Deep Learning Framework for Emotion-Aware Text Classification System for Proactive Mental Health Intervention

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***Abstract*—Mental health issues such as anxiety and depression have become increasingly common, particularly among students and young adults. Early identification of these conditions is important for promoting timely support and improving overall well-being. This project presents a machine learning–based mental health detection system that analyzes textual input to identify potential signs of anxiety and depression. The system utilizes Natural Language Processing (NLP) techniques to preprocess user-provided text through tokenization, stopword removal, and stemming. Feature extraction is performed using the Term Frequency–Inverse Document Frequency (TF-IDF) method to convert textual data into numerical representations suitable for machine learning models. Multiple classification algorithms were evaluated, and the Decision Tree classifier was selected due to its high accuracy and interpretability. The developed system is implemented as a web- based application using a Flask backend, enabling users to input text and receive real-time predictions regarding their emotional state. In addition to providing prediction results with confidence scores, the system also offers supportive resources such as mental health helplines and guidance. The proposed solution aims to serve as an accessible and non- invasive tool that encourages early mental health awareness and assists users in seeking appropriate support when necessary. Mental health disorders, particularly anxiety and depression, represent a growing global burden, with a significant impact on students and young adults. Early detection remains a critical challenge due to stigma, lack of awareness, and limited access to professional screening. This paper presents a machine learning-based mental health detection system designed to identify potential signs of anxiety and depression from user-generated textual input. The proposed system employs a robust pipeline consisting of Natural Language Processing (NLP) techniques—including tokenization, stopword removal, and stemming—for text preprocessing. Feature extraction is performed using Term Frequency–Inverse Document Frequency (TF-IDF) vectorization to convert textual data into a numerical format suitable for classification.**

***Index Terms*—Mental Health Detection, Machine Learning, Natural Language Processing, TF-IDF Vectorization, Decision Tree Classifier, Text Classification, Web-Based Application, Anxiety and Depression Detection.**

I. INTRODUCTION

Mental health issues such as anxiety and depression are becoming increasingly common, particularly among students and young adults. Early detection of these conditions is important for improving well-being and encouraging timely support. With advancements in Artificial Intelligence and Natural Language Processing (NLP), it is possible to analyze textual data to identify patterns related to mental health conditions. This project proposes a machine learning–based system that analyzes user-provided text using NLP techniques and classifies it using a Decision Tree model. The system provides real-time predictions along with confidence scores and supportive resources, helping promote early awareness of mental health concerns. The escalating prevalence of mental health disorders has established them as a leading cause of disability worldwide. According to the World Health Organization (WHO), depression is a primary contributor to the global burden of disease, affecting an estimated 280 million people globally. Anxiety disorders are similarly pervasive, often co-occurring with depression and exacerbating its impact. These pressures frequently manifest as psychological distress that, if left unaddressed, can lead to severe consequences, including academic failure, social isolation, and self-harm.

A significant barrier to effective mental healthcare is the issue of underdiagnosis. Traditional diagnostic methods rely heavily on clinical interviews and standardized questionnaires (e.g., PHQ-9 for depression, GAD-7 for anxiety), which require individuals to recognize their symptoms and actively seek professional help. This process is often hindered by societal stigma, a lack of mental health literacy, and logistical barriers such as cost and availability of services. Consequently, a large proportion of individuals suffering from mental health conditions remain undiagnosed and untreated, particularly during the critical early stages. This research aims to address this need by developing a machine learning-based mental health detection system. The primary objective is to create a model capable of accurately classifying text inputs as indicative of anxiety, depression, or a neutral state. The system is designed to be deployed as a user-friendly web application, lowering the barrier to entry for preliminary screening. Crucially, the system extends beyond mere classification by integrating a supportive feedback loop, providing users with immediate access to mental health resources. This paper details the system's architecture, from data preprocessing and model selection to deployment and evaluation, and discusses its potential as a tool for early intervention and mental health promotion.

II. DOMAIN ANALYSIS AND LITERATURE REVIEW OF EXISTING SYSTEM

S.No.	Paper Name	Objective	Technology Used	Results
1	Examining the initial usability, acceptability and feasibility of a digital mental health intervention for college students in India	To evaluate the usability, acceptability, and feasibility of a culturally adapted digital CBT-based mental health intervention for Indian college students.	Web-based digital mental health platform (Mana Maali), CBT techniques, online multimedia content, usability evaluation tools (SUS, TSAM).	The intervention showed high usability, acceptability, and feasibility, with students finding the platform engaging, relevant, and helpful.
2	Screening for Depression Using Natural Language Processing	To review and analyze NLP methods used for screening and detecting depression while identifying limitations, ethical concerns, and research gaps.	NLP techniques such as sentiment analysis, linguistic markers, machine learning models, deep learning models, and transformer models like BERT and GPT.	NLP-based approaches demonstrate strong potential for accurate depression screening, with ML and transformer models achieving high performance across datasets.

