report.

It is to be understood that, the undersigned does not necessarily endorse any statement made, opinion expressed or conclusion drawn thereof, but approves the report only for the purpose for which it has been submitted.

(Signature of the Internal Guide) (Signature of the HOD)

(Signature of the External Examiner)

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

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ACKNOWLEDGEMENTS

We would like to express our sincere gratitude to our project guide in Computer Science and Engineering department. We are extremely thankful for the keen interest he / she took in advising us, for the books and reference materials provided for the moral support extended to us.

Last but not the least we convey our gratitude to all the teachers for providing us the technical skill that will always remain as our asset and to all non-teaching staffs for the gracious hospitality they offered us.

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Contents

Abstract

This project presents a scalable, multimodal AI framework for the early detection of mental health issues that combines an ensemble of diverse classifiers with a hierarchical model to achieve up to 98.03% accuracy on standard benchmarks and 96.25% on larger datasets. Packaged as a web application, the system offers continuous model retraining and dynamic knowledge-base updates, interactive well-being assessments, and retrieval-augmented generation to deliver personalized, evidence-based insights, complemented by rich visual analytics and actionable recommendations to enable timely interventions. Extensive evaluations demonstrate the platform's effectiveness and extensibility for proactive mental health monitoring.

1 Introduction

1.1 Project Overview

Mental health disorders—including depression, anxiety, bipolar disorder, and PTSD—affect millions worldwide and often go undetected until they manifest in crises. Meanwhile, people increasingly share their thoughts, feelings, and experiences on social media platforms (Reddit, Twitter etc) and in digital documents, leaving behind rich clues about their emotional state. In this work, we develop a multimodal AI framework that ingests text, images, video, and document feeds, uses OCR and deep-learning emotion analysis, and aligns user responses to established well-being scales. By fusing these signals through an ensemble of machine-learning and neural models, our system aims to flag early warning signs of distress and guide users toward timely, personalized support.

1.2 Project Purpose

Early identification and intervention are critical for mitigating the severity of mental health crises, yet current screening methods often rely on self-report or occasional clinical encounters. This project aims to fill that gap by delivering a continuously learning, data-driven monitoring tool that passively and proactively analyzes digital footprints—from social posts to uploaded documents and survey responses—to surface warning signs long before a crisis point. By putting actionable insights directly into the hands of individuals, caregivers, and healthcare providers, it seeks to enable truly preventative mental-health care at scale.

1.3 Technical Domain Specifications

Domain	Specifications
Hardware	Standard machine with ≥ 8 GB RAM and a multi-core CPU. (Optional: GPU for larger datasets or complex model training.)
Operating System	Cross-platform support: macOS, Windows 10/11, Linux distributions (e.g. Ubuntu, Linux Mint).
Programming Languages	Python 3.x (primary language for ML, data analysis, NLP).
Libraries / Frameworks	• **Data processing:** Pandas, NumPy • **Machine learning:** Scikit-learn, XGBoost, TensorFlow, Transformers • **Image/text analysis:** OpenCV, Tesseract, Pytesseract, DeepFace • **Audio processing:** Librosa, PyDub, SpeechRecognition • **Social media integration:** PRAW, Tweepy • **Visualization:** Plotly, Matplotlib • **Additional tools:** Streamlit, NLTK, Google Generative AI
Development Environment	Google Colab (cloud execution with optional GPU for large datasets or model training).

1.4 Business Domain Specifications

Stakeholder	Role / Use Case
Mental Health Services	Mental health providers, including hospitals and therapy centers, can leverage machine learning to detect early signs of mental disorders from social media data. This proactive approach complements traditional self-reporting and clinical assessments, enabling earlier intervention and support for patients.
Social Media Platforms	Social media platforms like Twitter and Reddit are key spaces for expressing thoughts and emotions, including mental health struggles. This project's machine learning models can help these platforms safeguard user well-being by identifying concerns early, while maintaining ethical standards.
Public Health Organizations	Public health organizations can use real-time social media data to monitor mental well-being, identify trends, and design data-driven interventions. By analyzing language patterns, they can create targeted awareness campaigns that better engage individuals facing mental health challenges.

1.5 Glossary / Keywords

Term	Definition
Natural Language Processing (NLP)	A branch of artificial intelligence focused on the interaction between computers and humans through natural language, including tasks like text analysis.
Retrieval-Augmented Generation (RAG)	A hybrid NLP framework that combines information retrieval and text generation by fetching relevant context from a knowledge base before generating responses, improving factual accuracy and relevance.
Vectorization	The process of converting textual data into numerical form (such as a vector) so that it can be used as input for machine learning models.
Classifier	A machine learning model or algorithm that categorizes or labels data points into predefined classes.
Mental Health Disorder	A wide range of conditions that affect mood, thinking, and behavior, including depression, anxiety, schizophrenia, etc.
Data Preprocessing	The process of preparing raw data for analysis by cleaning, normalizing, and transforming it into a usable format for machine learning models.
Cross-validation	A model validation technique used to assess how well a model performs by dividing data into training and testing sets multiple times for better accuracy.
Precision	In the context of classification, precision refers to the accuracy of positive predictions, calculated as the ratio of true positives to the sum of true and false positives.
Recall	In classification, recall measures the ability of a model to identify all relevant instances within a dataset, calculated as the ratio of true positives to the sum of true positives and false negatives.
PRAW	PRAW (Python Reddit API Wrapper) is a Python library that provides a simple interface to interact with Reddit's API for accessing Reddit data, such as posts, comments, and user information.
TesseractOCR	TesseractOCR is an open-source Optical Character Recognition (OCR) engine that extracts text from images with high accuracy; it is widely used for various applications like scanning documents and digitalizing printed text.
Depression	There is a difference between depression and mood swings or short-lived emotional reactions to daily experiments; A mental state causing painful symptoms adversely disrupts normal activities (e.g., sleeping).

Term	Definition
Anxiety	Several behavioral disturbances are associated with anxiety disorders, including excessive fear and worry. Severe symptoms cause significant impairment in functioning cause considerable distress. Anxiety disorders come in many forms, such as social anxiety, generalized anxiety, panic, etc.
Bipolar Disorder	An alternating pattern of depression and manic symptoms is associated with bipolar disorder. An individual experiencing a depressive episode may feel sad, irritable, empty, or lose interest in daily activities. Emotions of euphoria or irritability, excessive energy, and increased talkativeness can all be signs of manic depression. Increased self-esteem, decreased sleep need, disorientation, and reckless behavior may also be signs of manic depression.
Post-Traumatic Stress Disorder (PTSD)	In PTSD, persistent mental and emotional stress can occur after an injury or severe psychological shock, characterized by sleep disturbances, constant vivid memories, and dulled response to others and the outside world.
DeepFace	DeepFace is a Python library for deep learning-based facial recognition and attribute analysis. It supports several pre-trained models and simplifies face recognition tasks, making it suitable for various applications in image analysis.
Transformers Module	The Transformers module in Python, developed by Hugging Face, is a library for natural language processing (NLP) tasks like text classification, translation, and summarization, using state-of-the-art models like BERT and GPT.
Gemini 2.0 Flash	Gemini 2.0 Flash is a cutting-edge AI model developed by Google, capable of performing advanced generative and analytical tasks across text, image, and other modalities.
FFmpeg	FFmpeg is a multimedia framework used for encoding, decoding, transcoding, streaming, and manipulating audio and video files, supporting a wide range of formats and codecs.
Hyperparameter Tuning	Hyperparameter tuning involves selecting the best parameters for a machine learning model to optimize its performance on a given task using grid search or random search.
Embedding Model	A neural network that transforms individual text inputs into fixed-length vector representations in a continuous semantic space, enabling efficient similarity search and downstream tasks like clustering or retrieval.
Cross-Encoder	A model that jointly processes a pair of inputs (e.g., query and document) through a shared encoder and directly produces a relevance score or classification, allowing for richer interaction at the cost of higher compute per pair.

2 Related Studies

Study	Summary
Choudhury et al. (2013)	Explored the predictive capabilities of social media content in identifying depression by analyzing Twitter data. They discovered that specific linguistic patterns (e.g., negative emotion words) correlated strongly with self-reported depressive symptoms [2].
Guntuku et al. (2017)	Conducted an integrative review which synthesized various methodologies highlighted that social media platforms are rich sources of data, revealing critical information about users' mental health [4].
Mathur et al. (2022)	Provided a systematic review analysing machine learning techniques for mental health detection using social media data, leveraging both individual assessments and broader epidemiological studies [5].
Nadeem (2016)	Investigated depression identification on Twitter by developing algorithms to discern emotional cues in tweets revealing that simple text analysis could lead to improvements in identifying mental risks [6].
AlSagri and Ykhlef (2020)	Introduced a machine learning–based approach for depression detection on Twitter that combined both content and activity features. Their work demonstrated that a fusion of linguistic and behavioral analysis can enhance the accuracy of depression identification [1].
Vaishnavi et al. (2022)	Examined various machine learning algorithms for predicting mental health illnesses using social media posts. Their findings emphasized that certain algorithms outperform others in classifying mental health conditions, underlining the importance of algorithm selection [9].
Safa et al. (2023)	Presented a roadmap for predicting mental health using social media, highlighting ongoing challenges such as ethical considerations and data privacy. They stressed the need for a robust ethical framework in research that leverages social media data [7].
Ensemble learning using transformers for NLP	Provided a comprehensive review of transformer models (BERT, XLNet, RoBERTa, GPT-2, ALBERT) across multiple NLP tasks. The study introduced ensemble learning with these models and demonstrated that ensemble approaches can significantly improve performance over single classifier methods [10].
Ensemble hybrid model for depression detection	Proposed an ensemble hybrid model combining SVM and MLP to improve depression prediction accuracy. Addressing class imbalance with SMOTE and cluster sampling, the model achieved an accuracy of 99.39% and an F1-score of 99.51%, outperforming previous approaches [8].
Single classifier vs. ensemble ML approaches	Explored various ML techniques to predict mental health issues using survey responses from OSMI. The study compared single classifiers with ensemble approaches, finding that Gradient Boosting achieved the highest accuracy [3].

PREFRAME STUDY REVIEW

SI No.	Paper Title and Author	Year	Aim and Objective	Uniqueness Claimed	Outcome Achieved	Algorithm/Tools	Feature Extraction	Modality of Data	Data Resource
1	Combining Sentiment Analysis Models Using Stacking Ensemble Learning Techniques on BIST30 Stocks by Mahmut Sami SIVRI	2024	Develop a stacking ensemble model to enhance sentiment analysis accuracy and robustness for BIST30 financial news.	Integrate diverse models (LSTM, BERT, Naive Bayes, SVM) in a stacking ensemble with a focus on BIST30 stocks, robust data strategies, and comparative analysis.	Enhance financial sentiment analysis with superior performance, generalization over baseline models with accuracy of 85%	Stacking ensemble with LSTM, BERT, Naive Bayes, SVM, and Logistic Regression, trained on 5,287 financial news articles (2020-2023) with an 80-10-10 split.	SVM uses TF-IDF with text preprocessing: cleaning, tokenization, stopwords removal, and lemmatization.	Financial news articles classified into Positive, Negative, and Neutral sentiment categories.	Thomson Reuters news articles
2	Predicting mental health using social media: A roadmap for future development by Ramin Safa, S. A. Edalatpanah, Ali Sorourkhah	2022	A roadmap for analyzing and predicting mental disorders using social media data, covering collection, feature extraction, and prediction methods.	Comprehensive analysis of mental state assessment methods on social data, categorizing approaches and discussing challenges and future directions.	Conceptual framework for e-mental health research via social media, covering assessment strategies, data methods, algorithms, metrics, and future challenges.	Machine learning, NLP, and sentiment analysis using platforms like Twitter and Facebook, with tools like LIWC and frameworks such as CNN and LSTM.	Tools like LIWC, OpinionFinder, SentiStrength, VADER, Word2Vec, LDA, tf-idf, VGG-Net, and Imagga	Textual Data and Visual Content	myPersonality project CLPsych workshop data, eRisk workshops data, AutoDep dataset, SDCNL dataset, CAMS dataset
3	Detecting Depression and Mental Illness on Social Media: An Integrative Review by Sharath Chandra Guntuku, David B. Yaden, Margaret L. Kern, Lyle H. Ungar, Johannes C. Eichstaedt	2016	Reviewing recent studies and comparing approaches for predicting mental illness through social media analysis.	Comprehensive review comparing mental illness detection methods and prediction performances with clinical baselines.	Social media-based screening shows AUCs between 0.70 and 0.91, bridging clinician assessment and screening surveys with accuracy of 87%	Using Linear Regression, SVM, Neural Networks, and Random Forest with analysis tools like LIWC and LabMT.	LIWC and N-Gram	Textual Data	Survey and Social media
4	Single classifier vs. ensemble machine learning approaches for mental health prediction by Jetli Chung and Jason Teo	2023	Empirically evaluate and compare single classifiers and ensemble approaches for predicting mental health problems.	Comprehensive comparison of traditional algorithms, Deep Neural Networks, XGBoost, and ensemble methods for mental health prediction using survey data.	Gradient Boosting led with 88.80% accuracy, followed by Neural Networks (88.00%) and XGBoost (87.20%).	Logistic Regression, Gradient Boosting, Neural Networks, K-NN, SVM, Deep Neural Networks, XGBoost, and Ensemble Voting Classifier.	Extra Trees Classifier was used for feature selection to reduce overfitting	Survey	OSMI's 2014 Mental Health in Tech Survey measured workplace mental health attitudes in the tech industry, available under Creative Commons.
5	Survey of transformers and towards ensemble learning using transformers for natural language processing by Hongzhi Zhang and M. Omair Shafiq	2024	Compare and analyze transformer models across six NLP tasks, developing ensemble models to leverage their strengths.	Compare 5 transformer models across 6 NLP tasks, analyzing nuances and developing novel ensemble approaches.	Outperformed single classifiers with two ensemble models, identifying optimal combinations for specific NLP tasks with accuracy of 79%	BERT, XLNet, GPT2, RoBERTa, and ALBERT on Google Colab using Transformers, Deep Neural Networks, BERTopic, EncoderDecoderModel, and Seq2SeqTrainer.	Using transformer-based embeddings, word vectors, BERTopic for topic modeling, class-based TF-IDF, and contextual semantic representations.	Using transformer embeddings, BERTopic, TF-IDF, and contextual semantic representations for NLP.	Using datasets like Kaggle's coronavirus tweets, SQuAD1.1, Groningen Meaning Bank, CNN daily mail, disaster tweets, and Trump 2020 election speeches for various NLP tasks.
6	Ensemble of hybrid model based technique for early detecting of depression based on SVM and neural networks by Dip Kumar Saha, Tuhin Hossain, Mejdl Safran, Sultan Alfarhood, M. F. Mridha & Dunren Che	2024	Develop an automated system to detect depression using psychological and sociodemographic characteristics.	Develop an automated system to detect depression using psychological and sociodemographic characteristics.	Developed an automated depression detection system with improved accuracy and reduced class imbalance.with accuracy of 99.39%	Algorithms like SVM, MLP, Hybrid DeprMVM, RFC, KNN, XGB with SMOTE, cluster sampling, and Scikit-learn for depression detection.	Using Label Encoder, Standard Scaler, and feature selection techniques for data preprocessing.	Survey data with 30 psychosocial/demographic predictors and 1 depression status target, including 25 BDC questions.	Dataset of 604 Bangladeshi participants (65.7% depressed, 34.3% not) collected from April to August 2020.
7	Machine Learning-based Approach for Depression Detection in Twitter Using Content and Activity Features by Hatoon AlSagri and Mourad Ykhlef	2023	Detect depression in Twitter users by analyzing tweet content and network behavior using machine learning techniques.	Incorporating tweet text, user behavior, and new features like activity categories, Dept_Sent lexicon, and synonyms for enhanced depression detection.	Developed a binary classification model with improved accuracy by combining user activities and tweets for better mental health detection with accuracy 82.5%.	Using SVM, Naive Bayes, and Decision Tree algorithms with R 3.3, RStudio, Twitter API, WordNet, and R packages for data analysis.	Feature extraction using TF-IDF, WordNet, Information Gain, sentiment analysis tools, and R packages.	Text data (tweets, pronouns, sentiment words, depression terms) and user activity data (followers, posts, mentions, retweets, emojis, hashtags, replies).	Collected over 300,000 tweets from 111 users via Twitter API, with manual verification of self-disclosed depression and data selection criteria.
8	Predicting Depression via Social Media" Authors : Munmun De Choudhury, Michael Gamon, Scott Counts, Eric Horvitz	2013	Leveraging social media behavioral patterns to detect and predict Major Depressive Disorder (MDD) early.	Pioneering crowdsourced clinical data and multifaceted behavioral analysis for early depression prediction.	Achieved 70% accurate depression prediction, highlighting key behavioral and linguistic markers.	Utilized SVM with RBF kernel, PCA, and 10-fold cross-validation on Twitter data for depression analysis.	Employed LIWC, ANEW, and custom lexicons for linguistic, emotional, and medication-related feature extraction.	Analyzed Twitter posts, surveys (CES-D, BDI), demographics, and social network data for depression detection.	Collected data from 1,583 U.S.-based crowdworkers, analyzed 2M+ tweets and surveys (CES-D, BDI) with strict quality controls.
9	Predicting Mental Health Illness using Machine Learning Algorithms by Konda Vaishnavi	2022	Evaluate and compare machine learning techniques for accurate mental health issue prediction.	Unique comparison of five ML techniques for mental health prediction using diverse accuracy metrics and ROC curves.	Achieved 81.75% accuracy with stacking, with all classifiers showing strong ROC values (0.8–0.9).	Utilized Logistic Regression, K-NN, Decision Tree, Random Forest, and Stacking for mental health prediction.	Performed feature selection to reduce 27 attributes to 8 for mental health prediction.	Used a dataset with 27 attributes and 1259 entries, including text documents for mental health prediction.	Not mentioned
10	Generalizability of Machine Learning to Categorize Various Mental Illness Using Social Media Activity Patterns by Ang, C.S. & Venkatachala, R.	2023	Explore linguistic patterns and cross-platform machine learning models for classifying mental health groups based on social media activity.	Improved accuracy by 2.11% with simpler cross-platform models for mental health classification on Twitter and Reddit.	Achieved 91.5% accuracy, with better Reddit model generalization and distinct linguistic patterns between platforms.	Used CNN, Word2Vec, NLTK, and Google Colab for Twitter and Reddit-based mental health classification.	Employed LIWC, Porter Stemmer, and NLTK for feature extraction in mental health classification.	Analyzed 606K Reddit posts and 23M tweets covering 6 mental health conditions from relevant subreddits and hashtags.	Used 23M Twitter tweets and 606K Reddit posts from mental health-related subreddits for cross-platform model training and testing.

3 Problem Definition and Preliminaries

3.1 Context and Background

Mental health disorders affect approximately 1 in 8 people globally. Social media platforms like Reddit and Twitter offer vast amounts of real-time data reflecting mental health struggles, but the unstructured nature of this data poses challenges for effective identification and categorization of specific disorders.

3.2 Objective and Challenges

The primary objective is to develop a system that uses NLP and machine learning to analyze Reddit and Twitter posts for detecting mental health disorders like depression, anxiety, bipolar disorder, and PTSD. It seeks to **classify posts** accurately and provide **data-driven insights** into mental health trends for researchers, professionals, and policymakers.

- **Data Variability**: Social media posts vary in structure, style, and language.
- **Imbalanced Data**: Uneven distribution of mental issues can impact model training.
- **Cultural Nuances**: Mental health discussions differ across cultures.
- **Privacy and Ethics**: Analyzing social media data raises concerns about user privacy.

3.3 Scope, Exclusions and Assumptions

The scope of the project is to develop a multimodal AI framework to detect mental disorders from social media inputs using ML and NLP. It analyzes text, images, videos, PDFs, dynamic responses to image shown and Reddit/Twitter data via APIs, classifying inputs into Normal, Anxiety, Depression, Bipolar, or PTSD using a Reddit dataset. Finally an association is created between mental health disorder and mental wellbeing paramters from Ryff's Psychological Well-being Scale.

This project excludes real-time sentiment analysis, platform-specific features like hashtags or subreddits, and ethical implications of data ownership. It also does not analyze comments, metadata, or Reddit/Twitter-specific elements, focusing solely on detecting mental health disorders from user profiles and mapping them to wellbeing insights, though the dataset has been made solely from Reddit posts from various subreddits.

The project assumes that the Reddit dataset obtained via PRAW represents diverse mental health discussions and that user posts accurately reflect emotions. NLP techniques are presumed effective for sentiment classification, and selected ML models (Logistic Regression, SVM, Naïve Bayes, LSTM, Transformer, XGBoost) are expected to perform optimally. Social media sentiments are considered valid proxies for public mental health perceptions. Data preprocessing is assumed sufficient to reduce noise, and ethical standards are maintained to protect user privacy. The users' responses to the well-being surveys are considered valid for updating the association matrix between mental health disorders and well-being parameters.

4 Proposed Solution

Special Contributions

Component	Description
Dataset Acquisition	Reddit data was sourced using PRAW from relevant subreddits (Normal, Depression, Anxiety, Bipolar, PTSD). Extensive preprocessing ensured data integrity.
Text Vectorization	TF-IDF and Bag-of-Words were used to convert text into numerical format via Scikit-learn, enabling efficient feature extraction and model training. Other vectorization techniques like Word2Vec, LIWC, and N-Grams were also explored.
Machine Learning Models	Logistic Regression, SVM, Naïve Bayes, LSTM, Transformer, and XGBoost were implemented for multi-class classification of mental health conditions.
Model Evaluation	Accuracy, precision, recall, and F1-score were used to assess performance. Confusion matrices and ROC curves were generated for detailed model evaluation.
Insights & Recommendations	Findings inform mental health professionals and policymakers on probable issues and provide well-being insights.
Documentation & Reproducibility	Detailed documentation ensures usability, including methodology, code, and instructions for result reproduction.

Reusable Components

Module / Function	Description
Data Collection Functions	Modular functions designed for data collection, which can be reused across different platforms.
Data Preprocessing Module	A component that cleans data by removing duplicates and empty rows, and adds a separate column for cleaned texts.
Machine and Deep Learning Model Functions	Functions for implementing Logistic Regression, Naïve Bayes, Support Vector Machine, Random Forest, XGBoost, Long Short Term Memory, and Transformer algorithms. These functions enable easy retraining on varying datasets and feature various evaluation metrics to assess model performance.
Deployment Function	A separate function that contains the main Python file for creating a web-based application on Streamlit Cloud, including the necessary requirements and package dependencies for deployment.

5 Project Planning

5.1 Software Life Cycle Model

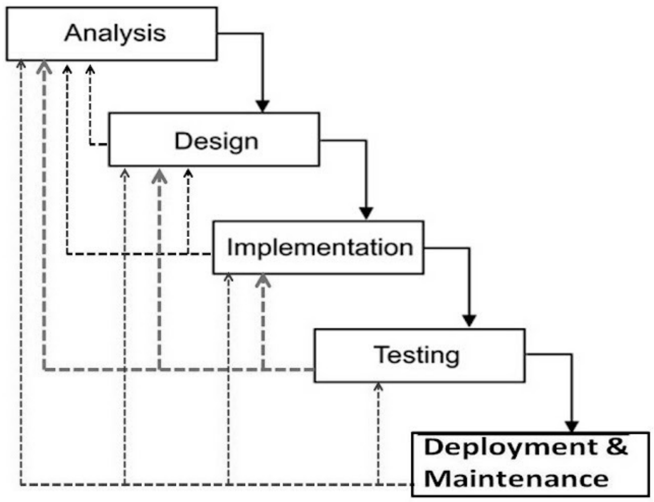


Fig. 5.1 Iterative Waterfall Model

Project Phases and Descriptions

Phase	**Description**
Requirement Gathering and Analysis	This initial phase involved understanding the project's goals, objectives, and stakeholder expectations.
Data Collection and Preparation	Utilizing the Reddit API, the data collection phase was executed. This included downloading the dataset, examining its structure, and performing data cleaning and preprocessing to ensure its suitability for analysis.
Model Development	This phase included the creation of a Bag-of-Words model, splitting the dataset into training and test sets, and implementing various machine learning algorithms.
Model Evaluation	Following model development, testing and validation of the models were performed to ensure they met the required accuracy benchmarks. Performance metrics such as accuracy, precision, recall, and F1-score were used to evaluate model effectiveness.
Final Deployment and Documentation	The last phase focused on deploying the best-performing model and creating comprehensive documentation. This included user manuals and technical documentation to facilitate future maintenance and enhancements.

5.2 Dependencies, Milestones and Scheduling

Key dependencies were identified for successful project progression. For instance, completion of the data preparation phase was critical before proceeding to model development. Milestones were established at the end of each phase to ensure accountability and track progress. The successful completion of the requirement gathering phase marked the first milestone, followed by the data preparation phase, and so on. Effective scheduling is vital for project success. A detailed timeline with tasks like requirement gathering, data preprocessing, model implementation, and testing was created, with flexibility for adjustments based on feedback. Key milestones, including data analysis, model validation, and user acceptance testing, ensure progress tracking. Using tools like Microsoft Project, we monitor tasks, manage resources, and maintain communication to deliver a high-quality solution on time.

ID		Task Mode	Task Name	Duration	Start	Finish	Predecessors	% Complete
1	✓		**GR29 MAFSMBMDDPWI**	**251 days**	**Mon 01-07-24**	**Thu 12-06-25**		**100%**
2	✓		**Phase 1: 7th Semester Activities**	**150 days**	**Mon 01-07-24**	**Wed 22-01-25**		**100%**
3	✓		**Project Startup**	**20 days**	**Mon 01-07-24**	**Fri 26-07-24**		**100%**
4	✓		Team Building	2 days	Mon 01-07-24	Tue 02-07-24		100%
5	✓		Brainstorm on Project Topic	2 days	Wed 03-07-24	Thu 04-07-24	4	100%
6	✓		Project agreed with Guide	2 days	Fri 05-07-24	Mon 08-07-24	5	100%
7	✓		Related Study& Documentation	4 days	Mon 08-07-24	Thu 11-07-24	6	100%
8	✓		Deliver Project Synopsis for Guide's review	2 days	Fri 12-07-24	Mon 15-07-24	7	100%
9	✓		Close review feedbacks	9 days	Mon 15-07-24	Thu 25-07-24	8	100%
10	✓		**Project Synopsis Finalized**	**1 day**	**Fri 26-07-24**	**Fri 26-07-24**	**9**	**100%**
11	✓		**Requirement Analysis**	**17 days**	**Thu 01-08-24**	**Fri 23-08-24**		**100%**
12	✓		Gather Requirements	7 days	Thu 01-08-24	Fri 09-08-24	10	100%
13	✓		Prepare Draft Requirement Matrix	9 days	Mon 12-08-24	Thu 22-08-24	10	100%
14	✓		**Requirement Matrix Finalized**	**1 day**	**Fri 23-08-24**	**Fri 23-08-24**	**13**	**100%**
15	✓		**Design**	**46 days**	**Mon 26-08-24**	**Thu 24-10-24**	**14**	**100%**
16	✓		**Detailed Design**	**25 days**	**Mon 26-08-24**	**Thu 26-09-24**	**14**	**100%**
17	✓		Data Collection	3 days	Mon 26-08-24	Wed 28-08-24	14	100%
18	✓		Data Preprocessing	4 days	Thu 29-08-24	Mon 02-09-24	17	100%
19	✓		Model Training and Evaluation	18 days	Tue 03-09-24	Thu 26-09-24	18	100%
20	✓		**Test Plan Preparation**	**21 days**	**Fri 27-09-24**	**Thu 24-10-24**	**19**	**100%**
21	✓		Text Classification	4 days	Fri 27-09-24	Wed 02-10-24	19	100%
22	✓		Image Classification	9 days	Thu 03-10-24	Tue 15-10-24	21	100%
23	✓		Video Classification	4 days	Wed 16-10-24	Sat 19-10-24	22	100%
24	✓		Reddit and Twitter User Analysis	4 days	Mon 21-10-24	Thu 24-10-24	23	100%
25	✓		**Phase 1 Closure**	**59 days**	**Fri 01-11-24**	**Wed 22-01-25**	**3**	**100%**
26	✓		Prepare 7th Semester Project Rep	14 days	Fri 01-11-24	Wed 20-11-24	20	100%
27	✓		**Updated Requirement Matrix**	**2 days**	**Thu 21-11-24**	**Fri 22-11-24**	**26**	**100%**
28	✓		**Updated Project Plan**	**1 day**	**Fri 22-11-24**	**Fri 22-11-24**	**27**	**100%**
29	✓		Project Viva	2 days	Mon 20-01-25	Tue 21-01-25	28	100%
30	✓		**Approved Project Report - 7th Semester**	**1 day**	**Wed 22-01-25**	**Wed 22-01-25**	**29**	**100%**
31	✓		**Semester Gap**	**9 days**	**Thu 23-01-25**	**Tue 04-02-25**	**30**	**100%**
32	✓		**Phase 2: 8th Semester Activities**	**92 days**	**Wed 05-02-25**	**Thu 12-06-25**	**31**	**100%**
33	✓		**Coding & Únit Testing**	**27 days**	**Wed 05-02-25**	**Thu 13-03-25**	**31**	**100%**
34	✓		Data Collection and Preprocessing	7 days	Wed 05-02-25	Thu 13-02-25	31	100%
35	✓		Model Training and Evaluation	6 days	Fri 14-02-25	Fri 21-02-25	34	100%
36	✓		Web Application Components	14 days	Mon 24-02-25	Thu 13-03-25	35	100%
37	✓		**System Integration Testing**	**45 days**	**Fri 14-03-25**	**Thu 15-05-25**	**36**	**100%**
38	✓		API Calls	23 days	Fri 14-03-25	Tue 15-04-25	36	100%
39	✓		Deployment	22 days	Wed 16-04-25	Thu 15-05-25	38	100%
40	✓		**Project Closure**	**22 days**	**Wed 14-05-25**	**Thu 12-06-25**	**39**	**100%**
41	✓		Prepare 8th Semester Project Report	5 days	Wed 14-05-25	Tue 20-05-25	39	100%
42	✓		**Updated Requirement Matrix**	2 days	Wed 21-05-25	Thu 22-05-25	41	100%
43	✓		**Updated Project Plan**	5 days	Fri 23-05-25	Thu 29-05-25	42	100%
44	✓		Review by Faculties	1 day	Tue 10-06-25	Tue 10-06-25	43	100%
45	✓		**Approved Project Report - 8th Semester**	1 day	Thu 12-06-25	Thu 12-06-25	44	100%

Fig. 5.2 Project Plan

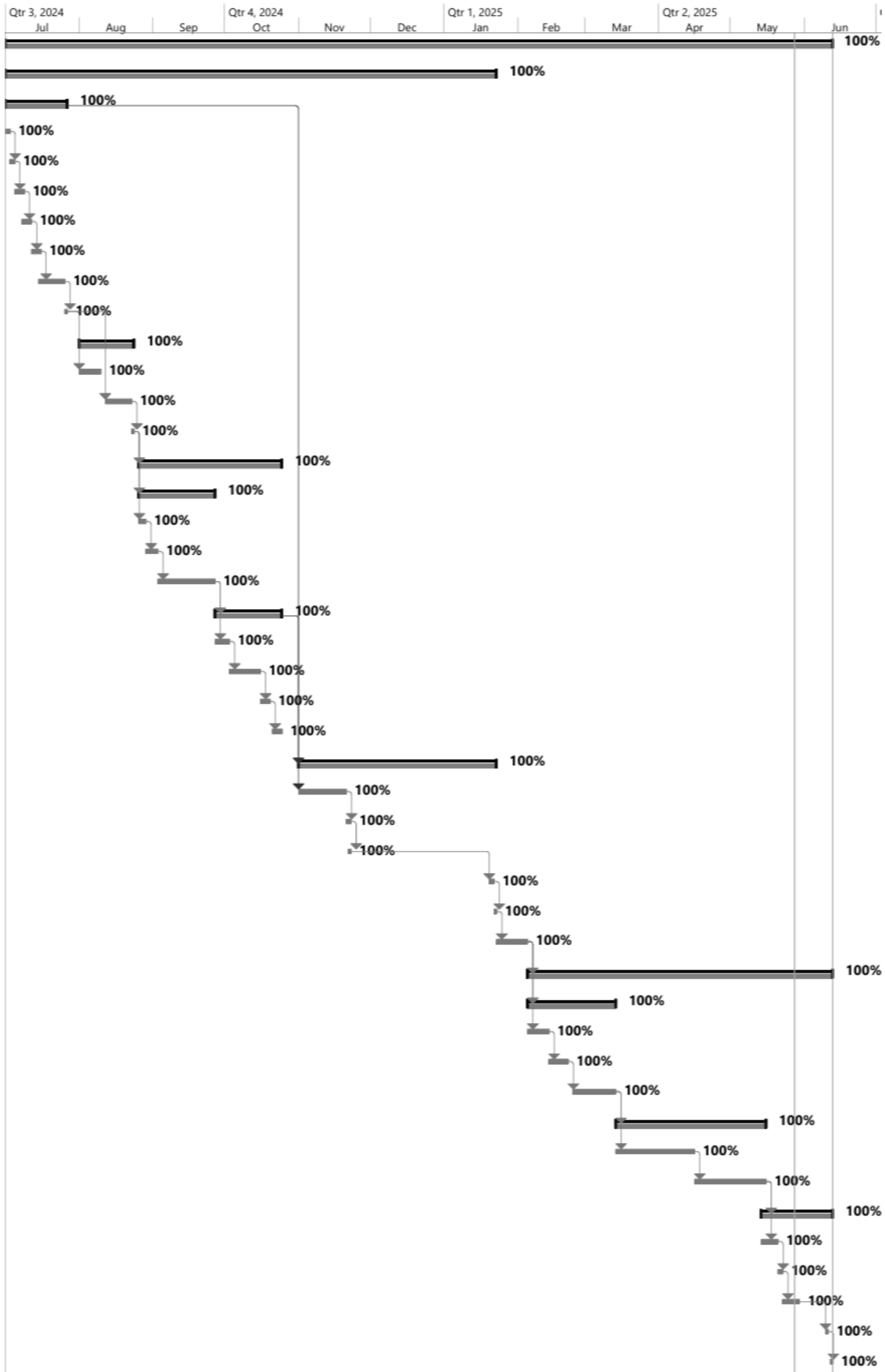


Fig. 5.3 Gantt Chart

6 Requirement Analysis

6.1 Requirement Matrix

Rqmt ID	Requirement Item	Requirement Analysis Status	Design Module (As per Prototype folder structure)	Design Reference (section# under project Report)
FR-001	Collect social media data from Reddit.	Completed	D01	8.2.1
FR-002	Implement data cleaning and preprocessing.	Completed	D02	8.2.2
FR-003	Train machine learning and deep learning models.	Completed	D03	8.2.3 - 8.2.10
FR-004	Evaluate models using performance metrics (accuracy, recall, F1 Score, Support).	Completed	D03	9.2 - 9.9
FR-005	Text Analysis	Completed	D04	APPENDIX A - PROTOTYPE
FR-006	Image Upload Analysis	Completed	D04	APPENDIX A - PROTOTYPE
FR-007	Video Upload Analysis	Completed	D04	APPENDIX A - PROTOTYPE
FR-008	PDF Upload Analysis	Completed	D04	APPENDIX A - PROTOTYPE
FR-009	User response to image	Completed	D04	APPENDIX A - PROTOTYPE
FR-010	Reddit and Twitter Username Analysis	Completed	D04	APPENDIX A - PROTOTYPE
FR-011	Wellbeing survey and mapping using association matrix	Completed	D04	APPENDIX A - PROTOTYPE
FR-012	Application Deployment and Model Retraining	Completed	D05	APPENDIX A - PROTOTYPE
NFR-001	Scalability and Performance	Completed	D03	10 - 11

Fig. 6.1 Requirement Matrix

6.2 Requirement Elaboration

No	Requirement	Input	Output
FR-001	Collect social media data from Reddit	API queries	Raw text data
FR-002	Implement data cleaning and preprocessing	Raw text data	Cleaned, structured text
FR-003	Train machine learning and deep learning models	Preprocessed data	Trained models
FR-004	Evaluate models using performance metrics	Trained models	Accuracy, Recall, F1 Score
FR-005	Text Analysis	User text input	Mental disorder classification
FR-006	Image Upload Analysis	Uploaded image	Extracted text, emotions for classification
FR-007	Video Upload Analysis	Uploaded video	Extracted frames, emotions and text for classification
FR-008	PDF Upload Analysis	Uploaded PDF	Extracted text and analysis
FR-009	User response to image	User input	Mental Disorder classification based on input text
FR-010	Reddit and Twitter Username Analysis	Username input	Mental disorder trends across the top posts
FR-011	Wellbeing survey and mapping using association matrix	Survey responses	Mental health insights
FR-012	Application Deployment and Model Retraining	Updated dataset	Improved/updated model accuracy within the web application
NFR-001	Scalability and Performance	Handling bigger dataset and subset models for a global ensemble model	Maintaining overall accuracy and response time

Functional and Non-Functional Requirements

7 Design

7.1 Technical Environment

The technical environment for the project "Multimodal AI Framework for Social Media Based Mental Disorder Detection and Personalized Wellbeing Insights" comprises a combination of hardware, software, and tools that enable smooth data analysis, machine learning model training, and deployment. Below is an overview of the minimum hardware configuration, software tools, and package details necessary to carry out this project effectively.

Component	Specification
Processor	Intel Core i5 (or equivalent) with a base clock speed of at least 2.5 GHz. A multi-core processor is preferred for parallel processing, essential for model training and data preprocessing.
RAM	8 GB recommended for handling data loading, cleaning, and transformation. For large datasets, 16 GB is ideal to prevent memory overflow and processing delays.
Storage	Minimum 256 GB SSD recommended. SSD offers faster read/write speeds, significantly improving dataset loading times, especially for large datasets like Reddit-based social media posts.
GPU	Not necessary for basic ML tasks like Logistic Regression or SVM. For deep learning, an NVIDIA GTX 1060 with 4 GB VRAM or higher is advantageous.
Operating System	Windows 10 (64-bit) or higher, macOS 10.13 (High Sierra) or higher, or any stable Linux distribution (e.g., Ubuntu 18.04 or higher). The OS should support ML libraries and project tools.

Minimum Hardware Configuration

Library/Package	Description
Python	Programming language for data processing and model training.
pandas	Data manipulation and preprocessing.
scikit-learn	Machine learning models and evaluation tools.
Streamlit	Web framework for deploying interactive ML applications.
pyngrok	Creates secure tunnels for sharing local applications.
Google Colab	Cloud-based Python environment with GPU/TPU support.
PRAW	Access and retrieve Reddit data via API.
pytesseract	OCR library for extracting text from images.
Pillow	Image processing and handling library.

Libraries and Packages Used

Library/Package	Description
joblib	Serialization and model saving utility.
protobuf	Efficient data serialization format by Google.
deep-translator	Multilingual text translation.
Requests	Library for making HTTP requests.
google-generativeai	Integrate Google's generative AI models.
ffmpeg	Multimedia framework for processing audio/video.
tesseract-ocr	OCR tool for text extraction.
portaudio19-dev	Required for handling audio input/output.
poppler-utils	Converts PDFs to images for text extraction.
pydub	Audio processing library.
sounddevice	Real-time audio recording/playback.
wavio	WAV file handling.
numpy	Numerical computing library.
PyAudio	Audio input/output handling.
SpeechRecognition	Converts speech to text.
pdf2image	Converts PDFs to images.
tweepy	Access and analyze Twitter data.
openai-whisper	Speech-to-text model from OpenAI.
tiktoken	Tokenizer for language models.
librosa	Audio analysis and feature extraction.
opencv-python	Computer vision and image processing.
xgboost	Gradient boosting for ML models.
deepface	Facial recognition and emotion analysis.
tf_keras	Keras API for TensorFlow.
transformers	Pre-trained NLP models from Hugging Face.
tensorflow	Deep learning framework.
nltk	Natural language processing toolkit.
plotly	Interactive data visualization.
matplotlib	Static and animated plots.
scipy	Scientific computing and signal processing.
networkx	Graph analysis and visualization.
yt-dlp	YouTube video/audio downloader.

Libraries and Packages Used

7.2 Hierarchy of Modules

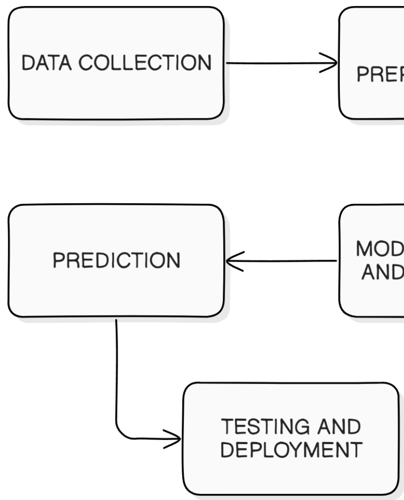


Fig. 7.1 Project Modules

Module	Description
Data Collection	Gathers relevant text data from posts in platforms like Reddit via PRAW.
Data Preprocessing	Cleans and prepares text data using: • Tokenization (splitting text into words/tokens) • Lowercasing for uniformity • Stop-word removal • Lemmatization or stemming Perform feature extraction to convert text into numerical features using: • Term Frequency-Inverse Document Frequency (TF-IDF) • Bag of Words (BoW) model • Word2Vec, LIWC (Linguistic Inquiry and Word Count) and N-Gram were also explored
Model Training and Validation	Splits dataset into training/testing sets and trains models such as: • Logistic Regression, Naive Bayes, SVM, XGBoost, KNN, LSTM, Transformer. These formed the base models for the ensemble model used in application where Random Forest was used as the meta-learner All were validated to assess performance.
Prediction	Processes received and combined text input for classification using trained models.
Testing and Deployment	Deploys models on Streamlit Cloud for real-time predictions and well-being insights using association matrix. Provides a user interface for easy access.

Hierarchy of Modules in the system

7.3 Detailed Design

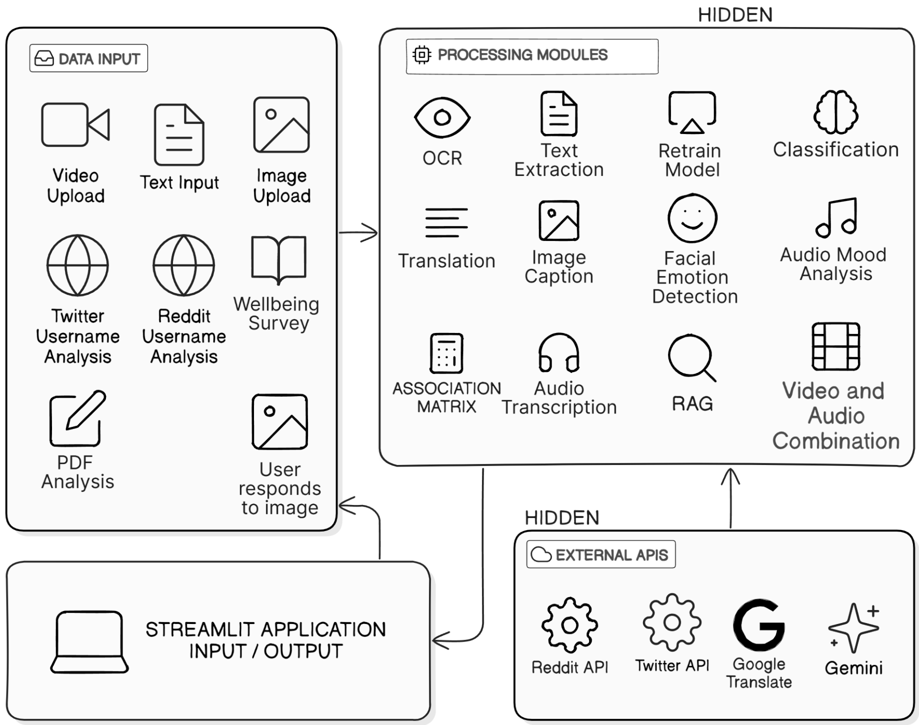


Fig. 7.2 System Overview

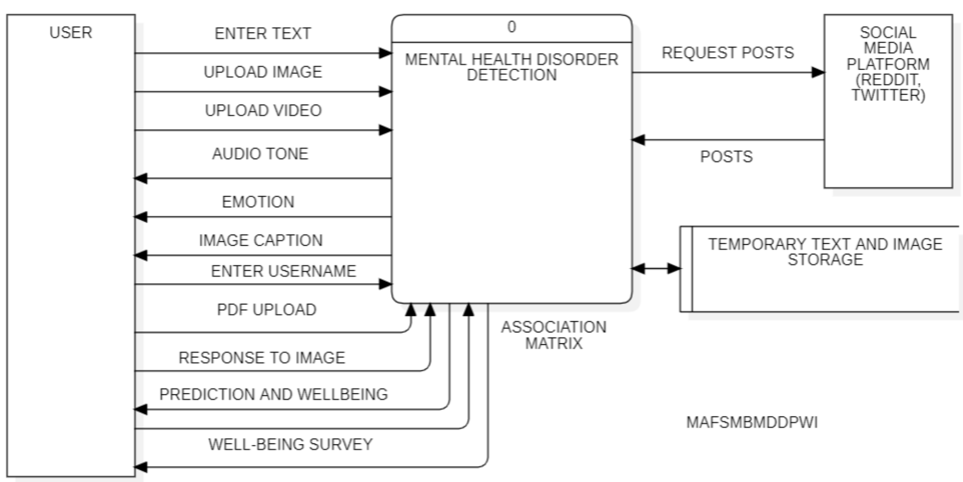


Fig. 7.3 DFD Level 0 of the System

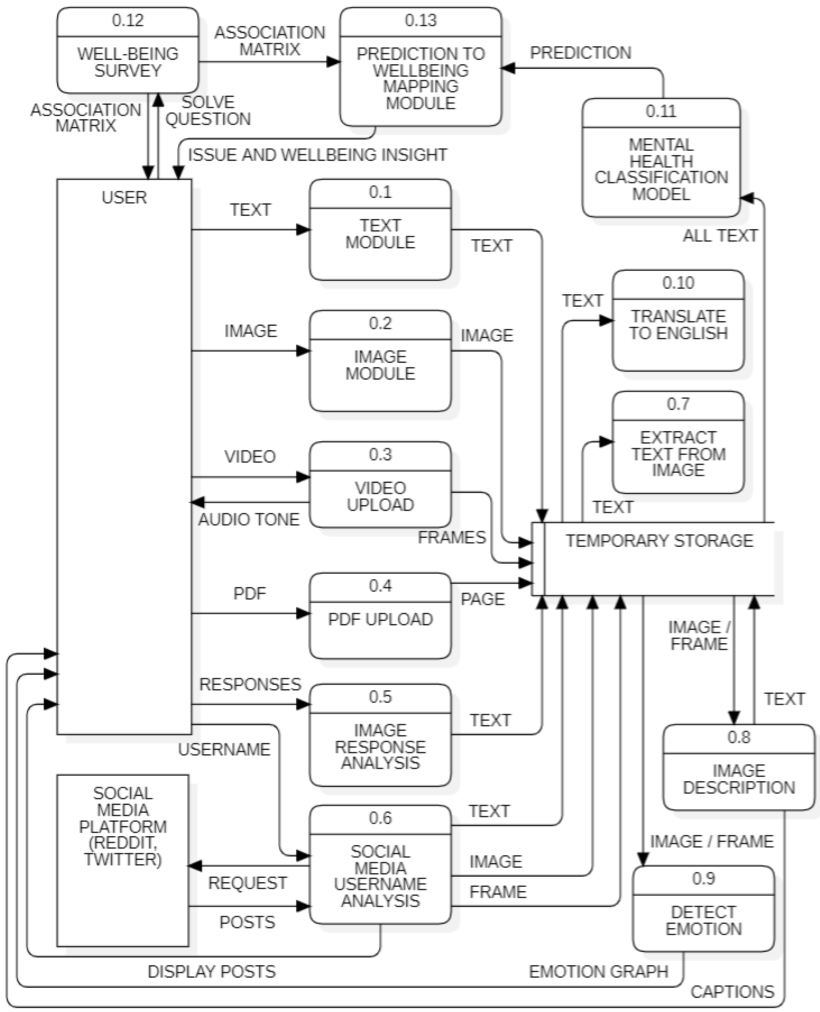


Fig. 7.4 DFD Level 1 of the System

Image Description

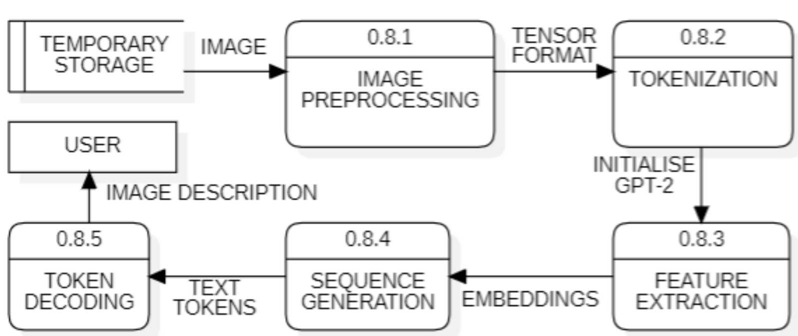


Fig. 7.5 DFD Level 2 of Image Description

The image captioning process using Python's Transformers module and the ViT-GPT2 model involves several key steps. The user uploads an image, which is preprocessed by resizing to

224×224 pixels, normalizing pixel values, and converting it into a tensor format. The Vision Transformer (ViT) divides the image into 16×16 patches, embeds them, and processes them through transformer layers to extract visual features. The resulting embedding is passed to GPT-2, which generates a sequence of text tokens iteratively using its language model. Tokens are decoded back into human-readable text using the GPT-2 tokenizer, cleaned for readability, and output as a concise description. This pipeline leverages ViT for feature extraction and GPT-2 for language generation, enabling efficient and almost accurate image captioning.

Emotion Detection Functionality

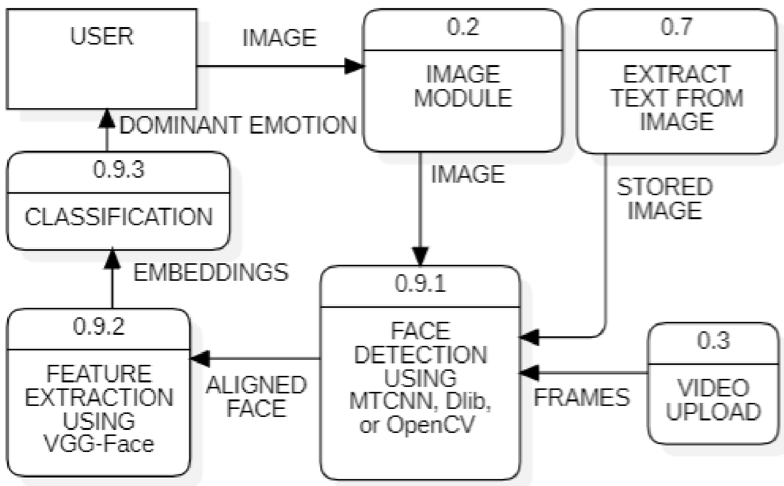


Fig. 7.6 DFD Level 2 of Emotion Detection Functionality

DeepFace analysis processes facial features from uploaded images or video frames through a structured pipeline. It starts with face detection using models like MTCNN, Dlib, or OpenCV to locate and align faces. The detected faces are cropped and passed to feature extraction, where pre-trained models like VGG-Face or Facenet generate numerical embeddings. These embeddings are compared using cosine similarity or Euclidean distance for tasks like emotion detection (e.g., happiness, sadness), demographic analysis (e.g., age, gender), or face verification. The results, such as detected emotions or attributes, are then displayed to the user. This process enables real-time analysis of facial expressions and emotions, providing valuable insights for mental health monitoring and wellbeing assessment.

Extract Text From Image

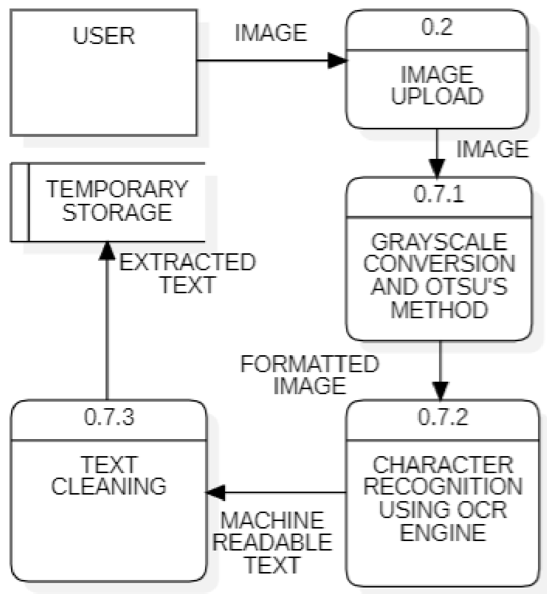


Fig. 7.7 DFD Level 2 of Text Extraction from Image

The process of extracting text from an image using Tesseract-OCR begins with preprocessing the uploaded image. The image is converted to grayscale, noise is reduced using Gaussian or Median Blur, and binarization (e.g., Otsu's thresholding) isolates text from the background. Text regions are detected using contour analysis or connected components. The processed image is then passed to Tesseract, which uses an LSTM-based neural network to recognize characters and generate machine-readable text, enhanced by language models for accuracy. Postprocessing corrects errors via spell-checking and rule-based replacements (e.g., `0` $\rightarrow$ `O`), and formats the text into paragraphs or lines. The final output, displayed or saved as `.txt` or `.docx`, is ready for applications like document analysis. This pipeline combines image enhancement, deep learning, and text correction for high-quality results.

Translation to English

The process of translating text to English using DeepTranslator begins with preprocessing the input to clean unwanted characters and detect the source language using machine learning models like Google's Compact Language Detector. The prepared text is passed to DeepTranslator, which interfaces with APIs like Google Translate or Microsoft Translator. These APIs use neural machine translation (NMT) with encoder-decoder architectures and attention mechanisms to translate the text into English. Transformer-based models enhance accuracy by capturing context and long-range dependencies. Postprocessing ensures quality by validating completeness, correcting errors, and preserving formatting. The final translated

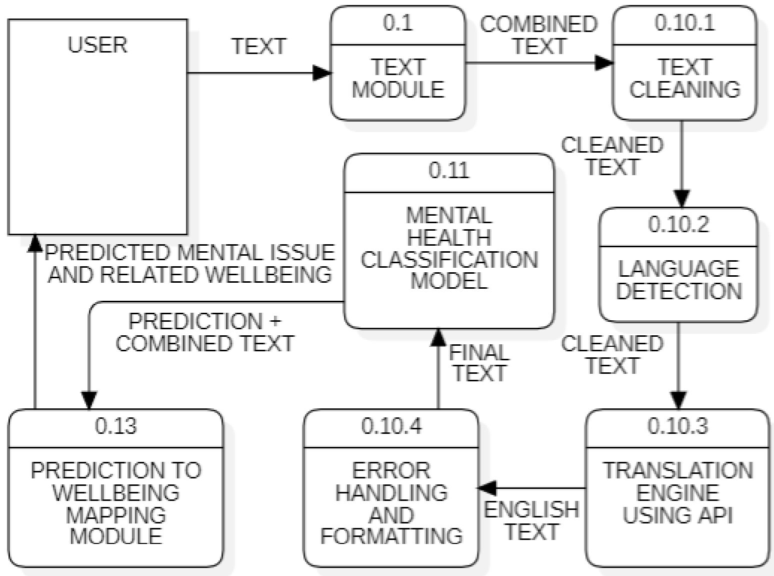


Fig. 7.8 DFD Level 2 of Translation to English

text is displayed or saved, ensuring accuracy and readability. This pipeline integrates NLP, deep learning, and error handling for reliable translations.

Audio Mood Analysis

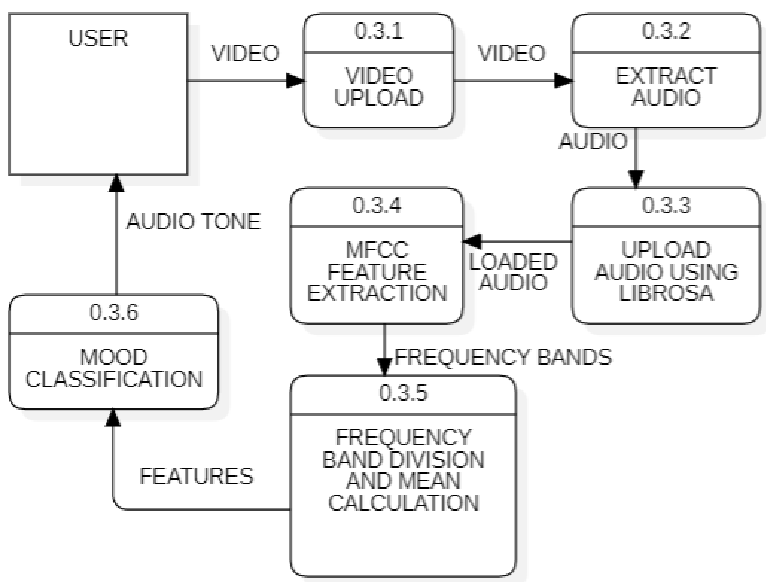


Fig. 7.9 DFD Level 2 of Audio Mood Analysis

The `analyze_audio_mood` function begins with the user providing a video file path. The audio is extracted using the `extract_audio_from_video` function and loaded into memory with the Librosa library. Mel-frequency cepstral coefficients (MFCCs) are computed using `librosa.feature.mfcc` to capture frequency patterns for mood analysis. The MFCC array is segmented into four frequency bands—low, mid-low, mid-high, and high—and the scalar mean of each band is calculated to simplify data for classification. The mood is classified (e.g., normal, calm, anxious) based on the dominant frequency characteristics. Results can be further enhanced using the Gemini API to provide tone, mood, and summary details for the audio. This process combines audio feature extraction and classification for comprehensive mood analysis.

Prediction to Wellbeing Mapping

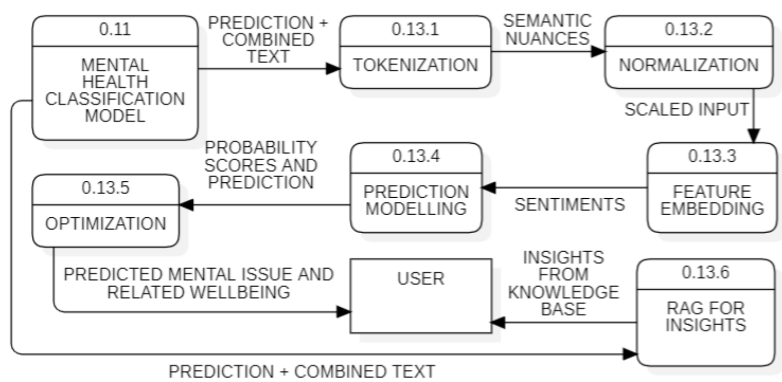


Fig. 7.10 DFD Level 2 of Prediction to Wellbeing Mapping

The system first processes user input (text, behavioral data, or health metrics) through preprocessing and feature extraction. Machine learning models then predict the most likely mental health condition along with associated probabilities. The top predicted issue and its probability are then fed into GEMINI 2.0 FLASH with a structured prompt to generate wellbeing insights based on Ryff's six parameters. To refine these insights, an association matrix maps the probabilities of all predicted issues to specific wellbeing parameters, selecting 1 to 3 key parameters (e.g., autonomy, personal growth, or self-acceptance). This ensures that the user receives targeted recommendations for improving their psychological wellbeing. There is also an additional feature where Retrieval Augmented Generation (RAG) is used to provide personalized recommendations based on the user's mental health condition. The system retrieves relevant information from a knowledge base and generates tailored suggestions.

The above 6 main functionalities are reused in the application for the options available to the user. These include **Text** analysis, **Image** analysis, **Video** analysis, **PDF** analysis, analysis of

User response to Image, analysis of **Reddit** and **Twitter** user profiles. **Wellbeing Survey Option** and **RAG for wellbeing Insights** have been added under *Implementation* section.

Below are the flow diagrams for the various *Analysis* options that the web application provides.

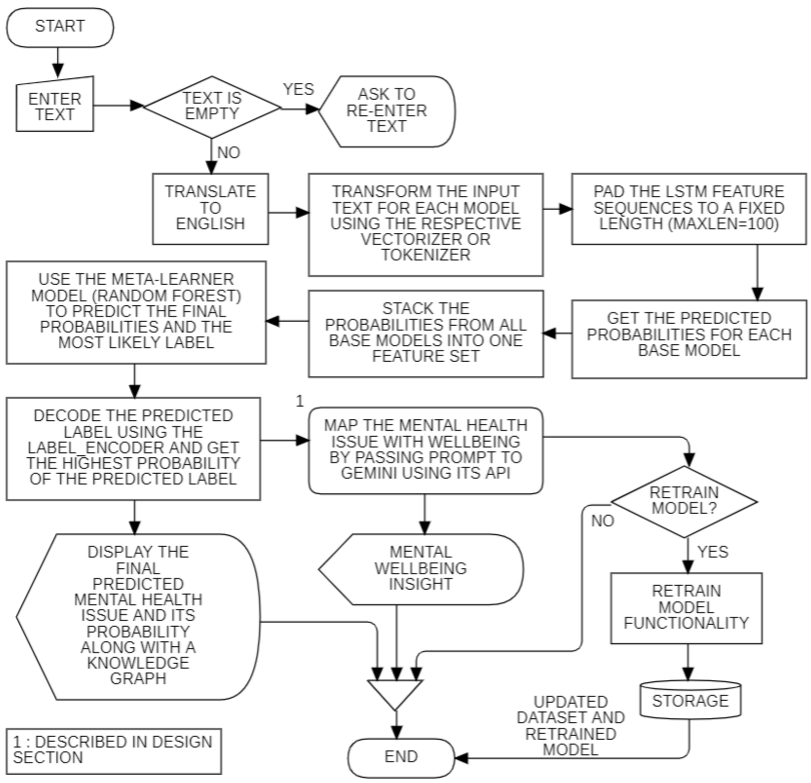


Fig. 7.11 Text Classification Flow Diagram

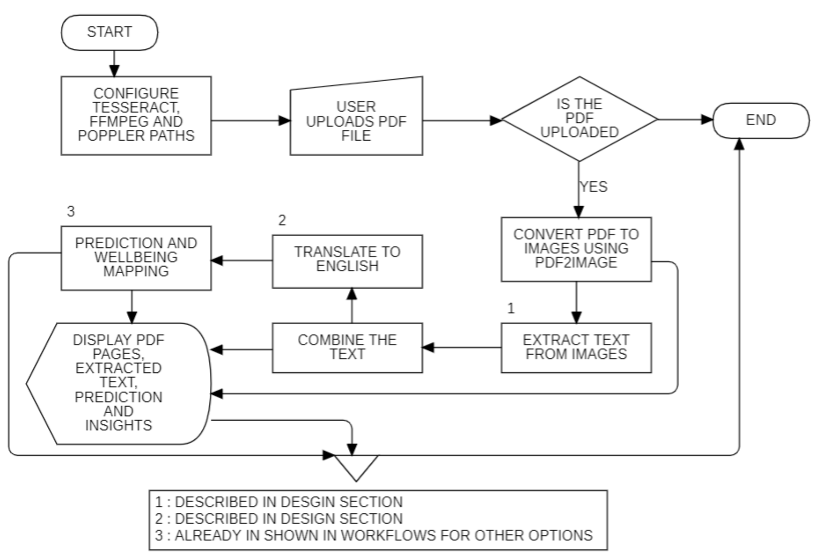


Fig. 7.12 PDF Upload Flow Diagram

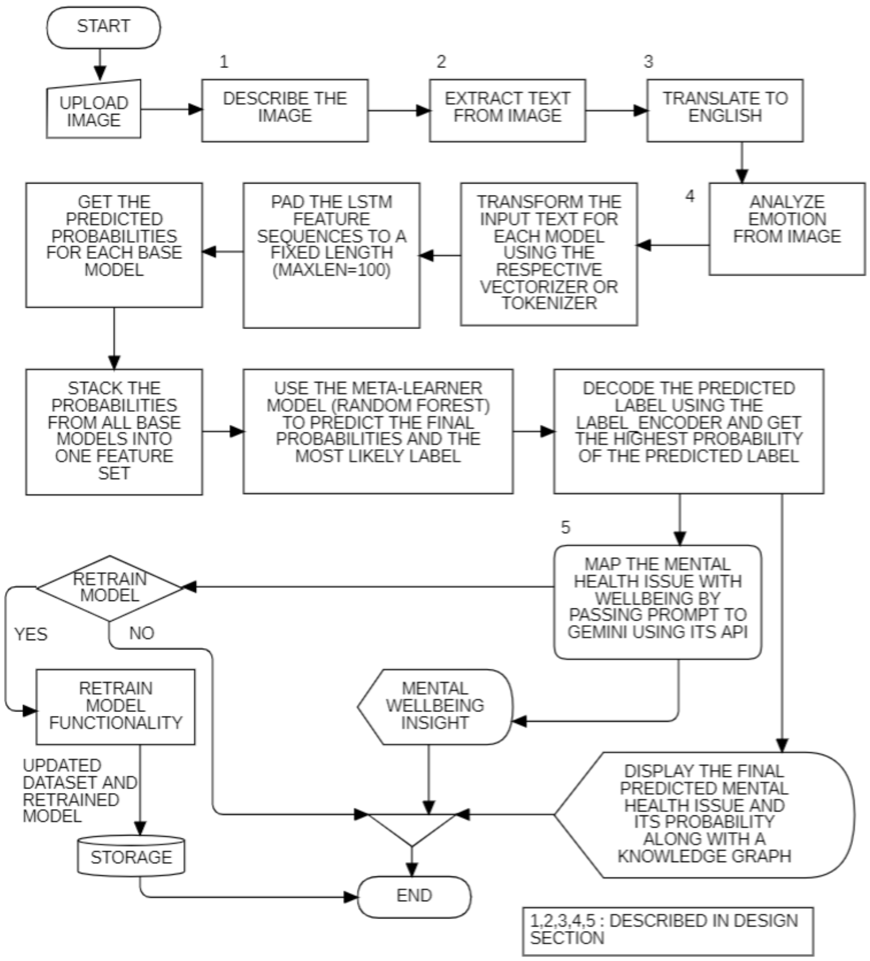


Fig. 7.13 Image Classification Flow Diagram

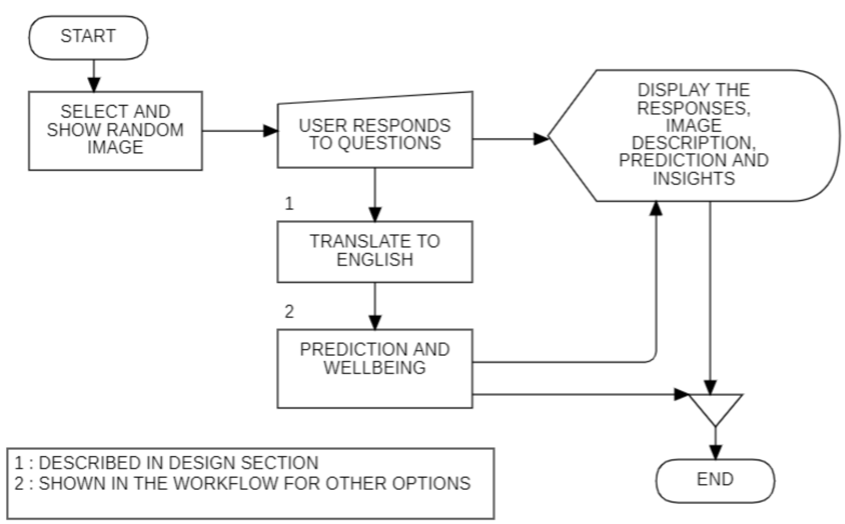


Fig. 7.14 User Response to Image Flow Diagram

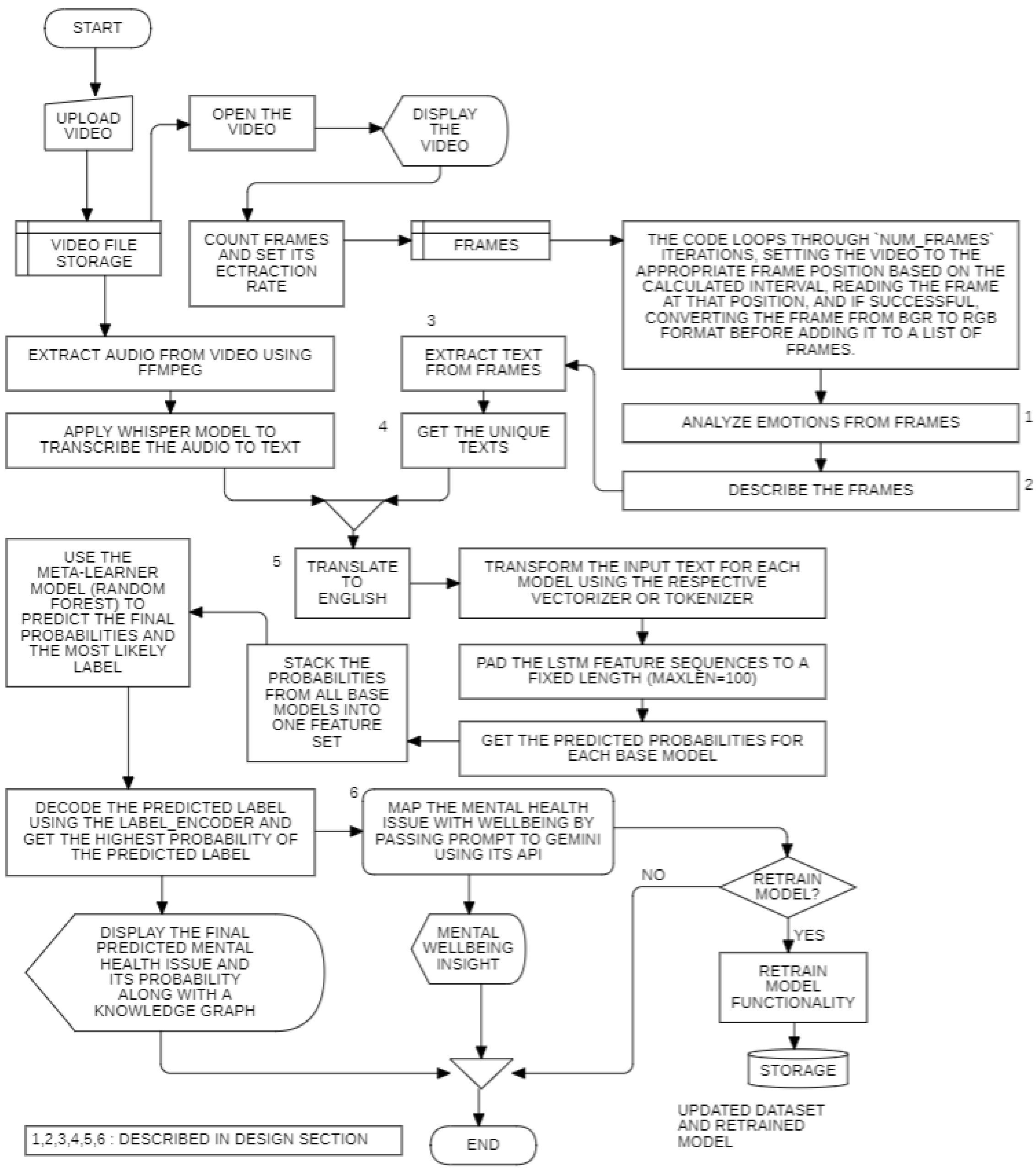


Fig. 7.15 Video Classification Flow Diagram

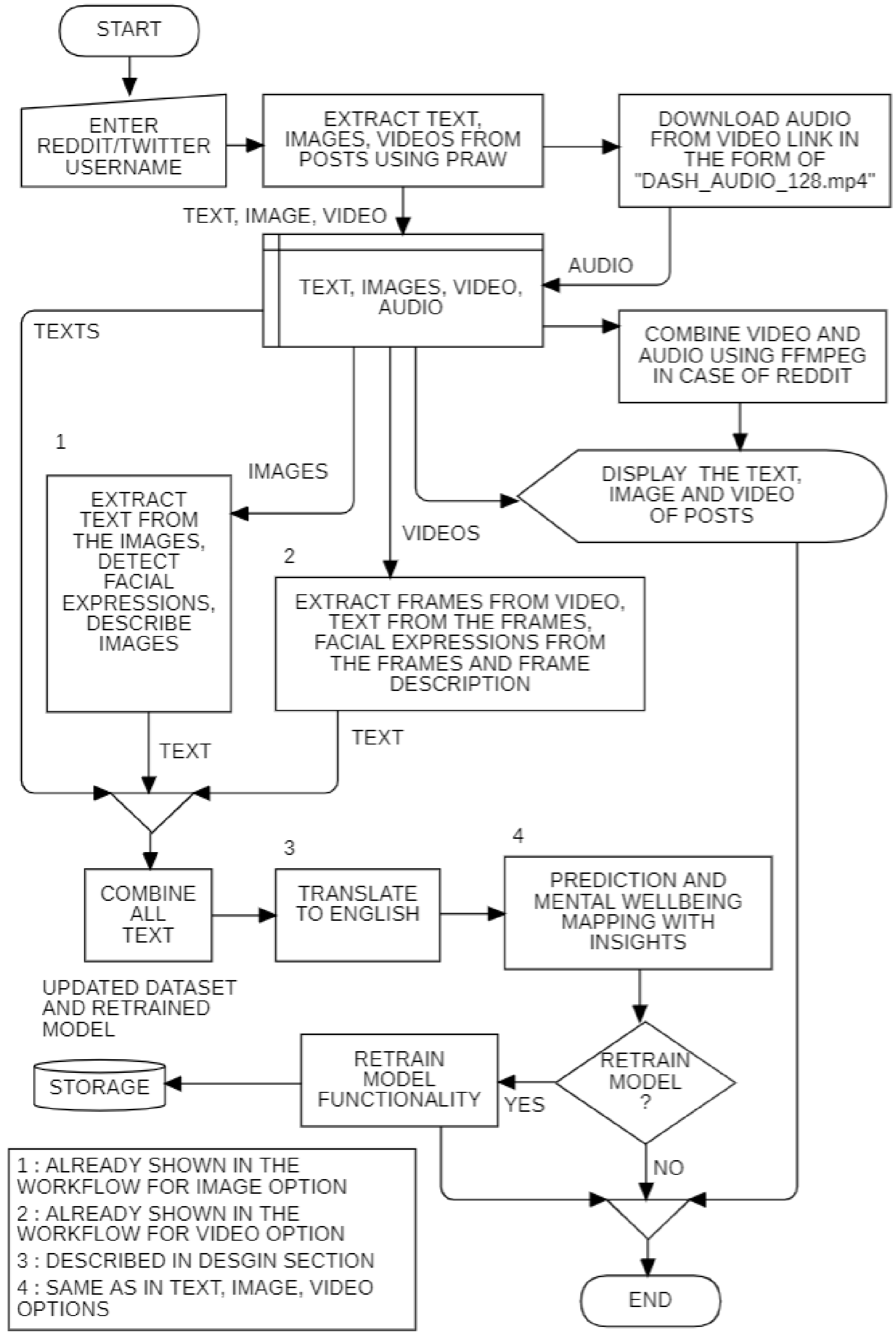


Fig. 7.16 Reddit and Twitter username Classification Flow Diagram

8 Implementation

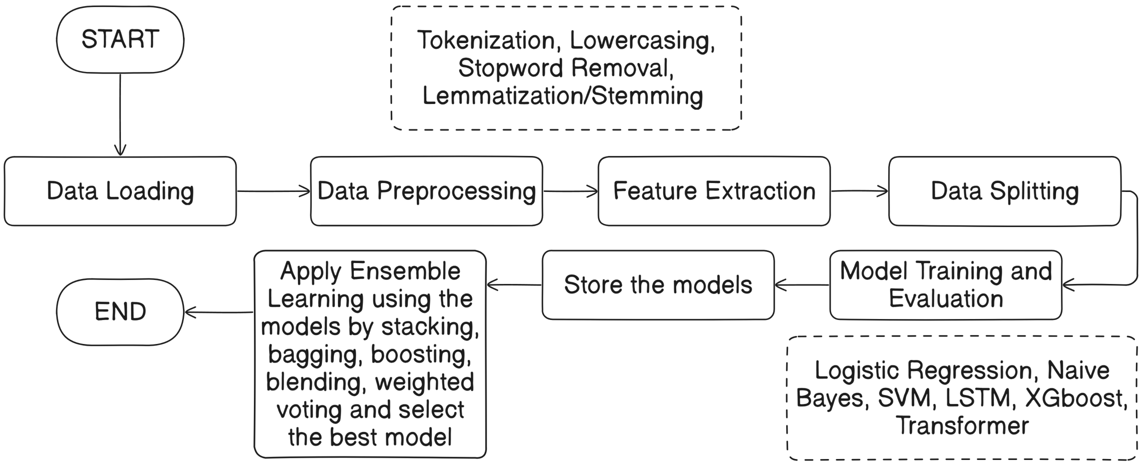


Fig. 8.1 Workflow for getting the model for the web application

8.1 Data Collection and Dataset Preparation

Stepwise Algorithm for Data Collection and Dataset Combination

Step	Description
1	**Import Libraries:** Import `praw, pandas, time` for data collection and `sklearn.utils.shuffle` for combining datasets.
2	**Initialize Reddit API:** Use the provided credentials (`client_id`, `client_secret`, `user_agent`) to create a Reddit instance.
3	**Define Subreddits and Labels:** Create a dictionary mapping labels to subreddit lists: • **normal**: `news, AskReddit` • **depression**: `depression` • **ptsd**: `PTSD` • **anxiety**: `Anxiety` • **bipolar**: `BipolarReddit`
4	**Set Post Types and Limit:** Define post types (`hot, new, top`) and set `posts_per_type` to 100.
5	**Collect Posts:** • For each label and its associated subreddits, iterate over each post type. • Retrieve posts from the subreddit (using the corresponding post type and a limit of 100). • For each post, combine the title and selftext, and append the result along with its label to a data list. • Pause for 1 second between requests.

Stepwise Algorithm for Data Collection and Dataset Combination

Step	Description
6	**Save Collected Data:** Convert the data list into a DataFrame with columns `text` and `label` and save it as `{label}_dataset.csv`.
7	**Load Datasets:** Read the individual CSV files for `bipolar, depression, normal, anxiety,` and `ptsd` into separate DataFrames.
8	**Determine Minimum Length:** Compute `min_length` as the minimum number of records among datasets (using `len(normal_df)//6` for the normal dataset to balance its count).
9	**Create a Balanced Pattern:** • Loop from 0 to `min_length - 1`. • For each iteration, append to a new list: – The `i`th record from `bipolar_df`. – The `i`th record from `depression_df`. – Six consecutive records from `normal_df` (indices `i*6` to `(i+1)*6`). – The `i`th record from `anxiety_df`. – The `i`th record from `ptsd_df`.
10	**Convert to DataFrame:** Transform the balanced list into a DataFrame (`pattern_df`).
11	**Prepare Remaining Data:** Concatenate the leftover records from each dataset (beyond `min_length` for all datasets and beyond `min_length*6` for the normal dataset) and shuffle them.
12	**Merge and Save Final Dataset:** Combine `pattern_df` with the shuffled remaining data, reset the index, and save the final DataFrame as `mental_health_combined.csv`.

```
                                                text mental_health_issue
0  2024 Election Due to the 2024 US Presidential ...             bipolar
1  Our most-broken and least-understood rules is ...          depression
2  Rules **UPDATED** 1. If you're here you must p...              normal
3  Happy Cakeday, r/Normal! Today you're 11 Let's...              normal
4  Happy Cakeday, r/Normal! Today you're 10 Let's...              normal
5  I am also a person I am very normal. Today I t...              normal
6  Happy Cakeday, r/Normal! Today you're 9 Let's ...              normal
7                         I am a person I am a person              normal
8  Elections and Politics Hello friends!\n\nIt's ...             anxiety
9                    You are more than just one emotion              ptsd
```

Fig. 8.2 Obtained Dataset

The dataset for mental health classification was compiled from subreddit communities, initially containing 385,800 records across five categories: anxiety (54 subreddits), PTSD (38), depression (80), bipolar disorder (60), and normal mental states (53). After data cleaning to ensure quality and relevance, the dataset was reduced to 167,279 records. A subset of 18,596 cleaned records was used for analysis to address computational constraints,

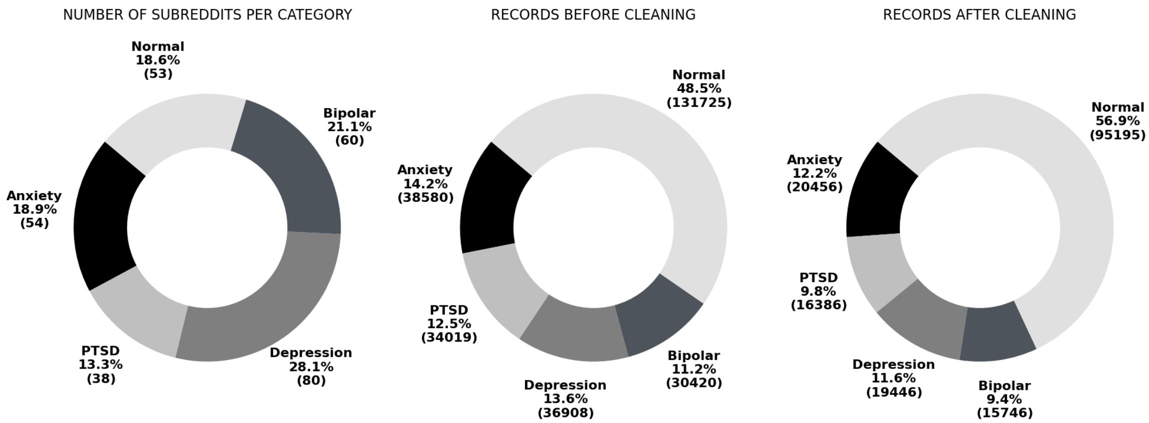


Fig. 8.3 Collected Data Statistics

such as memory and processing power, which would make training on the full dataset infeasible on standard hardware. This approach balances efficiency and performance, enabling faster experimentation and iterative model improvement while maintaining a representative sample.

8.2 Data Cleaning and Feature Extraction

Stepwise Algorithm for Data Cleaning and Feature Extraction

Step	Description
1	**Import Libraries & Resources**: Import `pandas`, `re`, `TfidfVectorizer` from scikit-learn, and NLTK modules. Download the necessary NLTK resources (e.g., `stopwords`, `punkt`, and `punkt_tab`).
2	**Load Dataset**: Read the CSV file `mental_health.csv` into a pandas DataFrame.
3	**Handle Missing Values**: Drop any rows where the `text` field is missing.
4	**Remove Duplicates**: Eliminate duplicate rows based on the `text` column.
5	**Define Negative Words**: Create a set of negative words (e.g., `not`, `no`, `nor`, etc.) that will be retained during stopword removal.
6	**Define Cleaning Function**: Write the function `clean_text(text)` to preprocess text by: (a) Removing URLs using regex. (b) Removing mentions (e.g., `@username`). (c) Removing special characters, numbers, and punctuation. (d) Converting text to lowercase. (e) Tokenizing the text using NLTK's `word_tokenize`. (f) Removing stopwords (while keeping negative words). (g) Rejoining tokens into a cleaned string.

Stepwise Algorithm for Data Cleaning and Feature Extraction

Step	Description
7	**Apply Cleaning Function**: Execute `clean_text` on the `text` column and store the result in a new column called `cleaned_text`.
8	**Initialize TF-IDF Vectorizer**: Create a TF-IDF vectorizer instance with a maximum of 10,000 features. (Other methods include Bag-Of-Words, LIWC, N-Gram, Word2Vec)
9	**Fit & Transform Data**: Apply the vectorizer to the `cleaned_text` to generate the TF-IDF feature matrix `X`.
10	**Optional - Convert to DataFrame**: Convert the TF-IDF sparse matrix `X` into a pandas DataFrame for easier inspection (e.g., print the first few rows).
11	**Optional - Save Preprocessed Data**: Save the final preprocessed DataFrame to `preprocessed_mental_health.csv`.

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
   aaa  aaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaa   ab  abandon  abandoned  \
0  0.0                                 0.0  0.0      0.0        0.0
1  0.0                                 0.0  0.0      0.0        0.0
2  0.0                                 0.0  0.0      0.0        0.0
3  0.0                                 0.0  0.0      0.0        0.0
4  0.0                                 0.0  0.0      0.0        0.0

   abandoning  abandonment  abc  abilities  ability  ...  zemeckis  zemlja  \
0         0.0          0.0  0.0        0.0  0.00000  ...       0.0     0.0
1         0.0          0.0  0.0        0.0  0.03726  ...       0.0     0.0
2         0.0          0.0  0.0        0.0  0.00000  ...       0.0     0.0
3         0.0          0.0  0.0        0.0  0.00000  ...       0.0     0.0
4         0.0          0.0  0.0        0.0  0.00000  ...       0.0     0.0

   zero  zoloft  zombie  zombieland  zombies  zone  zoom  zuckerberg
0   0.0     0.0     0.0         0.0      0.0   0.0   0.0         0.0
1   0.0     0.0     0.0         0.0      0.0   0.0   0.0         0.0
2   0.0     0.0     0.0         0.0      0.0   0.0   0.0         0.0
3   0.0     0.0     0.0         0.0      0.0   0.0   0.0         0.0
4   0.0     0.0     0.0         0.0      0.0   0.0   0.0         0.0

[5 rows x 10000 columns]
```

Fig. 8.4 Output of TF-IDF Vectorization

Datasets:

Before Cleaning: `mental_health.csv`

After Cleaning: `preprocessed_mental_helth.csv`

Stage	Schema	Description
Before Cleaning	`text`: Original text data `mental_issue`: Mental health issues	Contains raw, unprocessed text data with possible missing values, duplicates, URLs, mentions, and special characters.
After Cleaning	`text`: Original text data `mental_issue`: Mental health issues `cleaned_text`: Processed text data	Data is cleaned by removing URLs, mentions, special characters, and extra noise. The text is converted to lowercase, tokenized, stopwords (except key negative words) are removed, and the cleaned text is stored in the new column `cleaned_text`.

Dataset Schema Before and After Data Cleaning

The matrix dimensions for Bag of Words are determined by the number of records, which is 18,597 in this case, and the size of the vocabulary, which represents the number of unique words in the `cleaned_text` column. Similarly, for TF-IDF, the dimensions of the matrix are the same as BOW, calculated as the number of records multiplied by the vocabulary size. For N-gram, the matrix size depends on the range of n-grams used. For example, a unigram produces dimensions equivalent to BOW, while bigram or trigram models increase the vocabulary size due to the inclusion of word combinations. Word2Vec, on the other hand, creates a dense vector representation for each word, with dimensions based on the predefined vector size, such as 100 or 200. Aggregating these vectors at the sentence level, typically by averaging, results in a matrix of dimensions equal to the number of records multiplied by the vector dimensions. For LIWC, the dimensions are determined by the number of predefined LIWC categories, which is typically around 70. The resulting matrix dimensions are the number of records multiplied by the number of LIWC categories.

8.3 Machine Learning Models

Algorithms like Logistic Regression, K-Nearest Neighbors, Support Vector Machine, Random Forest, XGBoost and Naive Bayes are implemented for the classification of mental health issues. The code algorithm below demonstrates the implementation. The models are evaluated on the test set using metrics like accuracy and classification reports. Hyperparameter Tuning is performed using RandomizedSearchCV to optimize the model performance. Naive Bayes model after hyperparamter tuning is selected along with the basic Logistic Regression, Support Vector Machine, XGboost for the final ensemble model for the web application.

Stepwise Algorithm for Machine Learning Models

Step	Description
1	**Data Loading and Verification:** Load the dataset (`preprocessed_mental_health.csv`) using pandas, verify required columns (`cleaned_text` and `mental_health_issue`), and drop rows with missing values.
2	**Tokenization and Feature Extraction:** Choose a method (Bag-of-Words, TF-IDF, LIWC, Word2Vec, or N-gram) and transform `cleaned_text` into a numerical feature matrix X.
3	**Target Variable Preparation:** Extract the target variable y from the `mental_health_issue` column.
4	**Dataset Splitting:** Split X and y into training and test sets (e.g., 80/20 split) using `train_test_split` with a fixed random state.
5	**Model Initialization:** For each algorithm (Logistic Regression, Naive Bayes, SVM, KNN, Random Forest, XGBoost), initialize the model with appropriate hyperparameters.
6	**Model Training:** Train the selected model on the training data.
7	**Prediction:** Use the trained model to predict mental health issues on the test set.
8	**Model Evaluation:** Evaluate performance by computing accuracy, classification reports, and confusion matrices.
9	**Cross-Validation:** Apply Stratified K-Fold (e.g., 5 folds) cross-validation to record accuracies and calculate the mean and standard deviation.
10	**Performance Comparison:** Compare evaluation metrics across all models and feature extraction methods to select the best combination.
11	**Hyperparameter Tuning:** For Logistic Regression, Naive Bayes, SVM, and KNN, optimize hyperparameters using `RandomizedSearchCV` to search the parameter space and select the optimal configuration.

8.4 Deep Learning Models

Stepwise Algorithm for LSTM-based Model

Step	Description
1	**Data Loading:** Load `preprocessed_mental_health.csv` using pandas.
2	**Feature & Target Preparation:** • Extract text (X) and target (y). • Encode y using `LabelEncoder` and convert to one-hot with `to_categorical`.
3	**Tokenization & Padding:** • Initialize Keras `Tokenizer` with `num_words=25000`. • Fit on X, convert texts to sequences, and pad to `max_length=128` using `pad_sequences`.
4	**Cross-Validation Setup:** Define a 5-fold StratifiedKFold (shuffle=True, random_state=42).

Stepwise Algorithm for LSTM-based Model

Step	Description
5	**LSTM Model Building:** For each fold, build a Keras Sequential model with: • `Embedding(vocab_size, 128, input_length=128)` • `LSTM(128, return_sequences=True)` • `Dropout(0.2)` • `LSTM(64)` • `Dropout(0.2)` • `Dense(64, activation='relu')` • `Dense(num_classes, activation='softmax')`
6	**Model Training:** Compile the model with `optimizer='adamw'` and `loss='categorical_crossentropy'`. Train for 20 epochs with a batch size of 16 using the training fold and validate on the validation fold.
7	**Evaluation per Fold:** • Evaluate the model on the validation set to obtain loss and accuracy. • Predict probabilities on the validation set and compute the confusion matrix.
8	**ROC Curve Calculation:** • Concatenate true labels and predictions from all folds. • Binarize true labels and compute ROC curves and AUC for each class plus a micro-average.
9	**Visualization:** Plot ROC curves, validation loss/accuracy across folds, and the average confusion matrix using Matplotlib and Seaborn.
10	**Final Evaluation:** Compute the average cross-validated accuracy and display a classification report.

```
Epoch 1/10
/usr/local/lib/python3.10/dist-packages/keras/src/layers/core/embedding.py:90: UserWarning: Argument `input_length` is deprecated. Just remove it.
  warnings.warn(
465/465 ━━━━━━━━━━━━━━━━━━━━ 135s 280ms/step - accuracy: 0.6046 - loss: 1.1142 - val_accuracy: 0.6841 - val_loss: 0.7390
Epoch 2/10
465/465 ━━━━━━━━━━━━━━━━━━━━ 131s 281ms/step - accuracy: 0.6681 - loss: 0.7686 - val_accuracy: 0.6634 - val_loss: 0.8092
Epoch 3/10
465/465 ━━━━━━━━━━━━━━━━━━━━ 144s 286ms/step - accuracy: 0.6499 - loss: 0.8130 - val_accuracy: 0.6680 - val_loss: 0.7538
Epoch 4/10
465/465 ━━━━━━━━━━━━━━━━━━━━ 139s 280ms/step - accuracy: 0.6368 - loss: 0.8657 - val_accuracy: 0.6605 - val_loss: 0.7481
Epoch 5/10
465/465 ━━━━━━━━━━━━━━━━━━━━ 130s 280ms/step - accuracy: 0.6949 - loss: 0.6574 - val_accuracy: 0.6922 - val_loss: 0.6711
Epoch 6/10
465/465 ━━━━━━━━━━━━━━━━━━━━ 141s 278ms/step - accuracy: 0.7132 - loss: 0.6056 - val_accuracy: 0.6933 - val_loss: 0.6697
Epoch 7/10
465/465 ━━━━━━━━━━━━━━━━━━━━ 147s 289ms/step - accuracy: 0.7304 - loss: 0.5676 - val_accuracy: 0.7081 - val_loss: 0.6606
Epoch 8/10
465/465 ━━━━━━━━━━━━━━━━━━━━ 131s 282ms/step - accuracy: 0.7483 - loss: 0.5433 - val_accuracy: 0.7516 - val_loss: 0.6319
Epoch 9/10
465/465 ━━━━━━━━━━━━━━━━━━━━ 142s 282ms/step - accuracy: 0.8079 - loss: 0.4523 - val_accuracy: 0.7484 - val_loss: 0.6037
Epoch 10/10
465/465 ━━━━━━━━━━━━━━━━━━━━ 142s 282ms/step - accuracy: 0.8564 - loss: 0.3823 - val_accuracy: 0.8355 - val_loss: 0.5368
```

Fig. 8.5 Output for LSTM Epochs

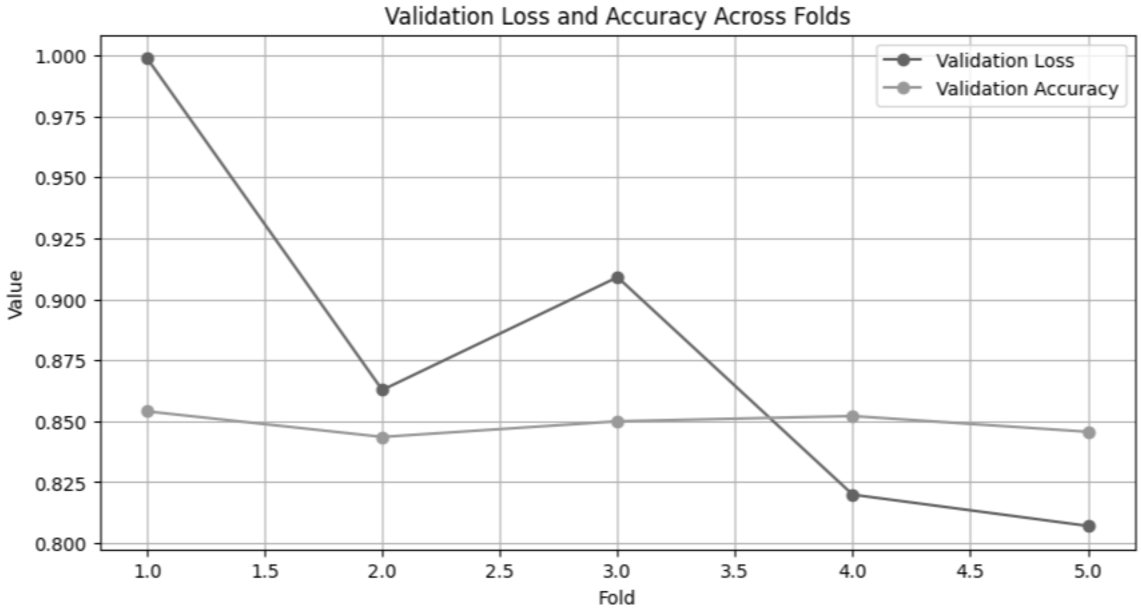


Fig. 8.6 LSTM Validation loss and accuracy

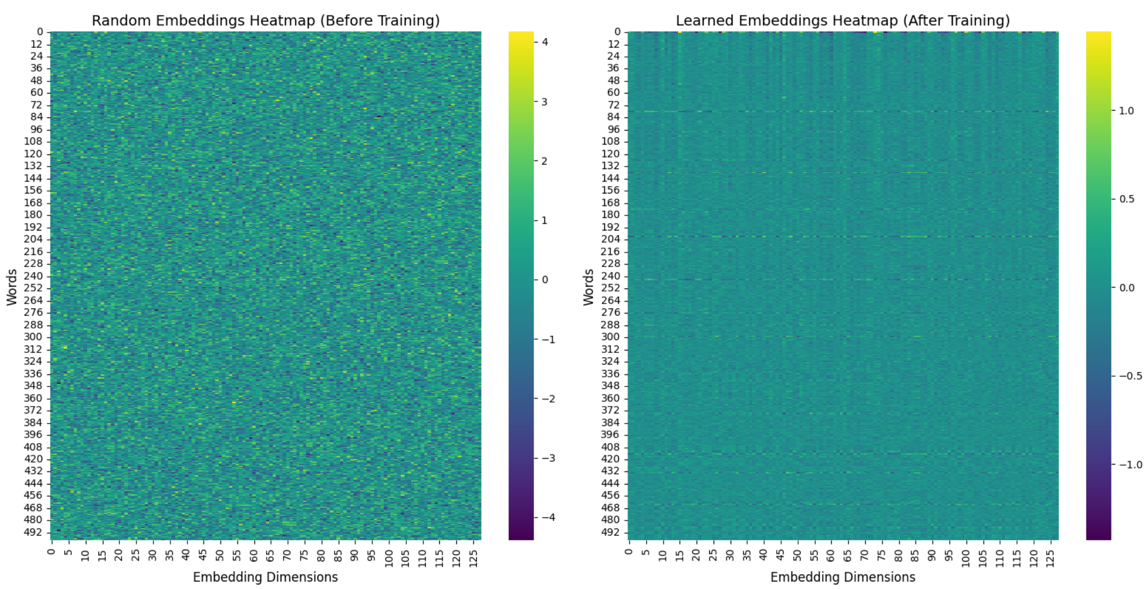


Fig. 8.7 LSTM Random and Learned Embeddings

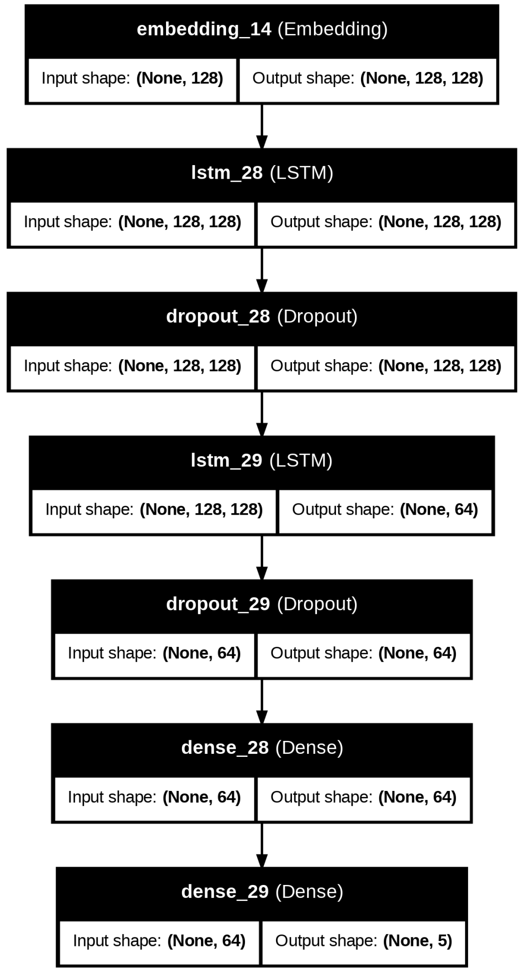


Fig. 8.8 LSTM Model Architecture

Stepwise Algorithm for Custom Transformer-based Model

Step	Description
1	**Import Libraries:** Import required packages including NumPy, pandas, Matplotlib, Seaborn, scikit-learn modules (e.g., `LabelEncoder`, `confusion_matrix`), and TensorFlow Keras modules (e.g., `TextVectorization`, `Embedding`, `LSTM`, `MultiHeadAttention`, etc.).
2	**Load Dataset:** Use Google Colab's file upload to import `preprocessed_mental_health.csv`. Drop rows with missing `cleaned_text` and extract features (`texts`) and labels (`labels`).
3	**Preprocess Labels:** Encode labels with `LabelEncoder`, convert them to one-hot format via `to_categorical`, and retrieve class names.
4	**Text Vectorization:** Set `vocab_size = 25000` and `sequence_length = 300`. Create a `TextVectorization` layer, adapt it on the input texts (using a TensorFlow `Dataset`), and vectorize the texts.

Stepwise Algorithm for Custom Transformer-based Model

Step	Description
5	**Define Custom Transformer Model:** • **EmbeddingLayer:** Custom layer that sums word embeddings with positional embeddings. • **EncoderLayer:** Custom layer using `MultiHeadAttention`, followed by a two-layer Dense network (with ReLU activation) and `LayerNormalization`. • **Model Architecture:** Build the model with an Input layer → `EmbeddingLayer` → `EncoderLayer` → `GlobalAveragePooling1D` → Dense (ReLU) → Output Dense (softmax). • Compile with optimizer `adamw` and loss `categorical_crossentropy`.
6	**Train the Model:** Convert vectorized texts to a NumPy array and split into training and validation sets (80/20 split, `random_state=42`). Train the model for 5 epochs with a batch size of 32.
7	**Evaluate the Model:** • Evaluate validation loss and accuracy. • Predict on the validation set and convert predictions to class labels. • Compute the confusion matrix using scikit-learn's `confusion_matrix`.
8	**Visualization:** Plot the confusion matrix with `ConfusionMatrixDisplay` (using Matplotlib) and optionally visualize random and learned embeddings.

Transformer Model Summary

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 300)	0
embedding_layer (EmbeddingLayer)	(None, 300, 64)	1,619,200
encoder_layer (EncoderLayer)	(None, 300, 64)	41,148
global_average_pooling1d (GlobalAveragePooling1D)	(None, 64)	0
dense_2 (Dense)	(None, 60)	3,900
dense_3 (Dense)	(None, 5)	305
Total params: 1,664,553 (6.35 MB)		
Trainable params: 1,664,553 (6.35 MB)		
Non-trainable params: 0 (0.00 B)		

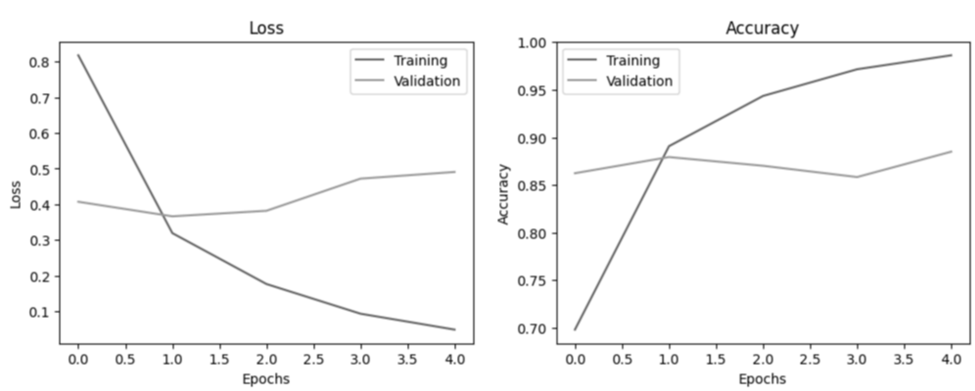


Fig. 8.9 Transformer Epoch, Loss, Accuracy

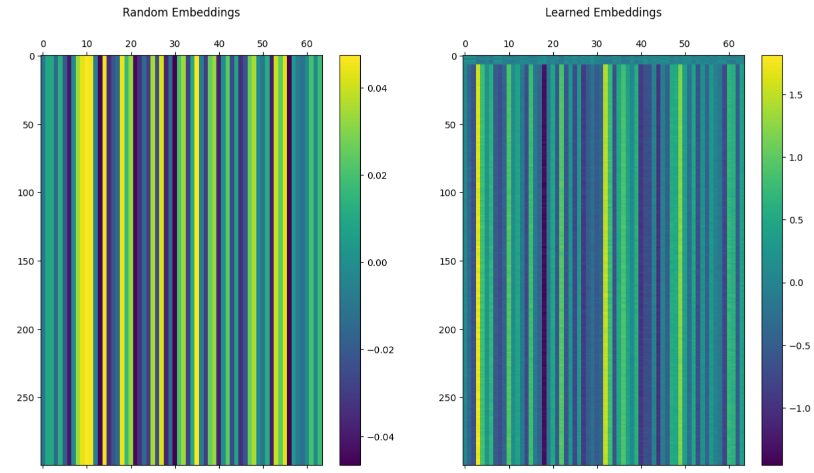


Fig. 8.10 Transformer Model Random and Learned Embeddings

8.5 Ensemble Model

General Stepwise Algorithm for Ensemble Models

Step	Description
1	**Import Libraries:** Import required packages including `numpy`, `pandas`, `tensorflow` (Keras modules such as `MultiHeadAttention`, `Embedding`, etc.), `scikit-learn` (e.g., `RandomForestClassifier`, `train_test_split`, `confusion_matrix`), and `pickle`.
2	**Load Pre-trained Base Models & Vectorizers:** Load saved models and vectorizers using `pickle` and `load_model`. Base models include: Logistic Regression (LR), Support Vector Machine (SVM), Naive Bayes (NB), XGBoost, LSTM, and Transformer. Also load corresponding vectorizers/tokenizers (e.g., `LRvectorizer`, `SVMvectorizer`, `NBvectorizer`, `tfidf_vectorizer`, `LSTM_tokenizer`, `Tvectorize_layer`) and label encoders.
3	**Load & Preprocess Test Data:** Read `preprocessed_mental_health.csv` with pandas, drop rows with missing `cleaned_text`, extract texts and labels, and encode labels using `LabelEncoder`.
4	**Text Preprocessing for Each Model:** Transform the raw texts using respective vectorizers/tokenizers: • LR, SVM, NB: Use `LRvectorizer`, `SVMvectorizer`, `NBvectorizer`. • XGBoost: Use `tfidf_vectorizer`. • LSTM: Convert texts using `LSTM_tokenizer` and apply `pad_sequences`. • Transformer: Process texts using `Tvectorize_layer`.
5	**Generate Base Model Predictions:** For each base model, compute prediction probabilities: • LR: `lr_model.predict_proba` • SVM: `svm_model.predict_proba` • NB: `nb_model.predict_proba` • XGBoost: `xgb_model.predict_proba` • LSTM: `lstm_model.predict` • Transformer: `transformer_model.predict`

General Stepwise Algorithm for Ensemble Models

Step	Description
6	**Stack Predictions:** Horizontally stack all base model prediction probabilities to form a new feature matrix (`stacked_features`) for the meta-learner.
7	**Ensemble Configuration & Data Splitting:** Split the stacked features and true labels (using `train_test_split`) into training and testing sets. Specify ensemble configurations: • **Ensemble Model 1:** Base models: LR, XGBoost; Meta-learner: XGBoost. • **Ensemble Model 2:** Base models: LR, NB, SVM, XGBoost, LSTM; Meta-learner: XGBoost. • **Ensemble Model 3:** Base models: LR, NB, SVM, XGBoost, LSTM; Meta-learner: Random Forest. • **Ensemble Model 4:** Same base models as in Ensemble Model 7 using Bagging. • **Ensemble Model 5:** Same base models as in Ensemble Model 7 using Blending. • **Ensemble Model 6:** Same base models as in Ensemble Model 7 using Weighted Voting. • **Ensemble Model 7:** Base models: LR, SVM, NB, LSTM, XGBoost, Transformer; Meta-learner: Random Forest.
8	**Train Meta-Learner:** Train the meta-learner (e.g., Random Forest, XGBoost, or ensemble strategies like Bagging, Blending, Voting) on the training portion of the stacked feature matrix.
9	**Evaluate Ensemble Model:** Predict on the test set using the meta-learner and compute evaluation metrics: accuracy, classification report, and confusion matrix. Also, perform cross-validation (e.g., using `cross_val_score`) to assess stability.
10	**Output Results:** Print final evaluation metrics (accuracy, report, confusion matrix) and cross-validation results.

8.6 Wellbeing Survey and Association Matrix

1	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	issue	p1	p2	p3	p4	p5	p6	Date
2	6	1	6	1	6	3	6	1	6	1	6	1	Normal	12	12	10	12	12	12	2025-02-07
3	1	6	2	5	2	5	1	6	1	6	1	6	Depression	2	4	4	2	2	2	2025-02-07
4	4	5	2	3	1	4	3	6	5	4	2	3	Anxiety	6	6	4	4	8	6	2025-02-07
5	1	4	6	5	1	2	5	4	4	5	3	4	Bipolar	4	8	6	8	6	6	2025-02-07
6	1	4	3	4	1	6	5	4	3	6	1	4	PTSD	4	6	2	8	4	4	2025-02-07
7	3	4	1	2	1	4	1	4	6	5	2	3	Anxiety	6	6	4	4	8	6	2025-02-07
8	2	5	3	2	3	4	3	4	3	2	3	4	Bipolar	4	8	6	6	8	6	2025-02-07
9	3	4	1	2	1	4	1	4	6	5	2	3	Anxiety	6	6	4	4	8	6	2025-02-07
10	5	1	5	1	5	3	5	1	5	2	5	1	Normal	11	11	9	11	10	11	2025-02-07
11	2	5	4	5	1	6	5	2	5	3	6	3	PTSD	4	6	2	10	9	10	2025-02-07

Fig. 8.11 Sample Response Collection Sheet

Step-by-Step Algorithm for the Well-being Survey Option

Step	Operation	Description / Formula
1	**Initialization:** - Define file paths: `csv_file_path`, `image_path`, `am_file_path`. - Display title *"Well-being Survey"*.	–
2	**Display Introductory Image:** - Check if the image file exists at `image_path` and display it.	–
3	**Display Instructions:** - Present informational messages and detailed instructions. - Describe the Ryff Scale	**1** $\rightarrow$ Strongly Disagree **2** $\rightarrow$ Disagree **3** $\rightarrow$ Slightly Disagree **4** $\rightarrow$ Slightly Agree **5** $\rightarrow$ Agree **6** $\rightarrow$ Strongly Agree
4	**Load or Create Response Data:** - Attempt to load `response.csv` into a DataFrame. - If not found, create a new DataFrame with columns: {Q1, Q2, ..., Q12, issue, p1, ..., p6, Date}. - (R) against questions {Q2, Q4, Q6, Q8, Q10, Q12} signify reverse scoring	**Q1-Q2** : Self Acceptance **Q3-Q4** : Positive relations with others **Q5-Q6** : Autonomy **Q7-Q8** : Environmental Mastery **Q9-Q10** : Purpose In Life **Q11-Q12** : Personal Growth
5	**Collect User Responses:** - Initialize an empty dictionary `responses`. - **Q00:** Record predicted mental issue (via radio buttons with options: Anxiety, Bipolar, Depression, Normal, PTSD). - **Q01–Q12:** Present 12 survey questions; record responses (scale 1–6).	**Follow these links for details:** https://positivepsychology.com/ryff-scale-psychological-wellbeing/ https://centerofinquiry.org/uncategorized/ryff-scales-of-psychological-well-being/
6	**Append Current Date:** - Add the current date in `YYYY-MM-DD` format to `responses`.	Date = current date (YYYY-MM-DD)
7	**Overall Score Calculation:** For each well-being parameter, compute a score using two survey responses. **Variables:** S_{SA}: Self Acceptance S_{PR}: Positive Relations with Others S_{A}: Autonomy	$S_{\text{SA}} = Q1 + \|7 - Q2\|$, $S_{\text{PR}} = Q3 + \|7 - Q4\|$, $S_{\text{A}} = Q5 + \|7 - Q6\|$, $S_{\text{EM}} = Q7 + \|7 - Q8\|$, $S_{\text{PL}} = Q9 + \|7 - Q10\|$, $S_{\text{PG}} = Q11 + \|7 - Q12\|$

Step-by-Step Algorithm for the Well-being Survey Option

Step	Operation	Description / Formula
	S_{EM}: Environmental Mastery S_{PL}: Purpose in Life S_{PG}: Personal Growth	
8	**Determine Score Levels:** - Compute the score level by dividing each parameter score by 2 (using integer division). - Classify as: **Low** if score level is in {1,2}, **Medium** if in {3,4}, and **High** otherwise.	$\text{Score Level} = \left\lfloor \frac{S}{2} \right\rfloor,$ $\begin{cases} \text{Low} & \text{if } S \in \{1,2\}, \\ \text{Medium} & \text{if } S \in \{3,4\}, \\ \text{High} & \text{if } S \geq 5. \end{cases}$
9	**Update Association Matrix:** - For each parameter ($p1$ to $p6$) and for each unique issue type in the responses, extract the corresponding values. - Divide these values by 2, compute their mean, round the result to obtain an integer, and update the association matrix.	$\begin{aligned} \text{For a parameter: } v_i &= \frac{\text{value}}{2}, \\ \bar{v} &= \frac{1}{n}\sum_{i=1}^{n} v_i, \\ \text{Final Value} &= \text{round}(\bar{v}) \end{aligned}$
10	**Submit Responses and Save Data:** - On clicking the `Submit Responses` button, display a success message. - Append the new response entry to the DataFrame and update `response.csv`. - Display the last 5 responses and count today's respondents.	–
11	**Display Updated Association Matrix:** - Call the function to update `am.csv` based on the latest responses, and display it as a table.	–

1	parameter	anxiety	bipolar	depression	normal	ptsd
2	self acceptance	3	2	1	6	2
3	positive relations with others	3	4	2	6	3
4	autonomy	2	3	2	4	1
5	environmental mastery	2	4	1	6	4
6	purpose in life	4	4	1	6	3
7	personal growth	3	3	1	6	4

Fig. 8.12 Sample Association Matrix

Step-by-Step Algorithm for Association Matrix Analysis

Step	Operation	Mathematical Formula / Description
1	**Load Dataset**	Read the CSV file (e.g., `am.csv`) to obtain the association matrix data.
2	**Define Row Names and Issue Columns**	Set row names: self acceptance, positive relations with others, autonomy, environmental mastery, purpose in life, personal growth
3	**Extract Association Matrix**	Let $A \in \mathbb{R}^{6\times 5}$, A_{ij} is the value for the i-th parameter and j-th issue with issue columns ordered as: anxiety, bipolar, depression, normal, ptsd.
4	**Define Probabilities Vector**	Define the probability vector where I_j refers to the mental issue probabilities. $\vec{p} = \begin{bmatrix} I1 \\ I2 \\ I3 \\ I4 \\ I5 \end{bmatrix}$, which satisfies $\sum_{j=1}^{5} I_j = 1.$
5	**Weighted Sum Analysis**	Compute the weighted sum for each row: $w_i = \sum_{j=1}^{5} A_{ij}\, p_j, \quad i = 1, \ldots, 6$. Identify the row index with maximum w_i, i.e., $i^* = \arg\max_i\, w_i$.
6	**Cosine Similarity Analysis**	For each row vector $\vec{a}_i$ of A, compute: $s_i = \dfrac{\vec{a}_i \cdot \vec{p}}{\lVert\vec{a}_i\rVert\, \lVert\vec{p}\rVert}, \quad i = 1, \ldots, 6$. Determine $i^* = \arg\max_i\, s_i$.
7	**Euclidean Distance Analysis**	For each row, compute the Euclidean distance: $d_i = \sqrt{\sum_{j=1}^{5} (A_{ij} - p_j)^2}, \quad i = 1, \ldots, 6.$ Find the row index with the smallest distance: $i^* = \arg\min_i\, d_i$.
8	**Consensus Decision**	Compare the row names identified by the three analyses. If all three methods return the same row name, that is the consensus; otherwise, list the unique names obtained.

Step-by-Step Algorithm for Association Matrix Analysis

Step	Operation	Mathematical Formula / Description
9	**Display Results**	Use Streamlit to display: • The original Association Matrix. • The computed weighted sums, cosine similarity scores, and Euclidean distances. • The row(s) corresponding to the maximum weighted sum, highest cosine similarity, and smallest Euclidean distance. • The consensus result.

8.7 RAG for Wellbeing Insights

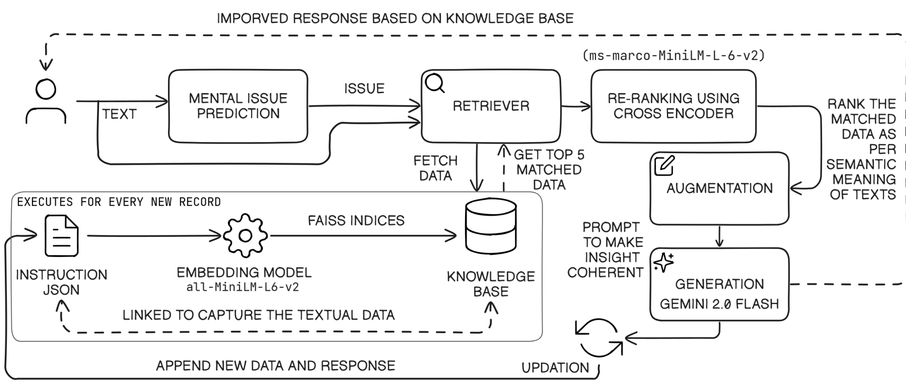


Fig. 8.13 OVERVIEW OF RAG FOR GENERATING INSIGHTS

Step-by-Step Algorithm for RAG-based Wellbeing Insight Generation

Step	Operation	Mathematical Formula / Description
1	**Import Libraries**	Import necessary packages: `streamlit`, `json`, `pickle`, `numpy`, `faiss`, `sentence_transformers`, `transformers`, `google.generativeai`, `plotly`, `sklearn.manifold.TSNE`, etc.
2	**Configure Gemini API**	Set the generation configuration parameters and initialize the Gemini model.
3	**Generate Instruction Dataset**	Create a dataset `instruction_data.json` with `text`, `issue`, and `response` using Gemini API through batching and rate limiting.

Step-by-Step Algorithm for RAG-based Wellbeing Insight Generation

Step	Operation	Mathematical Formula / Description
4	**Build FAISS Index**	Load the saved model via: `embedding_model = pickle.load("rag_embedding_gpu.pkl")`. Then load the instruction data from `instruction_data.json` to form `documents =` $\{$`instruction + input`$\}$ and `outputs =` $\{$`output`$\}$. Next, encode the documents using `embeddings = np.array([embedding_model.encode(doc)])` so that embeddings $\in \mathbb{R}^{n \times d}$. Build the FAISS L2-index by setting `index = faiss.IndexFlatL2(d)` and calling `index.add(embeddings)`. Finally, save the tuple $\{$`documents, outputs, index, embeddings`$\}$ into `"global_store_gpu.pkl"`.
5	**Load Global Store**	Retrieve data from `global_store_gpu.pkl` (documents, indices, outputs and embeddings).
6	**Compute Query Embedding**	Create the query by concatenating user text and mental issue. Encode it and and cast to a float32 NumPy array: $\mathbf{v}_q = \text{embedding\_model.encode(query)}$
7	**FAISS Retrieval (Top-k)**	Retrieve the top $k = 10$ matches using FAISS. The distance metric is the squared Euclidean (L2) norm: $d(\mathbf{v}_q, \mathbf{v}_i) = \lVert \mathbf{v}_q - \mathbf{v}_i \rVert^2$ The query is processed as: $(D, I) = \text{index.search}(\mathbf{v}_q, 5)$
8	**Re-ranking**	Re-rank the top $n = 5$ from the initially retrieved k documents to improve relevance using `ms-marco-MiniLM-L-6-v2`. (i) Extract text for each candidate: $\text{retrieved\_docs\_text} = \{\text{documents}[i] \mid i \in \text{indices}\}$ (ii) Form pairs by concatenating the query with each document: $\text{cross\_inp} = \{[\text{query},\ \text{doc\_text}]\}.$ (iii) Compute cross-encoder scores: $\text{cross\_scores} = \text{cross\_encoder.predict(cross\_inp)}.$ (iv) Sort candidates by score in descending order
9	**Filter by Ryff Parameters**	Apply text filtering to the retrieved output of the top candidate. Check if it contains any selected Ryff parameters (e.g., Autonomy, Positive Relations, etc.).
10	**Generate Refined Insight**	Construct a prompt for the Gemini model based on the retrieved text and selected parameters. Generate a refined insight: $\text{generated\_output} = \text{gemini\_model.generate\_content(prompt)}$

Step-by-Step Algorithm for RAG-based Wellbeing Insight Generation

Step	Operation	Mathematical Formula / Description
11	**3D t-SNE Visualization**	Combine the query embedding with the document embeddings and reduce the dimensionality using t-SNE: reduced $=$ TSNE$(n_components = 3)$(combined_embeddings) Separate the query and top-k points for visualization via Plotly.
12	**Plot Graph**	Plot the 3D scatter plot with annotations for the query, top-k matches, and connecting dotted lines.
13	**Append New Record**	Append a new record to `instruction_data.json` and rebuild the FAISS index. In this step, the updated documents are as below and the FAISS index is rebuilt with the new embeddings : documents $= \{\texttt{instruction} + \texttt{input}\}$

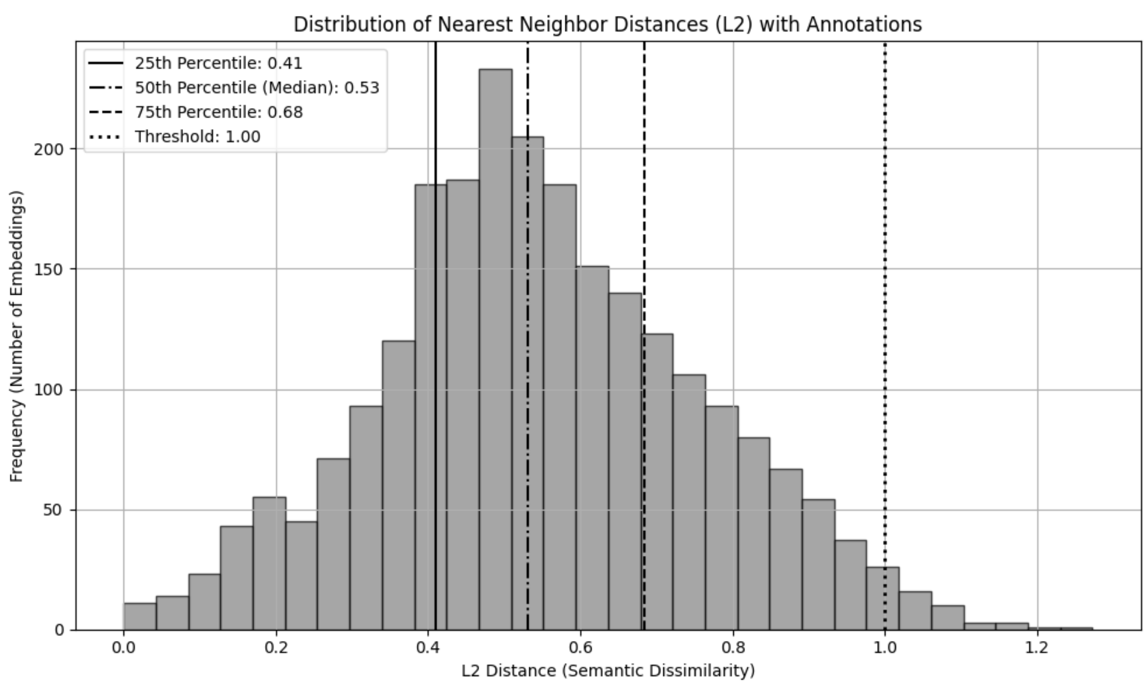


Fig. 8.14 Nearest Neighbours among the Embeddings

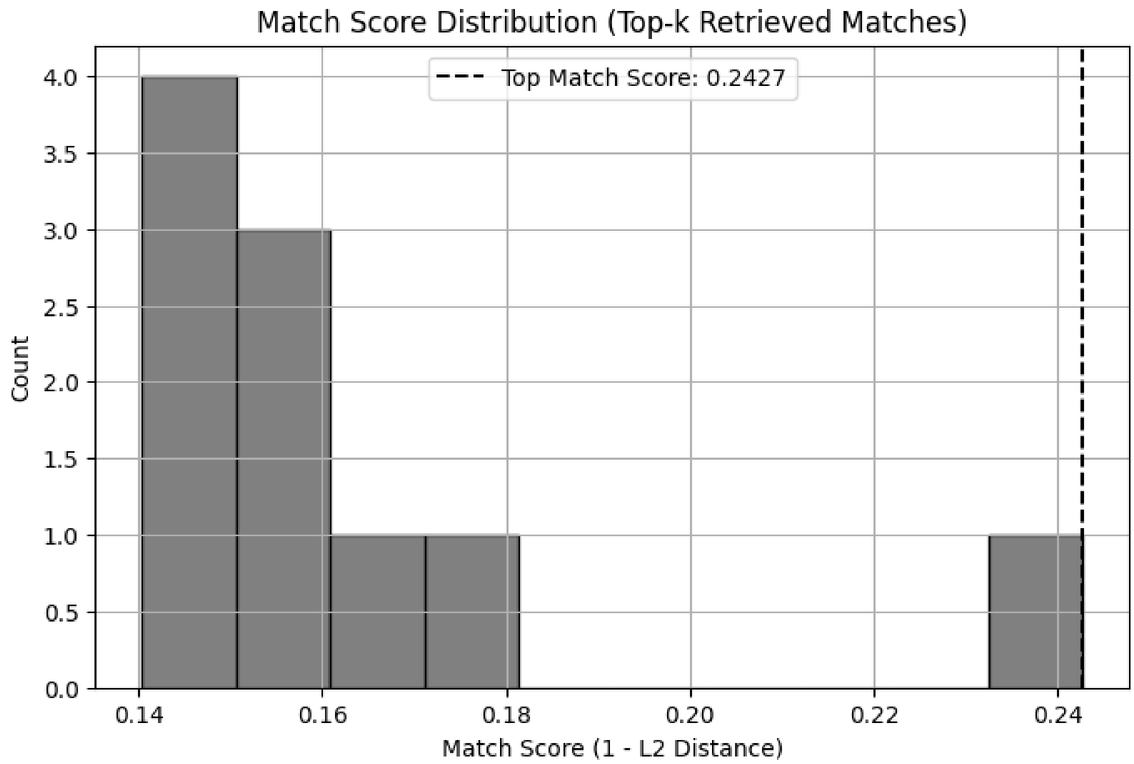


Fig. 8.15 Count of Matches and Top Score for an input

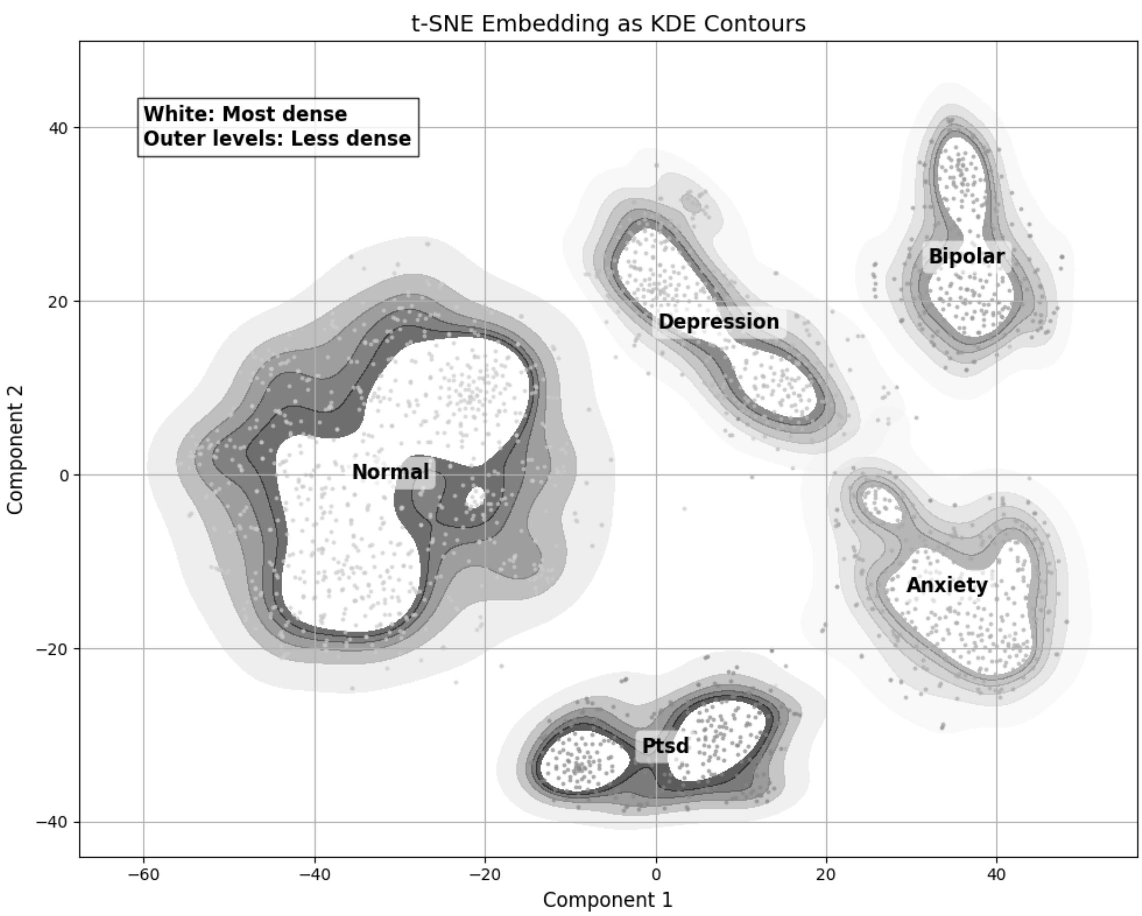


Fig. 8.16 Instruction Embeddings in 2D space

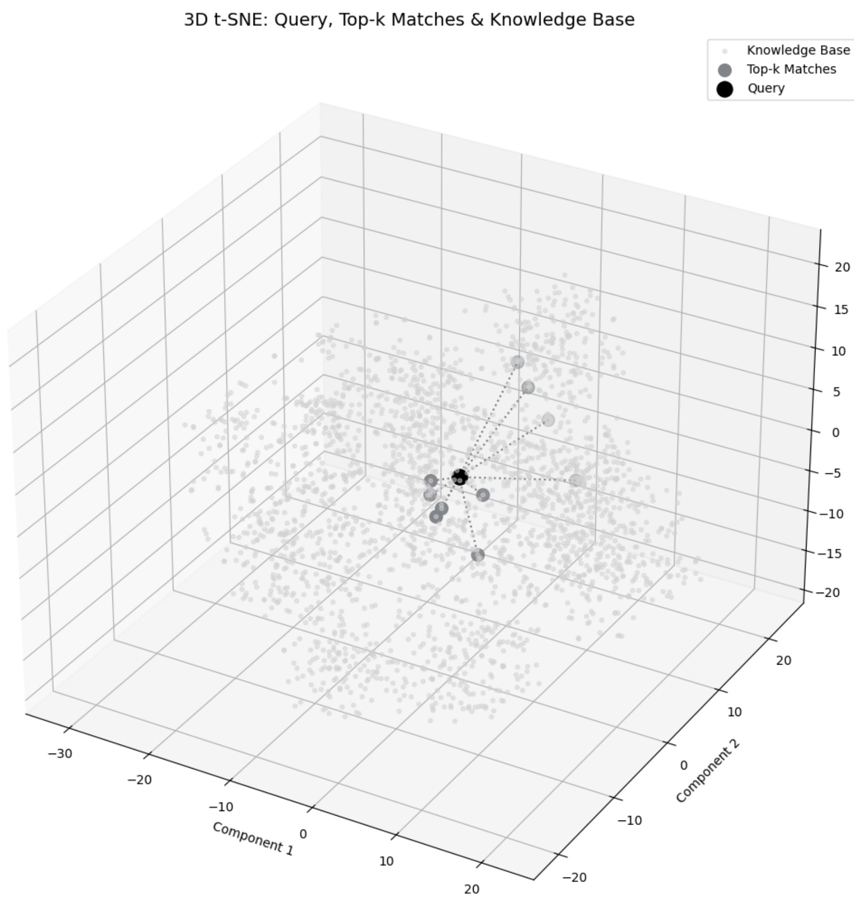


Fig. 8.17 Visualization of Query and Top-k Matches

9 Test Plans, Results and Analysis

Test Case Plan Table

Test Case ID	Description	Expected Result	Actual Result	Status
T01	User provides input in the text area.	Text is accepted for further processing.	Text is accepted for further processing.	✓
T02	Display mental health issues with probabilities for classes.	Probabilities for each mental health class are shown.	Probabilities for each mental health class are shown.	✓
T03	Highlight the mental health issue with the highest probability.	Correct issue with the highest probability is displayed.	Correct issue with the highest probability is displayed.	✓
T04	Accept username input and provide prediction.	Prediction is displayed based on the provided username.	Prediction is displayed based on the provided username.	✓

Test Case Plan Table

Test Case ID	Description	Expected Result	Actual Result	Status
T05	Translate multiple language inputs to English.	Non-English text is translated correctly to English.	Non-English text is translated correctly to English.	✓
T06	Extract text and detect emotion from image.	Extracted text and detected emotions are displayed accurately.	Extracted text and detected emotions are displayed accurately.	✓
T07	Pass a prompt to the system and retrieve a valid response.	Correct response is generated based on the prompt.	Correct response is generated based on the prompt.	✓
T08	Perform a combined test using multiple inputs.	Predictions for all inputs are displayed correctly.	Predictions for all inputs are displayed correctly.	✓
T09	Analyze uploaded audio files and transcribe them into text.	Audio transcription and analysis results are displayed.	Audio transcription and analysis results are displayed.	✓
T10	Extract frames, analyze emotions, audio from video.	Frame emotions and audio transcription are displayed.	Frame emotions and audio transcription are displayed.	✓
T11	Extract tweets and related media using a Twitter username.	Text and media are extracted and analyzed correctly.	Text and media are extracted and analyzed correctly.	✓
T12	Generate captions for uploaded images or video frames.	Captions are generated for images or frames.	Captions are generated for images or frames.	✓
T13	Upload a PDF file and analyze its text content.	Extracted text from the PDF is processed and analyzed for mental health cues.	Extracted text from the PDF is processed and analyzed for mental health cues.	✓
T14	Capture user response to a displayed image.	User response is captured and correctly classified for emotional analysis.	User response is captured and correctly classified for emotional analysis.	✓
T15	Fill out a survey form to update the association matrix.	Survey responses update the association matrix and generate targeted wellbeing insights.	Survey responses update the association matrix and generate targeted wellbeing insights.	✓
T16	RAG-based Wellbeing Insights	Generates wellbeing insights using context, prompts, and mental issue.	Generates refined insights using Gemini based on retrieved data.	✓

Metrics for Evaluation

Metric	Definition and Formula
Precision	The ratio of correctly predicted positive observations to the total predicted positives. $$\text{Precision} = \frac{TP}{TP + FP}$$ where TP = True Positives, FP = False Positives.
Recall	The ratio of correctly predicted positive observations to all observations in the actual class. $$\text{Recall} = \frac{TP}{TP + FN}$$ where TP = True Positives, FN = False Negatives.
F1-Score	The harmonic mean of Precision and Recall. $$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$
Support	The number of actual occurrences of each class in the dataset. $$\text{Support} = \text{Number of samples in the true class}$$
Confusion Matrix	A matrix used to evaluate classification performance: $$\begin{bmatrix} TP & FP \\ FN & TN \end{bmatrix}$$ where TP = True Positives, FP = False Positives, FN = False Negatives, and TN = True Negatives.

Note: Class Label Mapping for rows and columns in Confusion Matrices

Label	Class
0	Anxiety
1	Bipolar
2	Depression
3	Normal
4	PTSD

9.1 Results from Base Models

Logistic Regression

Class	Precision	Recall	F1-Score	Support
Anxiety	0.83	0.77	0.80	379
Bipolar	0.74	0.55	0.63	384
Depression	0.76	0.76	0.76	373
Normal	0.92	0.99	0.95	2183
PTSD	0.87	0.77	0.82	394
Accuracy	87.66%			
Macro Avg	0.82	0.77	0.79	3713
Weighted Avg	0.87	0.88	0.87	3713

Naive Bayes

Class	Precision	Recall	F1-Score	Support
Anxiety	0.70	0.73	0.72	379
Bipolar	0.83	0.45	0.58	384
Depression	0.59	0.87	0.70	373
Normal	0.96	0.92	0.94	2183
PTSD	0.71	0.83	0.76	394
Accuracy	83.63%			
Macro Avg	0.76	0.76	0.74	3713
Weighted Avg	0.85	0.84	0.84	3713

Support Vector Machine

Class	Precision	Recall	F1-Score	Support
Anxiety	0.72	0.76	0.74	379
Bipolar	0.62	0.61	0.61	384
Depression	0.74	0.71	0.72	373
Normal	0.94	0.95	0.95	2183
PTSD	0.78	0.74	0.76	394
Accuracy	85.13%			
Macro Avg	0.76	0.75	0.76	3713
Weighted Avg	0.85	0.85	0.85	3713

Random Forest

Class	Precision	Recall	F1-Score	Support
Anxiety	0.81	0.70	0.75	379
Bipolar	0.93	0.47	0.62	384
Depression	0.72	0.77	0.74	373
Normal	0.88	1.00	0.93	2183
PTSD	0.92	0.74	0.82	394
Accuracy	86.00%			
Macro Avg	0.85	0.73	0.77	3713
Weighted Avg	0.86	0.86	0.85	3713

XGBoost

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Anxiety	0.81	0.74	0.77	403
Bipolar	0.77	0.62	0.69	397
Depression	0.72	0.81	0.76	387
Normal	0.93	0.98	0.95	2137
PTSD	0.86	0.75	0.80	396
Accuracy	87.39%			
Macro Avg	0.82	0.78	0.80	3720
Weighted Avg	0.87	0.87	0.87	3720

K-Nearest Neighbour

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Anxiety	0.58	0.31	0.40	379
Bipolar	0.18	0.59	0.28	384
Depression	0.47	0.39	0.43	373
Normal	0.79	0.69	0.73	2183
PTSD	0.80	0.09	0.16	394
Accuracy	54.46%			
Macro Avg	0.56	0.41	0.40	3713
Weighted Avg	0.67	0.54	0.56	3713

Long Short Term Memory

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Anxiety	0.74	0.72	0.73	1999
Bipolar	0.66	0.70	0.68	1964
Depression	0.68	0.69	0.69	1959
Normal	0.97	0.94	0.95	10688
PTSD	0.72	0.78	0.75	1987
Accuracy	84.91%			
Macro Avg	0.75	0.77	0.76	18597
Weighted Avg	0.85	0.85	0.85	18597

Custom Transformer

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Anxiety	0.75	0.78	0.76	379
Bipolar	0.76	0.69	0.73	384
Depression	0.82	0.72	0.77	373
Normal	0.95	0.97	0.96	2183
PTSD	0.79	0.80	0.79	394
Accuracy	88.5%			
Macro Avg	0.81	0.79	0.80	3713
Weighted Avg	0.88	0.88	0.88	3713

Hyperparameter Tuning on Logistic Regression

Class	Precision	Recall	F1-Score	Support
Anxiety	0.83	0.77	0.80	379
Bipolar	0.74	0.55	0.64	384
Depression	0.76	0.76	0.76	373
Normal	0.92	0.99	0.95	2183
PTSD	0.87	0.77	0.82	394
Accuracy	87.72%			
Macro Avg	0.83	0.77	0.79	3713
Weighted Avg	0.87	0.88	0.87	3713

Hyperparameter Tuning on KNN

Class	Precision	Recall	F1-Score	Support
Anxiety	0.73	0.23	0.35	379
Bipolar	0.18	0.60	0.27	384
Depression	0.47	0.40	0.43	373
Normal	0.74	0.65	0.69	2183
PTSD	0.83	0.10	0.18	394
Accuracy	52.03%			
Macro Avg	0.59	0.40	0.39	3713
Weighted Avg	0.66	0.52	0.53	3713

Hyperparameter Tuning on SVM

Class	Precision	Recall	F1-Score	Support
Anxiety	0.72	0.76	0.74	379
Bipolar	0.62	0.61	0.61	384
Depression	0.74	0.71	0.72	373
Normal	0.94	0.95	0.95	2183
PTSD	0.78	0.74	0.76	394
Accuracy	85.13%			
Macro Avg	0.76	0.75	0.76	3713
Weighted Avg	0.85	0.85	0.85	3713

Hyperparameter Tuning on Naive Bayes

Class	Precision	Recall	F1-Score	Support
Anxiety	0.69	0.76	0.72	379
Bipolar	0.75	0.55	0.64	384
Depression	0.60	0.83	0.70	373
Normal	0.96	0.91	0.94	2183
PTSD	0.73	0.79	0.76	394
Accuracy	83.95%			
Macro Avg	0.75	0.77	0.75	3713
Weighted Avg	0.85	0.84	0.84	3713

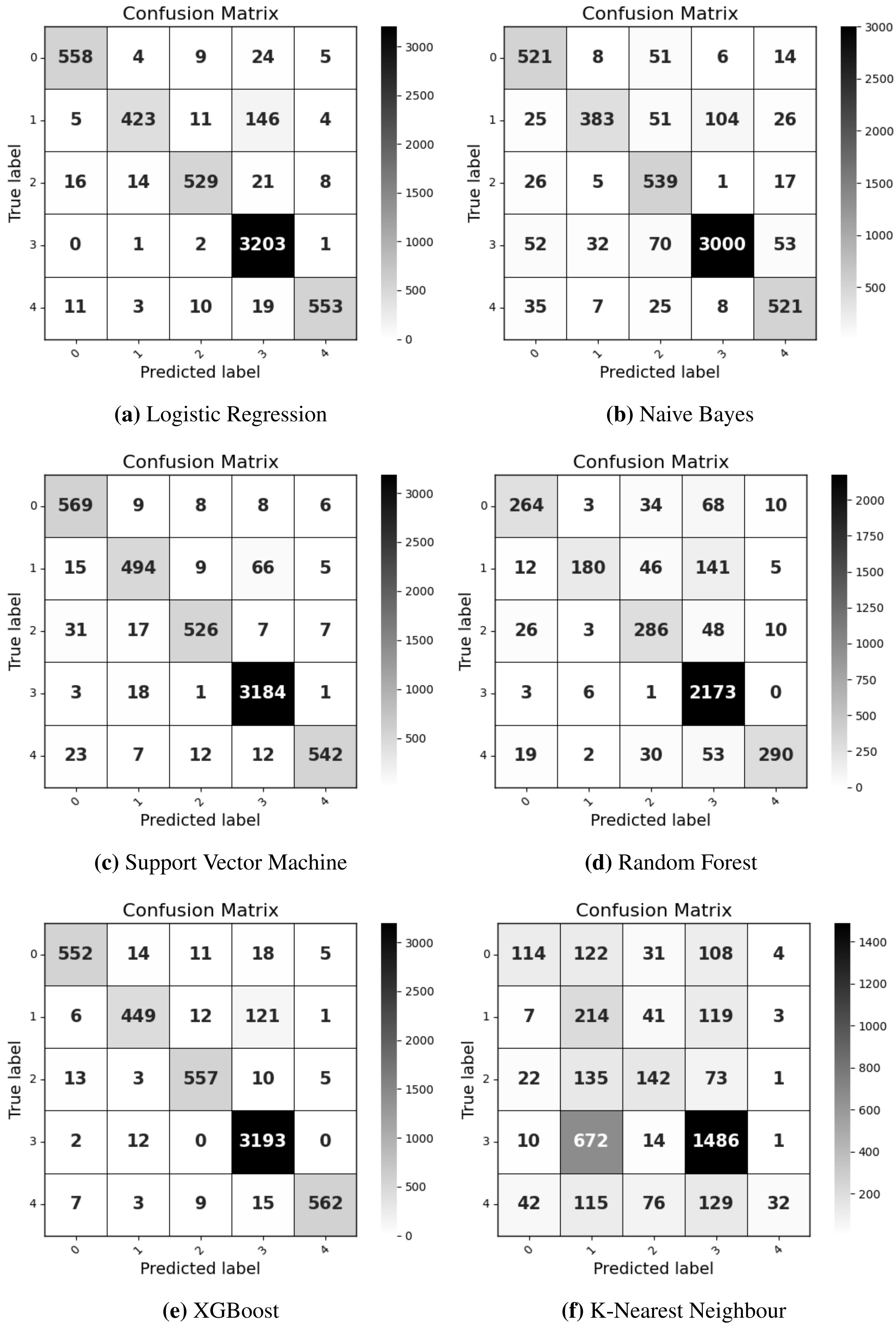
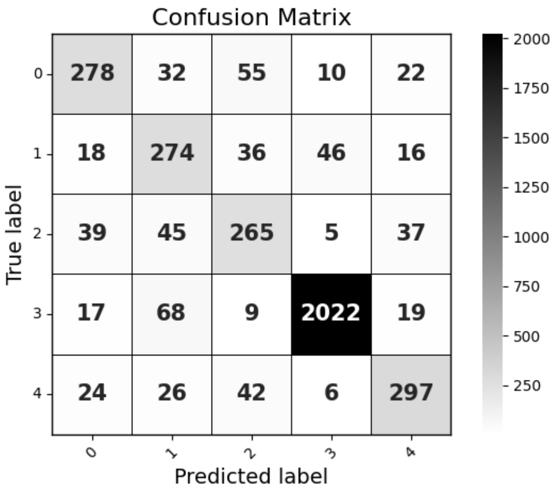
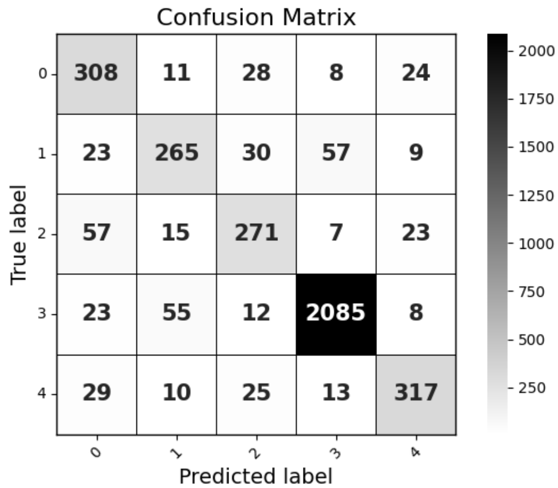


Fig. 9.1 Confusion Matrices for ML Models

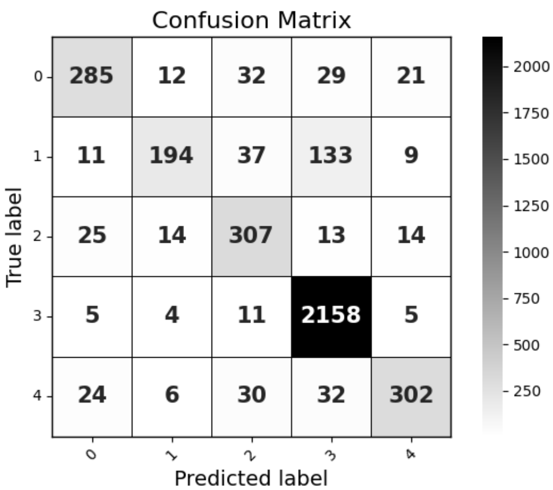


(a) Long Short Term Memory

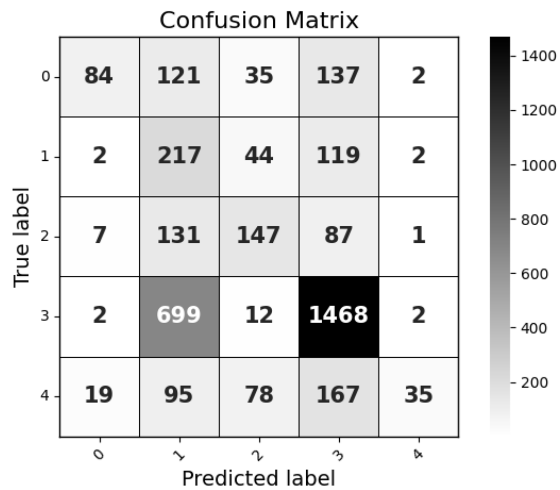


(b) Transformer based Model

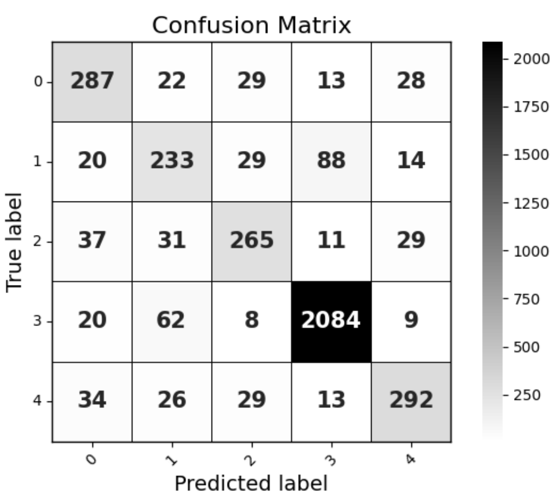
Fig. 9.2 Confusion Matrices for DL Models



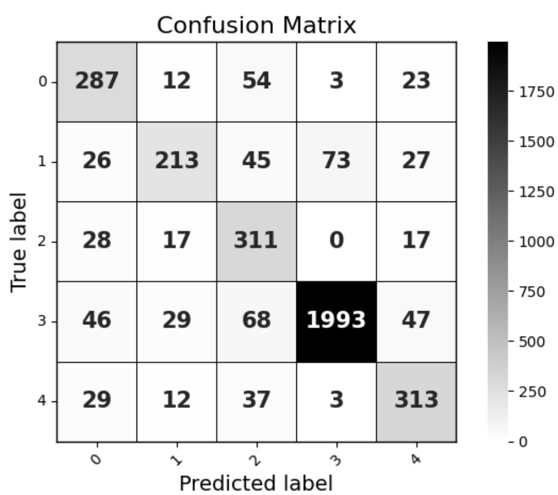
(a) Logistic Regression



(b) K-Nearest Neighbour

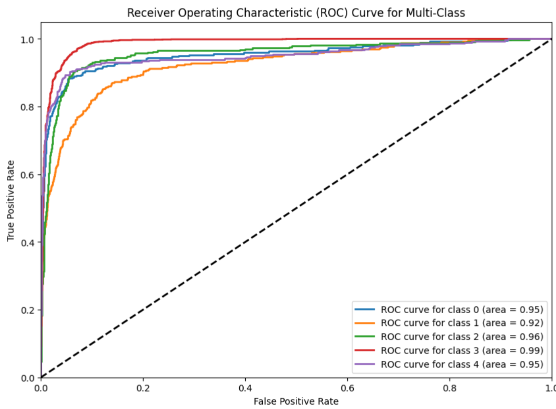


(c) Support Vector Machine

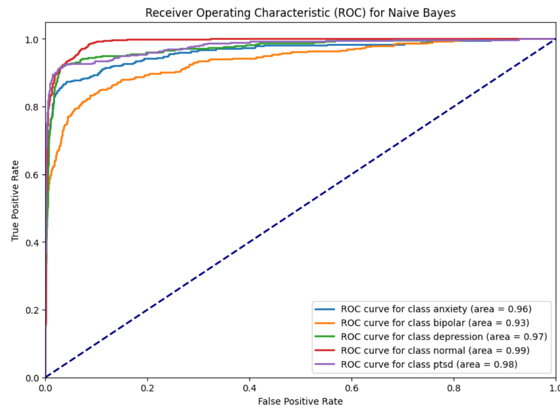


(d) Naive Bayes

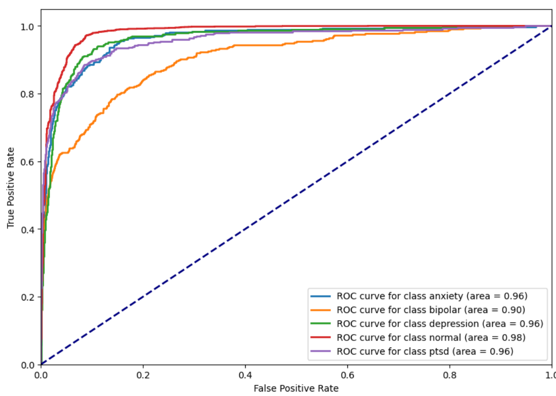
Fig. 9.3 Confusion Matrices for Models after Hyperparameter Tuning



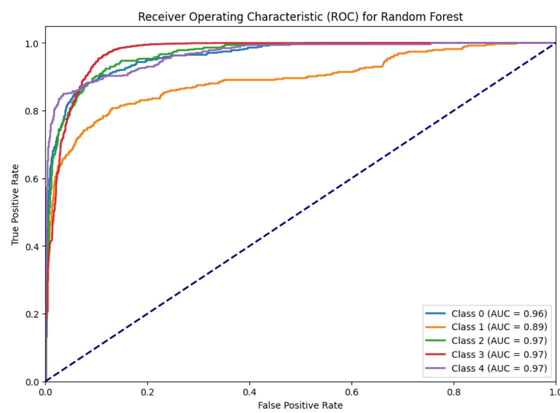
(a) Logistic Regression



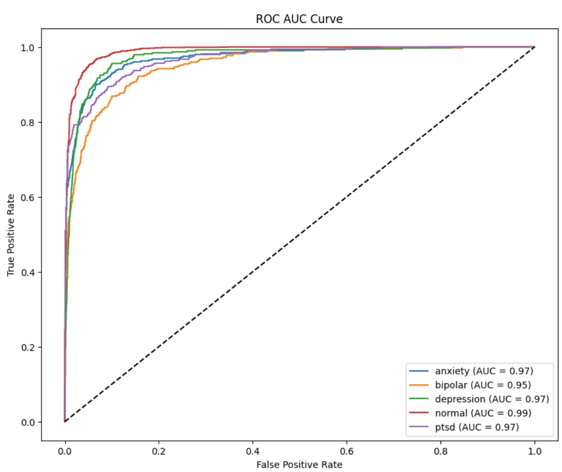
(b) Naive Bayes



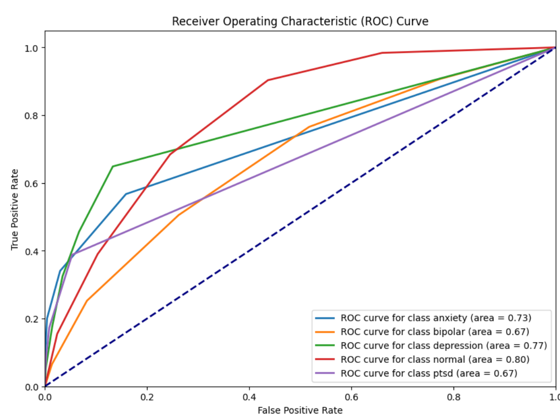
(c) Support Vector Machine



(d) Random Forest

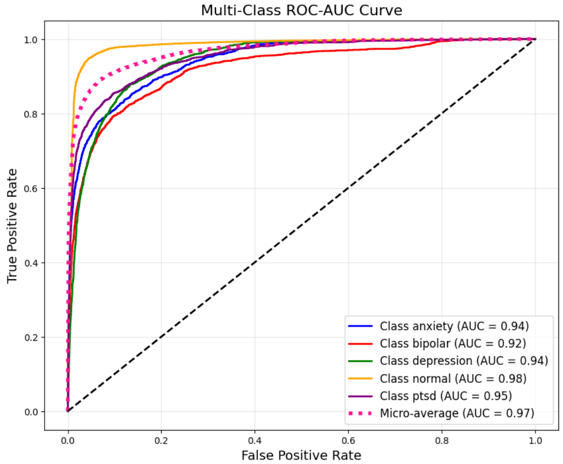


(e) XGBoost

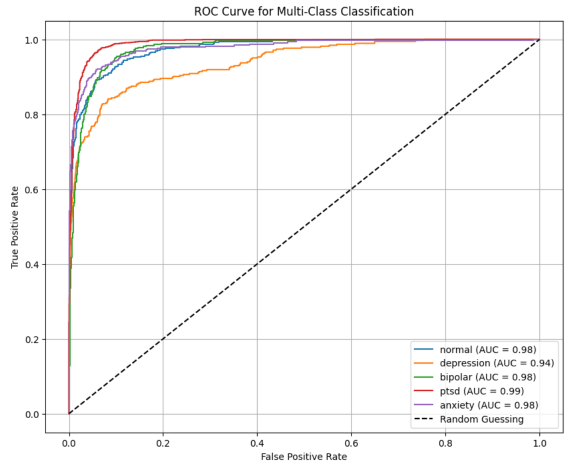


(f) K-Nearest Neighbour

Fig. 9.4 ROC AUC for ML Models

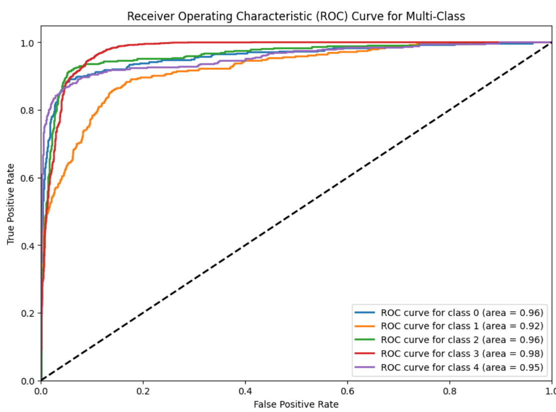


(a) Long Short Term Memory

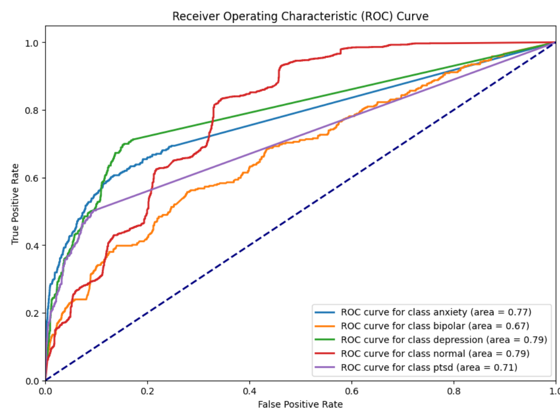


(b) Transformer based Model

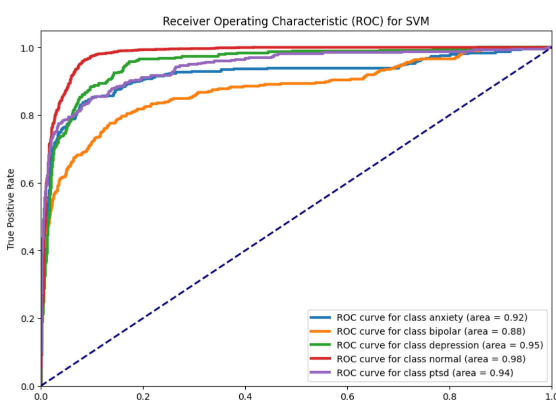
Fig. 9.5 ROC AUC for DL Models



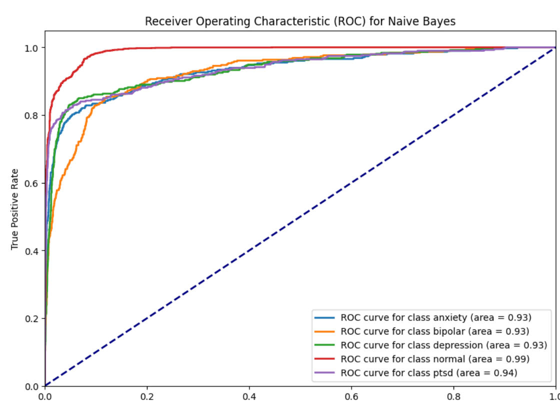
(a) Logistic Regression



(b) K-Nearest Neighbour



(c) Support Vector Machine



(d) Naive Bayes

Fig. 9.6 ROC AUC for Models after Hyperparameter Tuning

Model	**Accuracy (%)**	**Key Observations**
Logistic Regression	87.66	High precision, recall, and F1 for the *Normal* class; struggles with *Bipolar* and *Anxiety*. ROC AUC: Normal (0.99), Anxiety (0.95), Depression (0.97).
Naive Bayes	83.63	Excellent for *Normal* (Precision 0.96, Recall 0.92, F1 0.94) but poor for *Bipolar* (Recall 0.45, F1 0.58). ROC AUC: Normal (0.99), Depression/PTSD (0.97), Bipolar (0.93).
SVM	85.13	Best for *Normal* (Precision 0.94, Recall 0.95, F1 0.95); *Bipolar* underperforms (Precision 0.62, Recall 0.61); *Anxiety* is balanced (Recall 0.76, Precision 0.72). ROC AUC: Normal (0.98), others 0.99, Bipolar (0.90).
Random Forest	86.00	*Normal* class achieves perfect recall (1.00) with high precision (0.88, F1 0.93); *Bipolar* is weak (Recall 0.47, F1 0.62). ROC AUC: For most classes it is greater than equal to 0.96; Bipolar (0.89).
XGBoost	87.39	Strong performance for *Normal*; *Anxiety* shows good metrics (Precision 0.81, Recall 0.74) while *Bipolar* has lower recall (0.62). ROC AUC: 0.97 for Anxiety; 0.99 for Normal, Depression, PTSD.
KNN	54.46	Overall low performance; *Normal* is moderate (Precision 0.79, Recall 0.69) but *PTSD* has very low recall (0.09). ROC AUC: Normal (0.80), indicating weak discrimination.
LSTM	84.91	High performance for *Normal*; *Anxiety* acceptable (Precision 0.74, Recall 0.72); *Bipolar* (Precision 0.66, Recall 0.70) and *PTSD* (Precision 0.72, Recall 0.78) are moderate. Effective ROC AUC for Normal.
Transformer	88.50	Best overall with balanced high precision and recall across all classes. Captures contextual cues effectively and handles class imbalance well. ROC AUC scores range between 0.94 and 0.99.

Summary Comparison of Classification Models without Hyperparameter Tuning

Model	Best Hyperparameters	Accuracy & Metrics	Key Observations
Logistic Regression	`solver=liblinear, penalty=l2, C=1`	Accuracy: 87.72%; Normal: 92% accuracy; ROC AUC: Normal 0.98, Depression 0.96	High precision, recall, and F1 for Normal; Bipolar shows lower F1 (64%); overall robust performance, especially for Normal and Anxiety.
k-NN	`weights=distance, n_neighbors=10, metric=euclidean`	Accuracy: 52.03%; Normal F1: 0.69; ROC AUC: Bipolar 0.67, PTSD 0.71, Normal/Depression 0.79	Struggles with minority classes: Anxiety (recall 0.23) and PTSD (recall 0.10); not suitable for this dataset.
SVM	`kernel=linear, gamma=scale, C=1`	Accuracy: 85.13%; F1-scores: Normal 0.95, Depression 0.72, Anxiety 0.74, Bipolar 0.61; ROC AUC: Normal 0.98, Others $>$ 0.90, Bipolar 0.88	Solid overall performance; excellent for Normal and Anxiety, but slightly lower performance for Bipolar.
Naive Bayes	`alpha=0.2914`	Accuracy: 83.95%; F1-scores: Normal 0.94, PTSD 0.76, Anxiety 0.72; ROC AUC: Normal 0.99, Others $>$ 0.90	Performs very well for Normal and PTSD; lower scores for Bipolar and Depression.

Summary Comparison of Models after Hyperparameter Tuning

K-Nearest Neighbors (KNN) performs poorly on this mental health dataset compared to other algorithms, even after hyperparameter tuning. KNN relies on distance-based metrics, which struggle with the sparse, high-dimensional nature of text data, making it difficult to capture meaningful relationships between Reddit posts and mental health labels. Despite optimizing parameters like `weights='distance'`, `n_neighbors=10`, and `metric='euclidean'`, KNN's performance remains suboptimal, with lower accuracy, precision, recall, and F1-score than Logistic Regression, Naive Bayes, or SVM. Its inability to handle non-linear, context-dependent patterns in text, especially for nuanced categories like anxiety, PTSD, or bipolar disorder, highlights its limitations in text classification tasks. KNN's reliance on proximity without considering textual context likely explains its poor performance.

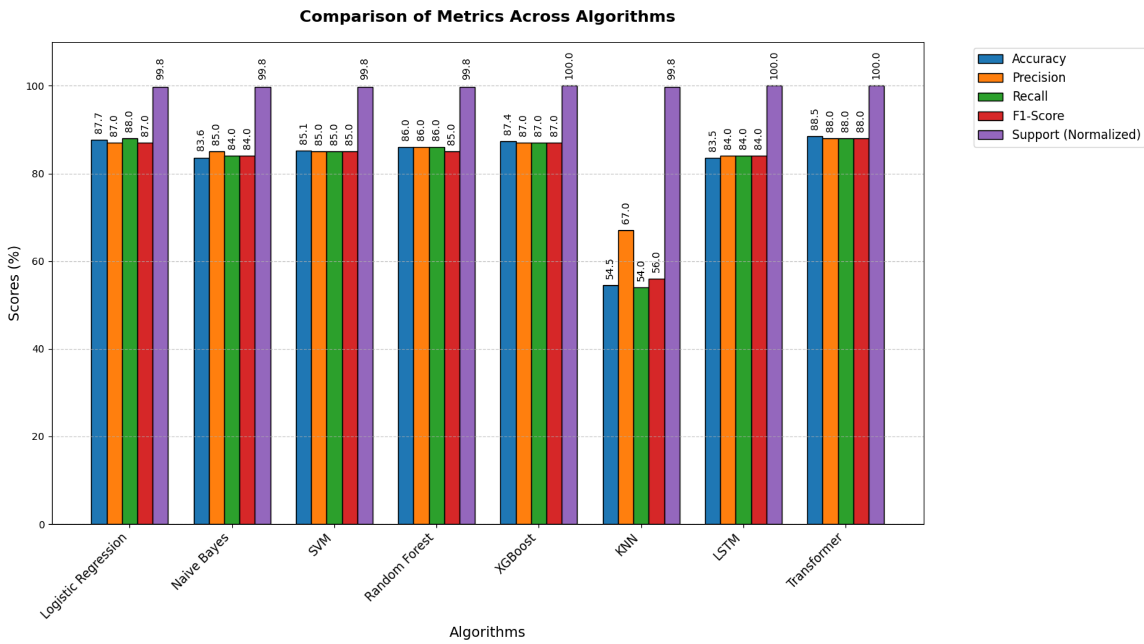


Fig. 9.7 Result Comparison of the Algorithms

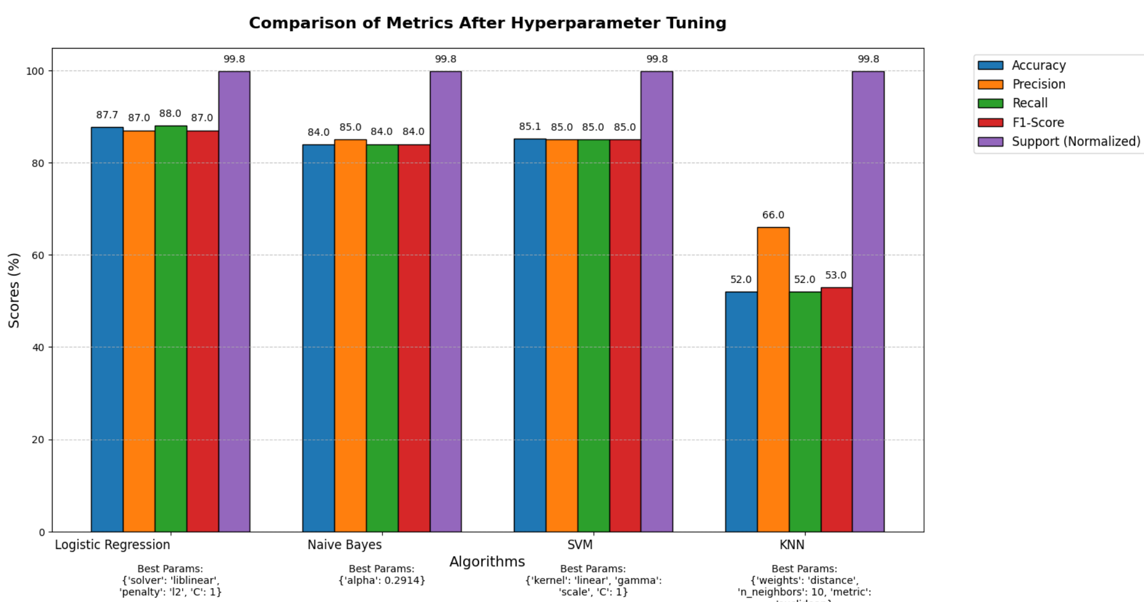


Fig. 9.8 Result Comparison after Hyperparameter Tuning

9.2 Comparison of different tokenizations

Model Performance Comparison

Model	BoW	TFIDF	LIWC	Word2Vec	N-Gram
Logistic Regression	87.66	86.02	66.36	79.40	87.13
KNN	54.56	75.06	70.70	75.52	43.06
SVC	85.13	88.26	68.14	77.89	84.33
Naive Bayes	83.63	79.42	59.63	60.44	81.71
Random Forest	85.32	85.73	76.73	79.88	79.02
XGB	87.42	87.39	78.56	81.01	87.96

In ensemble learning, combining models like Logistic Regression (LR), Naive Bayes (NB), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), XGBoost (XGB), Random Forest (RF), and Long Short-Term Memory (LSTM) poses challenges in computational efficiency, model size, and accuracy. Each model has unique strengths and limitations, making their integration complex. LR, NB, and SVM perform well with simpler vectorization methods like Bag of Words (BoW), which efficiently represents text data as sparse vectors. BoW's simplicity ensures these models remain computationally lightweight while maintaining good classification accuracy. In contrast, XGBoost benefits from more complex feature extraction methods like TFIDF (Term Frequency-Inverse Document Frequency), which captures nuanced relationships by weighting words based on their importance across documents. However, combining TFIDF-based models like XGBoost with BoW-based models can degrade ensemble performance, as the feature representations may not align well. KNN is excluded due to its computational intensity, as it requires storing the entire training dataset and performs poorly with large, high-dimensional datasets. Similarly, Random Forest is omitted because its multiple decision trees increase model size and inference time, outweighing its individual performance benefits. XGBoost, while highly accurate with N-Gram features, is computationally expensive and impractical for real-time systems or large-scale deployment. The choice of feature extraction methods—BoW for LR, NB, and SVM, and TFIDF for XGBoost—balances simplicity and complexity. BoW ensures efficient, interpretable representations for simpler models, while TFIDF provides richer, context-aware features for XGBoost. This combination leverages the strengths of both methods, ensuring each model operates effectively without excessive computational strain. Ultimately, this approach strikes a balance between accuracy and efficiency, enabling the ensemble to perform well while remaining scalable and practical for real-world applications.

9.3 Results from Ensemble Model Training and Testing

Ensemble Model 1

Class	Precision	Recall	F1-Score	Support
Anxiety	0.97	0.94	0.95	400
Bipolar	0.92	0.85	0.88	388
Depression	0.95	0.94	0.94	392
Normal	0.97	0.99	0.98	2136
PTSD	0.97	0.96	0.96	397
Accuracy	**96.08%**			
Macro avg	0.96	0.93	0.95	3713
Weighted avg	0.96	0.96	0.96	3713

Ensemble Model 2

Class	Precision	Recall	F1-Score	Support
Anxiety	0.97	0.97	0.97	400
Bipolar	0.95	0.92	0.93	388
Depression	0.98	0.96	0.97	392
Normal	0.99	0.99	0.99	2136
PTSD	0.97	0.98	0.98	397
Accuracy	**97.93%**			
Macro avg	0.97	0.97	0.97	3713
Weighted avg	0.98	0.98	0.98	3713

Ensemble Model 3

Class	Precision	Recall	F1-Score	Support
Anxiety	0.98	0.97	0.98	400
Bipolar	0.96	0.90	0.93	388
Depression	0.97	0.96	0.96	392
Normal	0.98	1.00	0.99	2136
PTSD	0.97	0.97	0.97	397
Accuracy	**97.76%**			
Macro avg	0.97	0.96	0.97	3713
Weighted avg	0.98	0.98	0.98	3713

Ensemble Model 4

Class	Precision	Recall	F1-Score	Support
Anxiety	0.97	0.97	0.97	400
Bipolar	0.95	0.90	0.92	388
Depression	0.97	0.95	0.96	392
Normal	0.99	0.99	0.99	2136
PTSD	0.97	0.98	0.97	397
Accuracy	**97.63%**			
Macro Avg	0.97	0.96	0.96	3713
Weighted Avg	0.98	0.98	0.98	3713

Ensemble Model 5

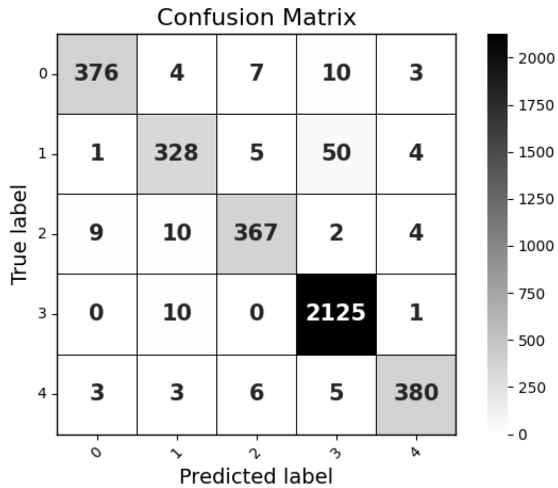
Class	Precision	Recall	F1-Score	Support
Anxiety	0.96	0.95	0.96	400
Bipolar	0.94	0.89	0.92	388
Depression	0.96	0.95	0.95	392
Normal	0.98	0.99	0.99	2136
PTSD	0.97	0.97	0.97	397
Accuracy	**97.17%**			
Macro avg	0.96	0.95	0.96	3713
Weighted avg	0.97	0.97	0.97	3713

Ensemble Model 6

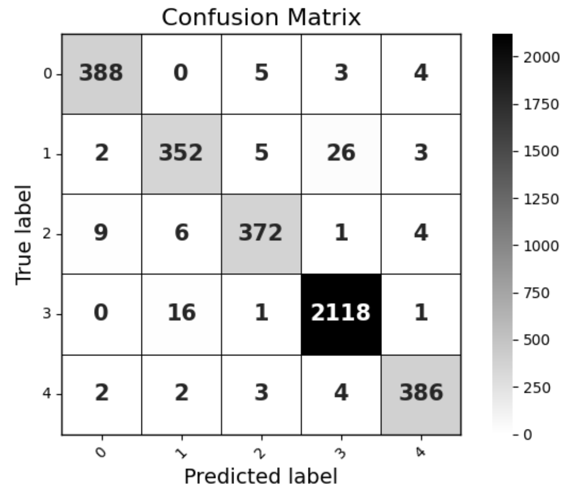
Class	Precision	Recall	F1-Score	Support
Anxiety	0.95	0.92	0.94	400
Bipolar	0.96	0.74	0.84	388
Depression	0.92	0.94	0.93	392
Normal	0.95	1.00	0.97	2136
PTSD	0.98	0.93	0.96	397
Accuracy	**95.15%**			
Macro avg	0.95	0.91	0.93	3713
Weighted avg	0.95	0.95	0.95	3713

Ensemble Model 7

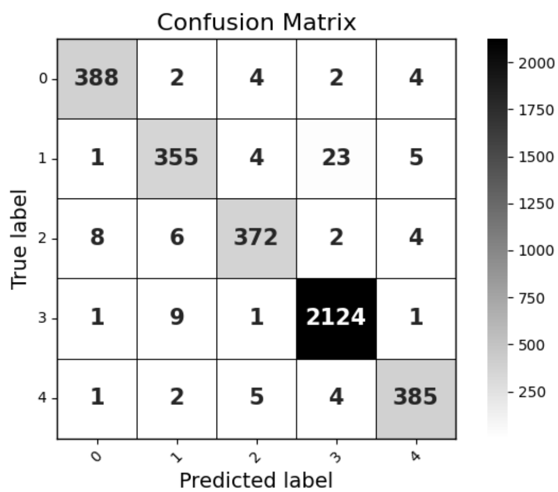
Class	Precision	Recall	F1-Score	Support
Anxiety	0.98	0.97	0.98	400
Bipolar	0.96	0.93	0.95	388
Depression	0.97	0.97	0.97	392
Normal	0.99	1.00	0.99	2136
PTSD	0.98	0.98	0.98	397
Accuracy	**98.03%**			
Macro avg	0.98	0.97	0.97	3713
Weighted avg	0.98	0.98	0.98	3713



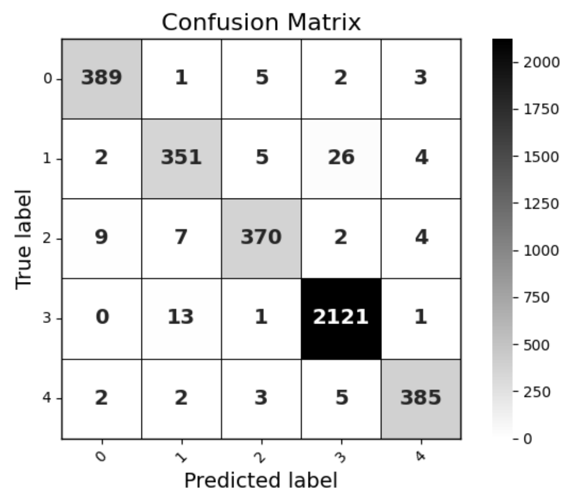
(a) Ensemble Model 1



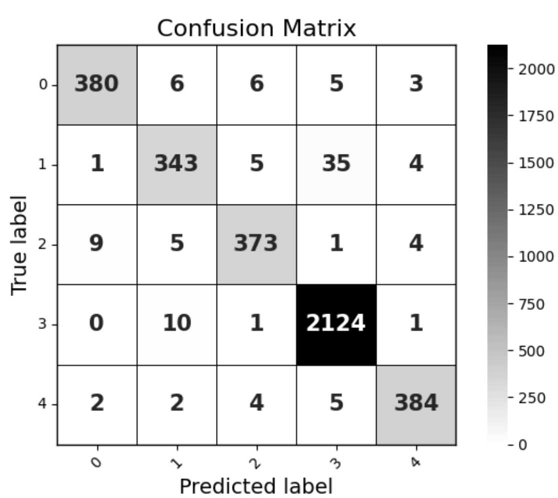
(b) Ensemble Model 2



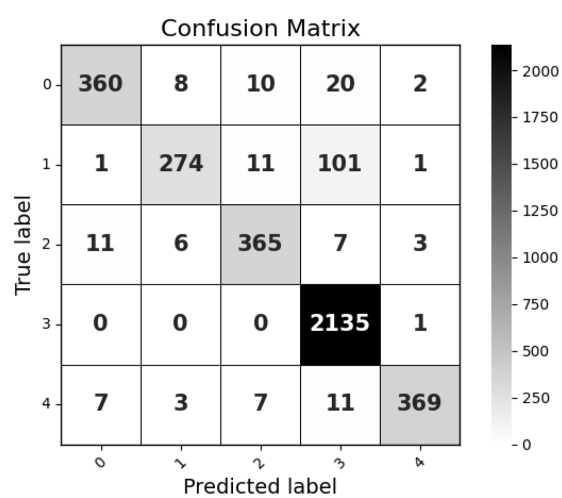
(c) Ensemble Model 3



(d) Ensemble Model 4

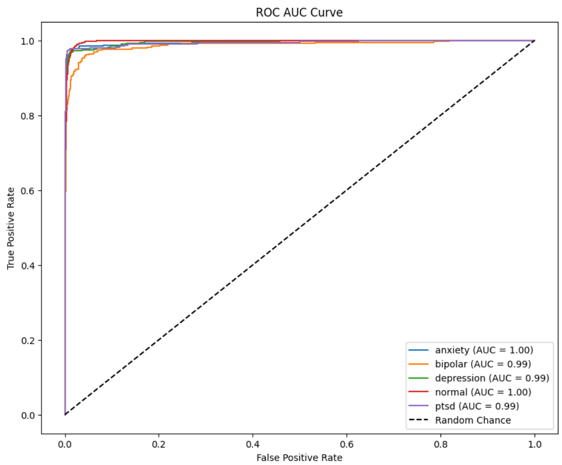


(e) Ensemble Model 5

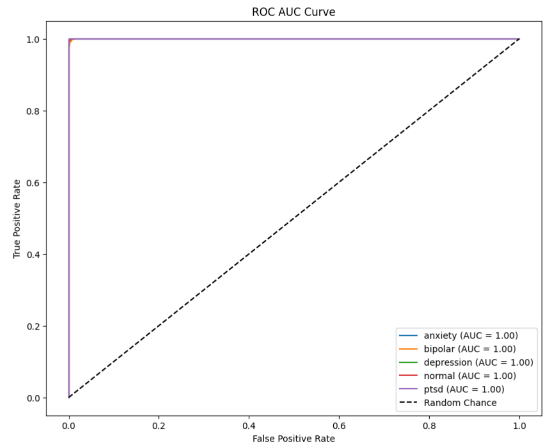


(f) Ensemble Model 6

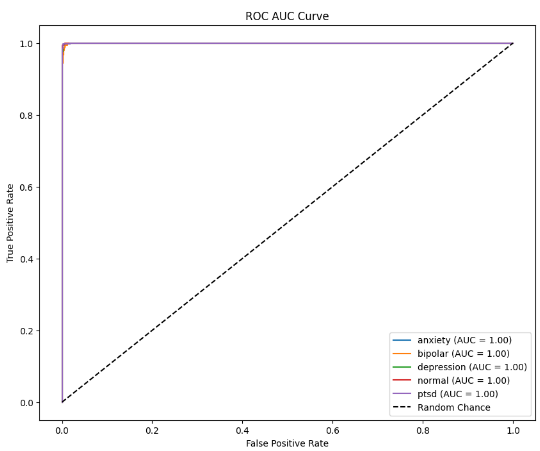
Fig. 9.9 Confusion Matrices for Ensemble Models 1 to 6



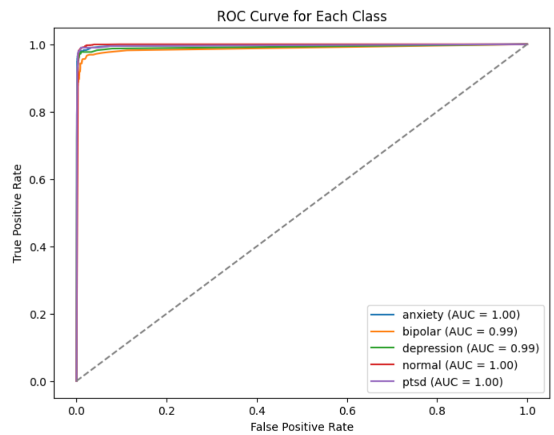
(a) Ensemble Model 1



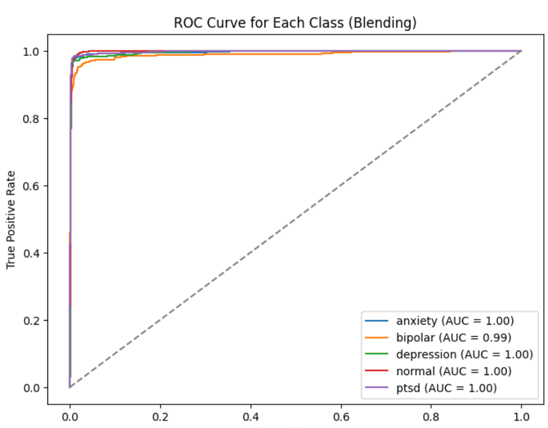
(b) Ensemble Model 2



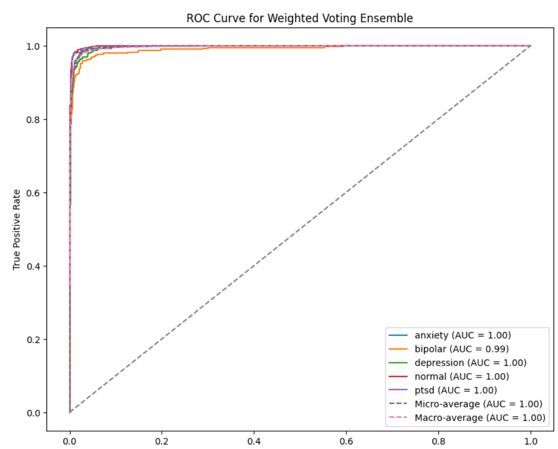
(c) Ensemble Model 3



(d) Ensemble Model 4



(e) Ensemble Model 5



(f) Ensemble Model 6

Fig. 9.10 ROC AUC for Ensemble Models 1 to 6

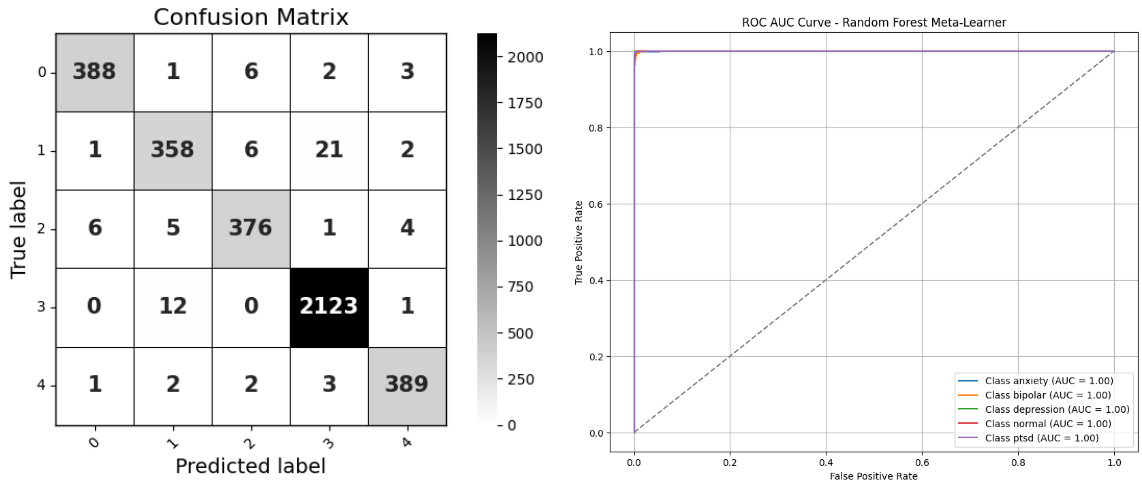


Fig. 9.11 Confusion Matrix, ROC AUC for Ensemble Model 7 (used in web app)

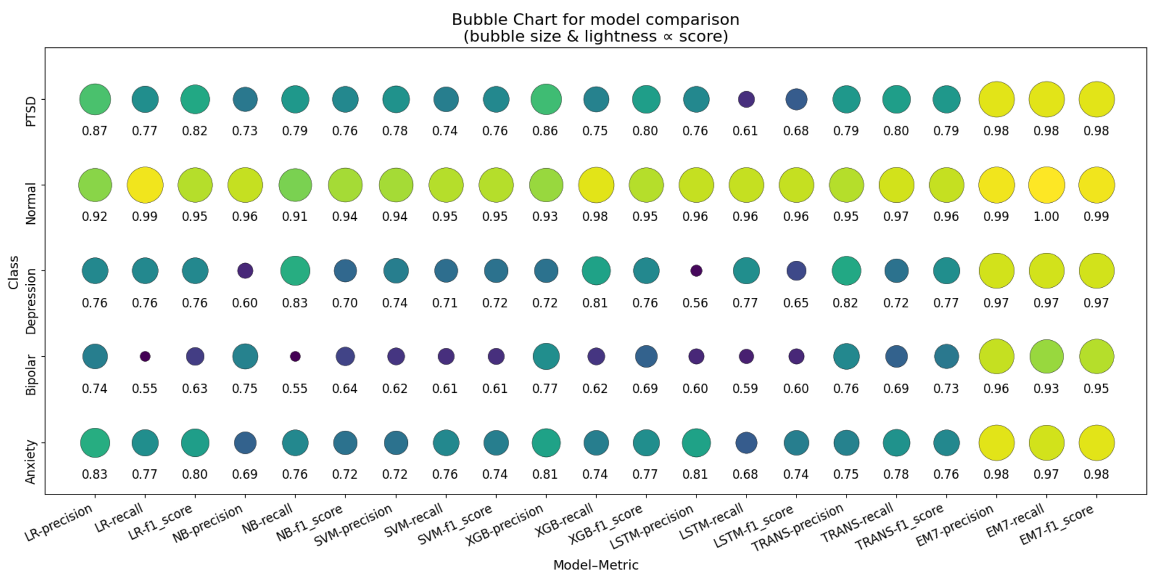


Fig. 9.12 Comparison of Base Models and Ensemble Model 7

Summary of Ensemble Models 1 to 7

Model	**Accuracy**	**Key Components**	**Advantages**	**Limitations**
Ensemble Model 1	96.08%	Logistic Regression + XGBoost	Balanced performance (e.g., Anxiety: Prec=0.97, Rec=0.94, F1=0.95); robust macro/weighted averages	May not fully capture complex, non-linear, context-dependent patterns

Summary of Ensemble Models 1 to 7

Model	**Accuracy**	**Key Components**	**Advantages**	**Limitations**
Ensemble Model 2	97.93	XGBoost as meta-learner combining base models (LR, SVM, NB, LSTM)	Near-perfect ROC AUC (1.0 for Anxiety, Normal, PTSD, Bipolar, Depression); effective handling of imbalanced data	Potential overfitting if base model predictions are highly correlated
Ensemble Model 3	97.76	Random Forest used as meta-learner	High overall accuracy with very few misclassifications; robust due to bootstrapping and random feature selection	Slightly lower recall in some classes (e.g., Bipolar)
Ensemble Model 4	97.63%	Bagging classifier (similar to Random Forest)	Excellent performance with near-perfect results for the "Normal" class	Tendency to overfit due to using all features without feature-level randomness
Ensemble Model 5	97.17%	Blending Meta-Learner trained directly on base model predictions	Strong precision, recall, and F1-scores across classes; stable cross-validation performance	More prone to overfitting compared to stacking ensembles (e.g., with a Random Forest meta-learner)
Ensemble Model 6	95.15%	Weighted Voting ensemble combining base model outputs	Solid overall performance with high recall for "Normal" and computational efficiency	Lacks optimal inter-model learning; struggles with distinguishing bipolar disorder
Ensemble Model 7	98.03%	Transformer-based model (base) + meta-learner (Random Forest and others)	Near-perfect ROC AUC (1.0 across classes); excellent accuracy and robust classification	Increased computational complexity due to Transformer integration

Below is a comparison of all the ensemble models for reference

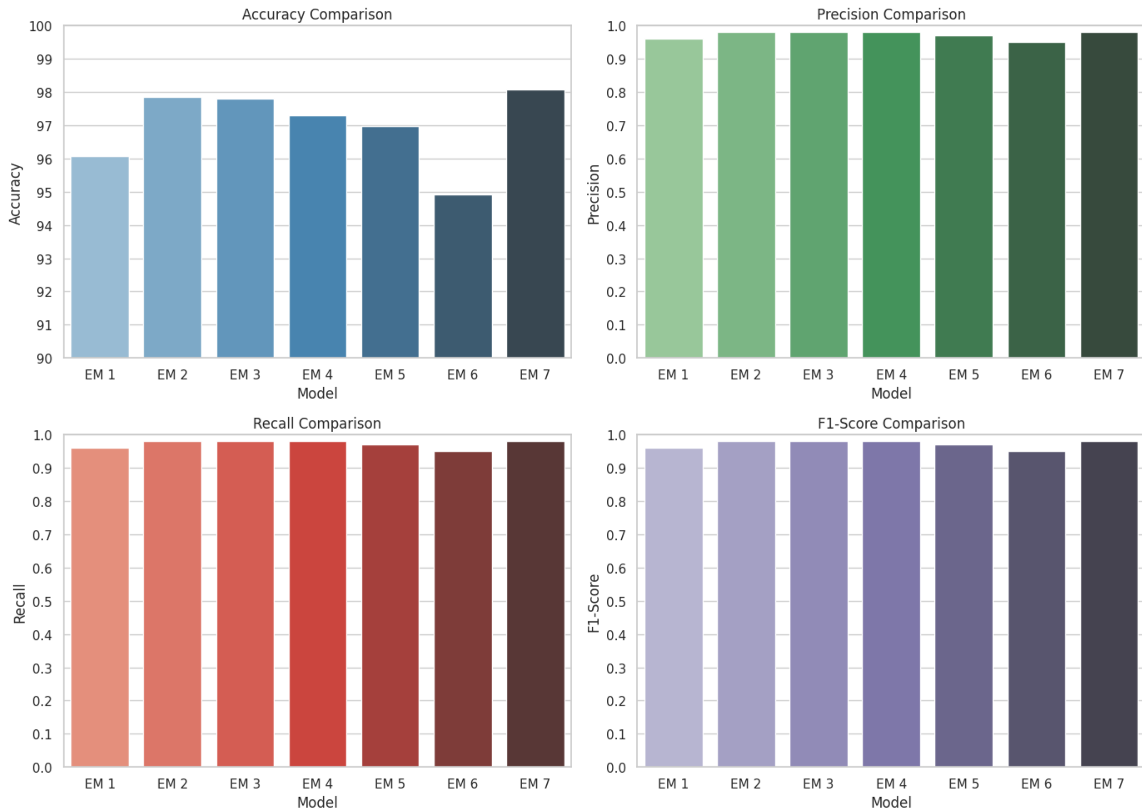


Fig. 9.13 Comparison of all Ensemble Models

9.4 Results from hierarchical Ensemble Models

Ensemble Model 7 is applied on different subsets of a very large dataset to create hierarchical ensemble models. The performance of each model is evaluated, and the results are compared to the global ensemble model.

Performance Comparison of Models

Model	Subset 1	Subset 2	Subset 3	Subset 4	Subset 5	Subset 6	ENSEMBLE
Logistic Regression	87.66	85.07	86.74	90.61	88.17	72.62	**90.90**
Naive Bayes	83.63	81.71	83.50	84.44	85.93	64.33	**84.15**
SVM	85.13	82.30	83.50	88.34	85.45	67.81	**91.79**
XGBoost	87.39	85.79	86.78	91.37	86.32	70.95	**67.67**
LSTM	84.91	81.63	81.83	87.22	85.38	67.74	**87.48**
Transformer	88.50	84.50	86.50	89.35	87.62	72.40	**91.53**
ENSEMBLE	**98.03**	**94.85**	**96.96**	**97.79**	**96.86**	**92.57**	**96.24** / **96.25**

Note: The final ensemble models from two different architectures achieved accuracies of **96.24%** and **96.25%** respectively.

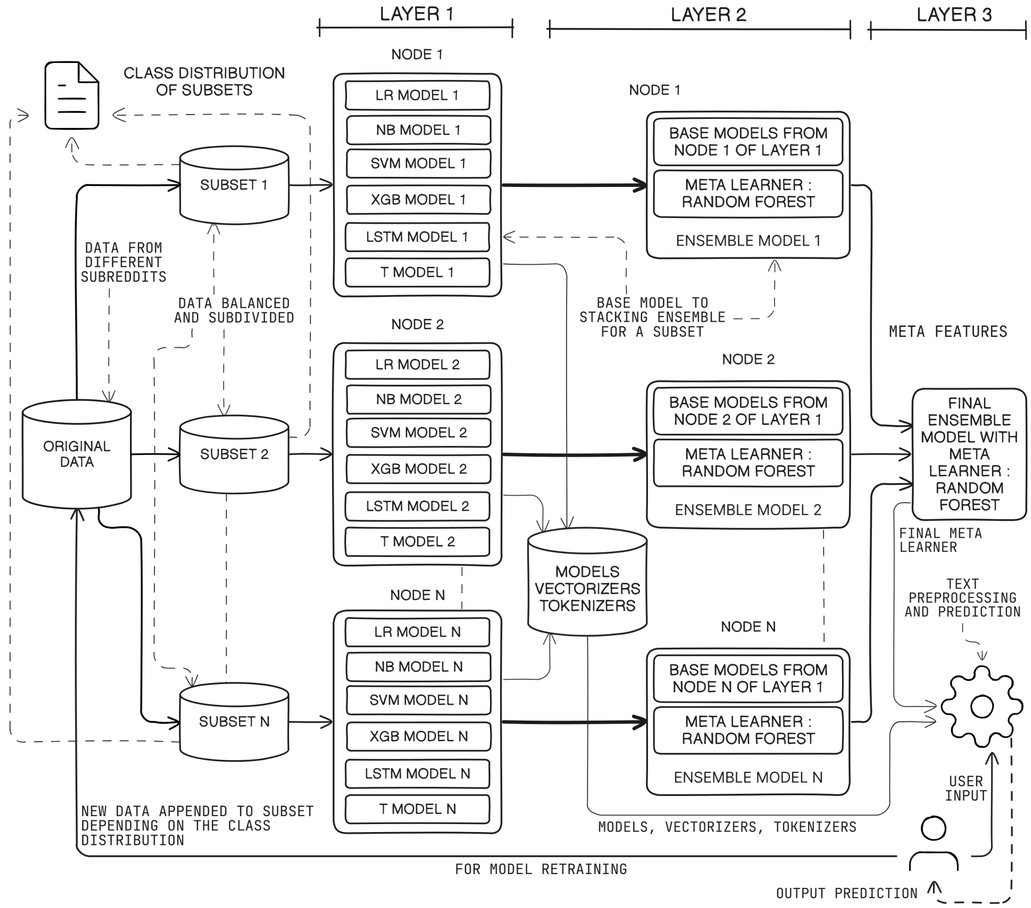


Fig. 9.14 Scalable Distributed Architecture 1

Summary of Architecture 1: Hierarchical Ensemble

Aspect	**Description**
Data Partitioning	The dataset is divided into manageable subsets for independent processing.
Base Models	Each subset trains base models (Logistic Regression, Naive Bayes, SVM, LSTM, XGBoost, and Custom Transformers).
Subset Ensemble	For each subset, a Random Forest meta learner is used to combine the base models into a subset-specific ensemble.
Global Aggregation	The subset-specific ensembles are aggregated to form a final global ensemble, capturing comprehensive learning.
Scalability	Designed for distributed processing; subsets can be processed in parallel across multiple nodes.
Fault Tolerance	Modular design ensures that failure in one subset does not impact the overall ensemble performance.
Distributed Processing	Worker nodes independently train base models and report to a central controller that aggregates the results.

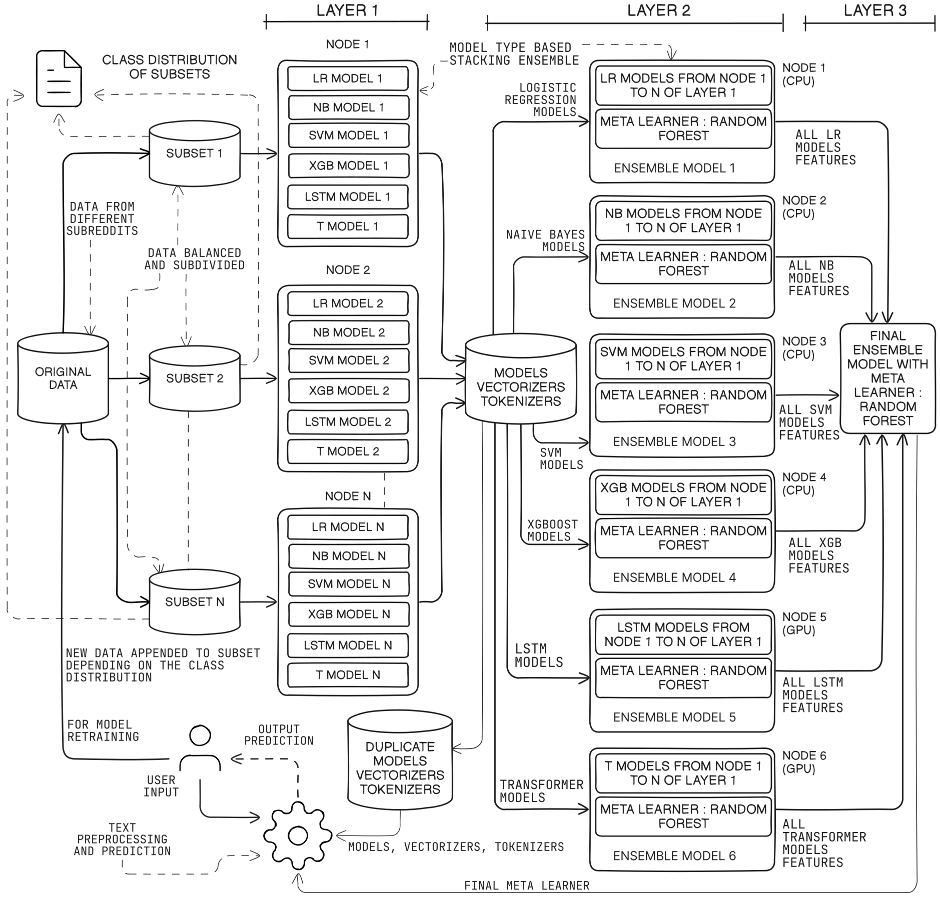


Fig. 9.15 Scalable Distributed Architecture 2

Summary of Architecture 2: Optimized Hierarchical Ensemble

Aspect	**Description**
Optimized Aggregation	Models of the same type from all subsets are combined into a single intermediate ensemble for that model type.
Intermediate Ensembles	Produces six intermediate ensembles (one each for Logistic Regression, Naive Bayes, SVM, XGBoost, LSTM, and Transformer).
Final Ensemble	The six intermediate ensembles are aggregated via a meta learner (Random Forest) to form the final ensemble.
Fixed Ensemble Count	The number of intermediate ensembles is fixed at six, regardless of the number of subsets, reducing computational overhead.
Efficient Resource Utilization	GPUs are reserved for training the computationally intensive LSTM and Transformer ensembles; lightweight meta learners (e.g., Logistic Regression or Random Forest) optimize aggregation.
Data Bus Implementation	A structured data bus efficiently transfers models from subsets to intermediate nodes, reducing latency and synchronization overhead.
Improved Cross-Validation	Streamlined aggregation minimizes redundancy, resulting in faster cross-validation and training on large datasets.

To determine n, the number of subsets, based on the size of the original dataset, it is crucial to consider computational efficiency, memory constraints, and sequential execution. Given that the dataset has $D = 167,229$ records and is processed sequentially in Google Colab with 12GB of RAM per node, the number of subsets n must strike a balance between memory usage and model performance. In this case, we chose $n = 6$ subsets, which implies a subset size S of:
$$S = \frac{D}{n} = \frac{167,229}{6} \approx 27,872 \text{ records per subset.}$$

The choice of $n = 6$ is reasonable given the following factors:

1	**Memory Constraints** : Google Colab provides 12GB of RAM. Each subset must fit within this memory while accommodating the model's requirements for training and validation. Processing approximately 27,833 records at a time is well-suited to this memory limit for most machine learning models, including Logistic Regression, SVM, LSTM, and Transformer-based models.
2	**Sequential Execution** : Since the architectures are implemented sequentially, the number of subsets n does not need to align with the number of computational nodes. Instead, the goal is to divide the dataset into manageable chunks that reduce training time and memory overhead for each subset.
3	**Performance and Aggregation** : With $n = 6$, both architectures remain computationally feasible. In Architecture 1, $n = 6$ leads to six independent intermediate ensemble models, which are aggregated into the final ensemble. In Architecture 2, models of the same type from all six subsets are combined into six intermediate ensemble models, one for each type of algorithm.

The web application uses only the model from the first intermediate node of Architecture 1, as retraining the larger dataset model takes over 20 minutes.

9.5 User Interface of the Application

Below are some snapshots from the web application.

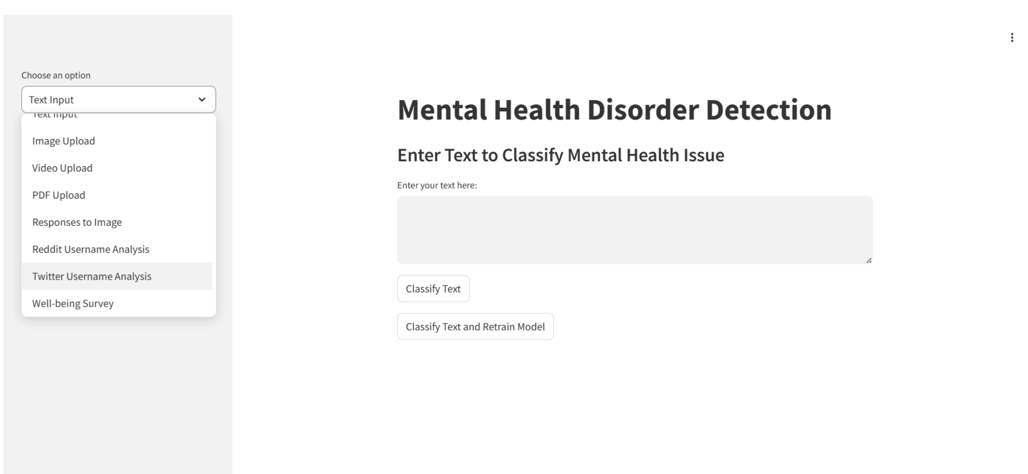
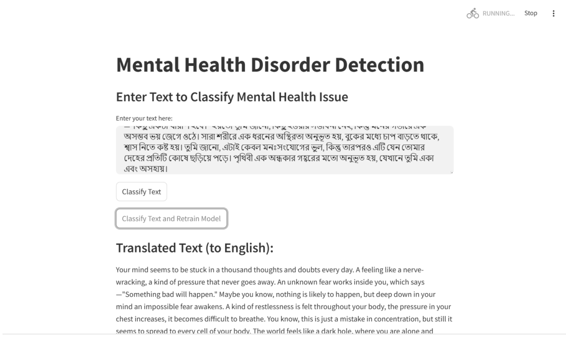
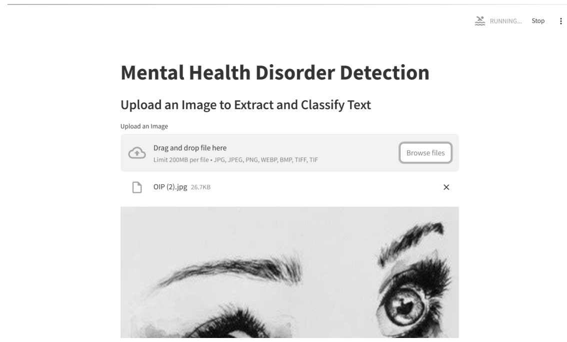


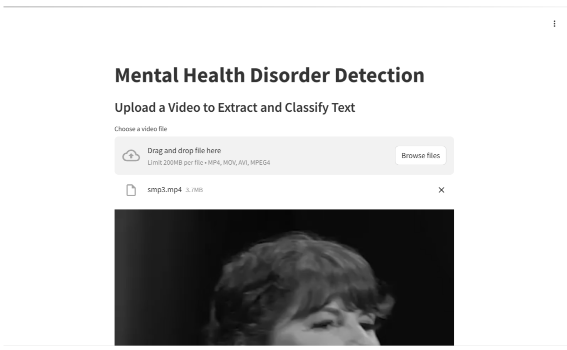
Fig. 9.16 List of Options for the User



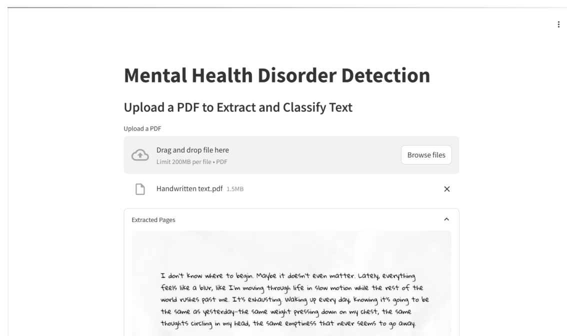
(a) Text Input Option



(b) Upload Image Option

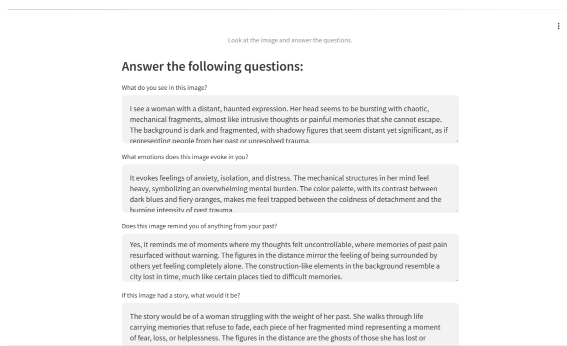


(c) Upload Video Option

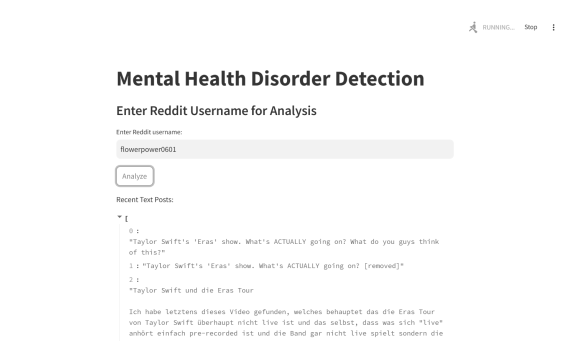


(d) PDF Upload Option

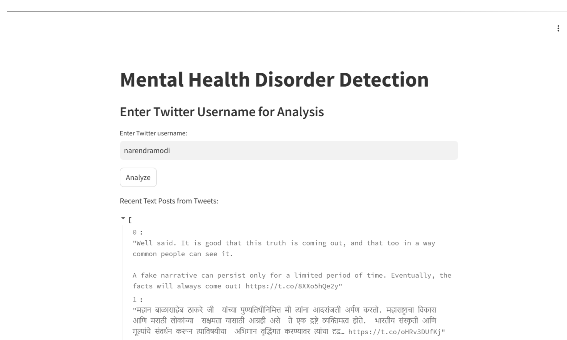
(e) User response to Image Option



(f) Questions related to image

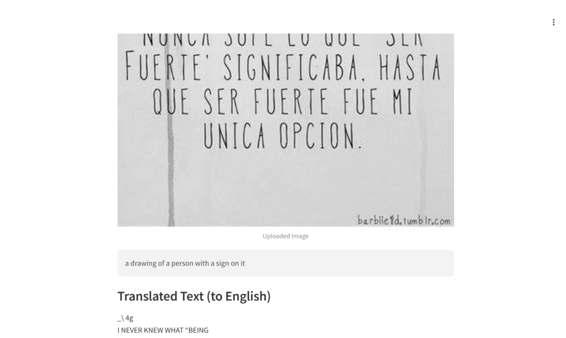


(g) Reddit User Analysis Option

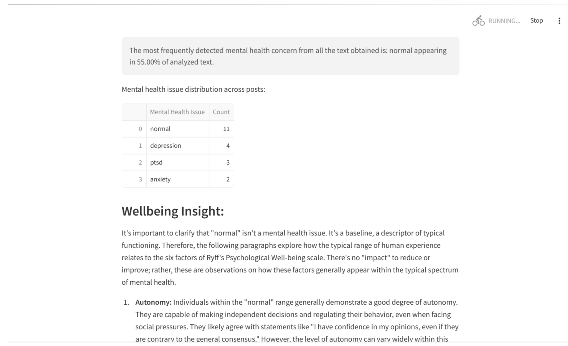


(h) Twitter User Analysis Option

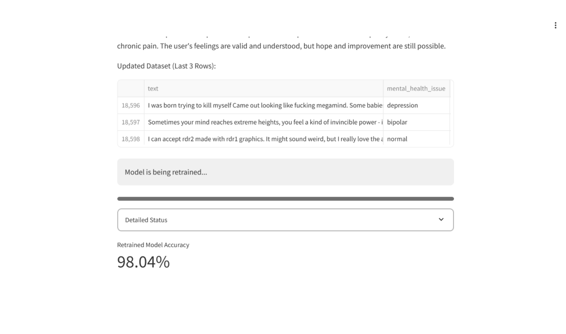
Fig. 9.17 Visuals from user inputs in web application



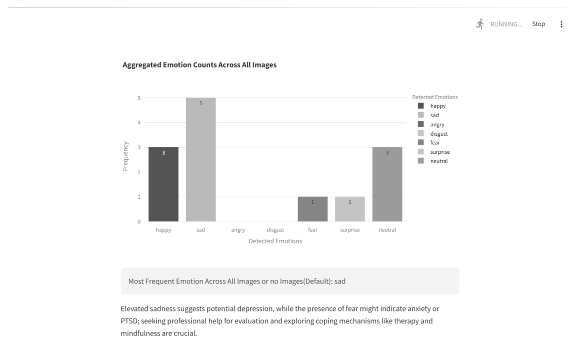
(a) Generate Image Caption



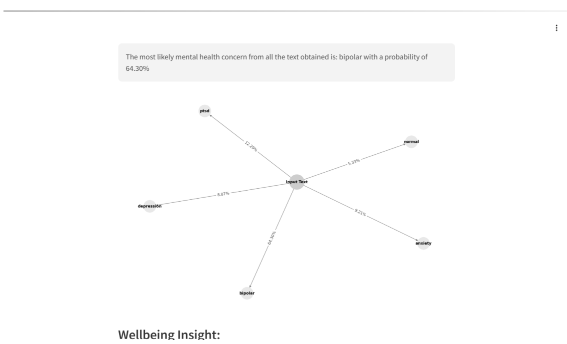
(b) Social Media User Analysis



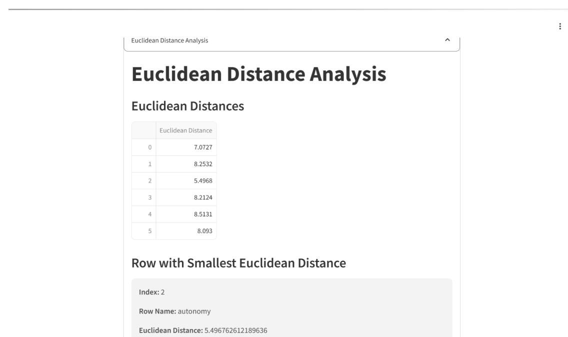
(c) Model Retraining Result



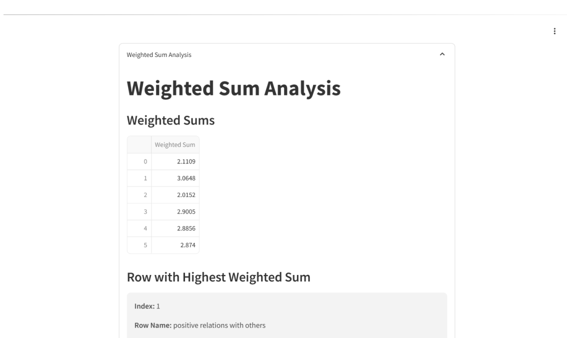
(d) Emotion analysis



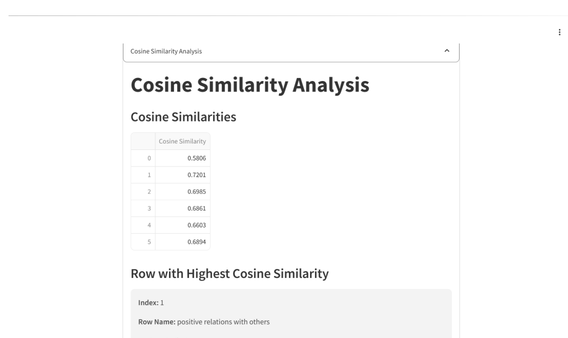
(e) Knowledge Graph after prediction



(f) Euclidean Distance Analysis

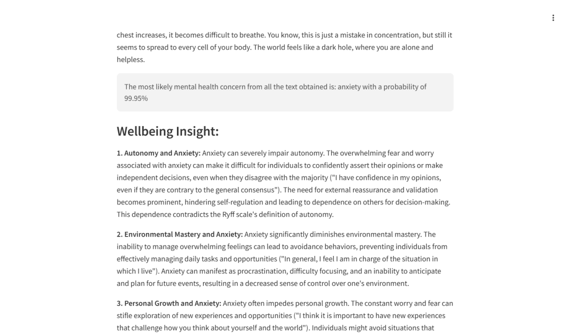


(g) Weighted Sum Analysis

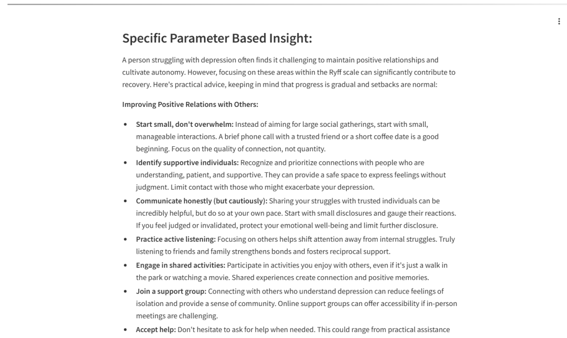


(h) Cosine Similarity Analysis

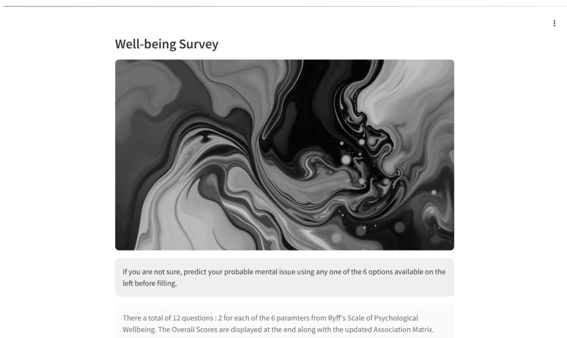
Fig. 9.18 Visuals from analysis of the user inputs



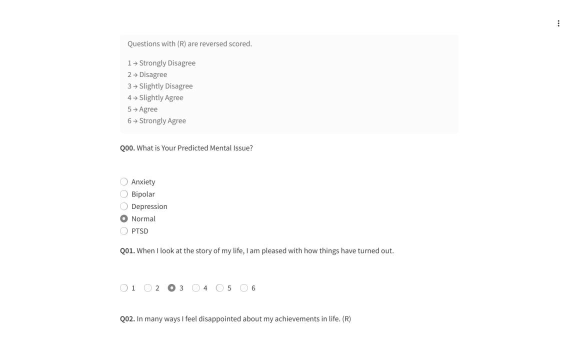
(a) Prediction and Insights



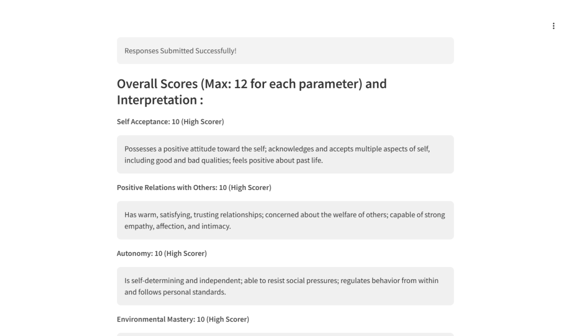
(b) Specific Parameter based Insights



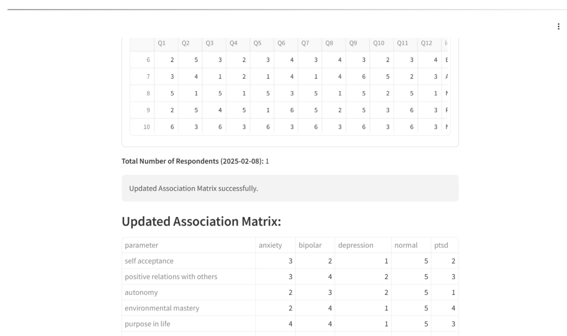
(c) Well-being survey option



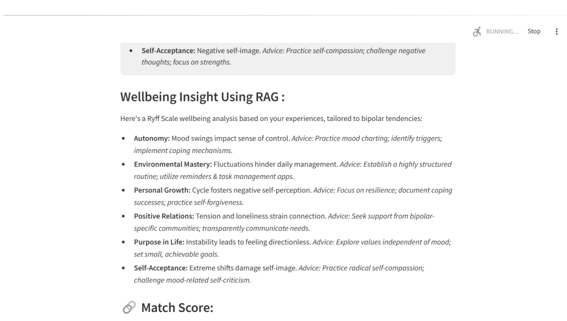
(d) Well-being survey questions



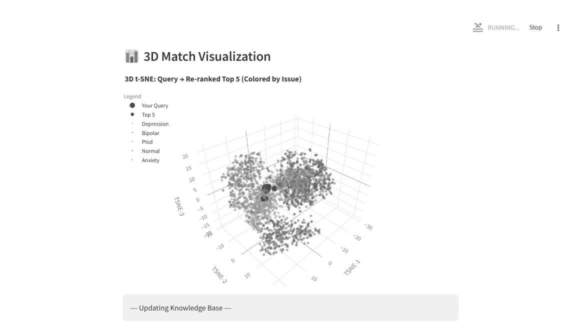
(e) Well-being survey result



(f) Updated Association Matrix after responses



(g) RAG based Wellbeing Insights



(h) Match Visualization and Dataset Updation

Fig. 9.19 Visuals of wellbeing survey and insights

10 Conclusion

Aspect	Summary
Project Benefits	• Early detection and intervention through social media analysis. • Leverages ML/DL to process large-scale data for objective, scalable diagnostics. • Reduces mis-/under-diagnosis by providing real-time insights. • Offers reusable components applicable in other domains (e.g., market sentiment, cyberbullying detection).
Future Scope	• Incorporate additional data sources (Facebook, Instagram, niche forums) for comprehensive analysis using bigger datasets. • Integrate real-time monitoring and feedback capabilities. • Enhance user privacy using techniques like differential privacy. • Collaborate with psychologists and ethicists to refine ethical and diagnostic guidelines.
Distributed Architecture	• Partition dataset using Hadoop HDFS, Amazon S3, or Google Cloud Storage. • Use Apache Spark or Dask for parallel processing and training on worker nodes (Docker/VMs). • Train base models (e.g., Logistic Regression, SVM) in parallel and aggregate them via a meta learner (Random Forest, XGBoost). • Aggregate subset-specific ensembles using stacking or weighted averaging, and deploy the final model via TensorFlow Serving, Kubernetes, or AWS SageMaker.
Threading Enhancements	• Implement threading to handle I/O-heavy tasks (e.g., video/image downloading, audio extraction, transcription) concurrently. • Overlap network and disk operations to reduce idle time. • Improve scalability and responsiveness, enabling the system to serve multiple requests simultaneously.
Custom SLM (Small Language Model) Challenges in Google Colab	• Finding proper weights and biases is difficult. • Epoch 1 takes excessively long, making pretraining or fine-tuning on larger datasets unfeasible. • Using pre-trained OpenAI weights builds a foundation but fails to generate meaningful texts. • Generating 1024-token sequences takes approximately 20 minutes, which is impractical.

11 References

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