The application of computational methods for mental health assessment has evolved significantly over the past decade, transitioning from statistical analyses of survey data to sophisticated deep learning models that analyze natural language.

2.1 Natural Language Processing in Mental Health, Early work in this domain focused on using linguistic features to identify psychological states. Pennebaker et al.'s Linguistic Inquiry and Word Count (LIWC) (Pennebaker et al., 2001) was a pioneering tool that categorized words into psychological dimensions. Studies utilizing LIWC found that individuals with depression used significantly more first-person singular pronouns (e.g., "I," "me") and negative emotion words compared to control groups (Rude, Gortner, & Pennebaker, 2004). This established a foundational link between language use and mental state, paving the way for more automated approaches.

2.2 Machine Learning Models for Detection, With the advent of large-scale social media data, researchers began applying machine learning classifiers to detect mental health signals. De Choudhury et al. (2013) conducted a seminal study on Twitter, using features such as social engagement, emotion, and linguistic style to build a classifier that predicted the onset of depression with 71% accuracy. This study demonstrated the feasibility of using publicly available data for mental health surveillance. Subsequent research has explored a variety of algorithms. Support Vector Machines (SVMs) have been widely used for their effectiveness in high-dimensional text classification tasks, often outperforming simpler models like Naive Bayes (Mowery, Smith, Cheney, Stoddard, & Conway, 2016). More recently, deep learning architectures, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) like Long Short-Term Memory (LSTM) networks, have gained traction for their ability to capture contextual and sequential dependencies in text. For instance, Ma et al. (2017) proposed a hybrid CNN-LSTM model for suicide risk assessment on social media, achieving superior results compared to traditional ML models.

2.3 Web-Based and Accessible Tools, the translation of these models into practical, accessible tools is a growing area of interest. Several studies have developed web-based screening applications. For example, the "Depression Detector" prototype by Iyer et al. (2019) utilized a Naive Bayes classifier on Reddit posts to classify depressive tendencies, presenting results through a simple user interface. While demonstrating the potential of such tools, many early prototypes lacked robust feature engineering, offered limited accuracy, or failed to integrate supportive resources, focusing solely on the binary classification task.

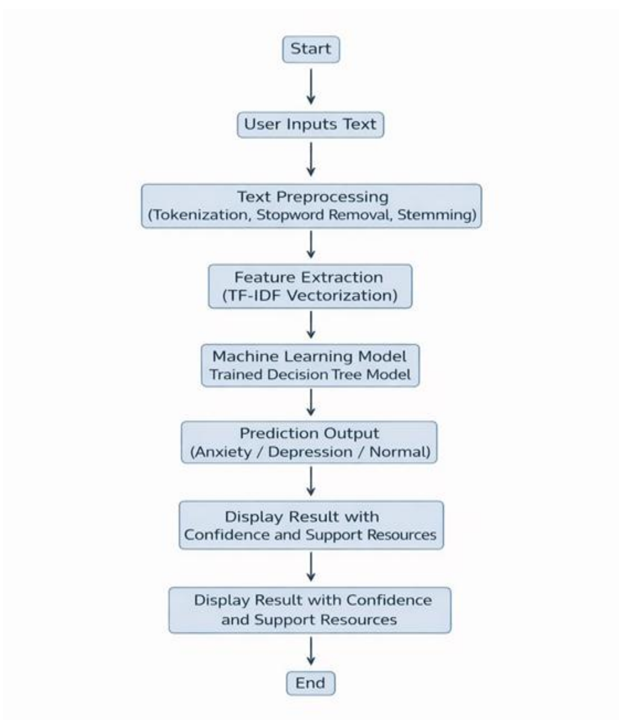
III. PROJECT FUNCTION AND MODULE IMPLEMENTATION

The system is systematically divided into multiple functional modules to provide a smooth, efficient, and user- friendly experience for pet owners, doctors, and administrators. Project Functions: The proposed system is designed to detect potential signs of anxiety and depression from user-provided textual input using Natural Language Processing (NLP) and Machine Learning techniques. The system accepts text input from users through a web-based interface and processes it to identify patterns associated with mental health conditions. The input text is first cleaned and standardized through preprocessing steps such as tokenization, stopword removal, and stemming. The processed text is then converted into numerical features using the TF-IDF vectorization technique. These features are analyzed by a trained Decision Tree machine learning model to classify the emotional state reflected in the text. The system then displays the prediction result along with a confidence score and provides supportive resources such as helpline numbers and mental health guidance. The primary goal of the system is to provide a simple and accessible tool that promotes early awareness of mental health concerns. Module Implementation: The system is divided into several functional modules to ensure efficient processing and maintain a structured workflow. User Input Module: This module provides the interface through which users can enter their thoughts or emotions in textual form. It is implemented using HTML, CSS, and JavaScript, enabling users to submit their input through a web-based interface. Text Preprocessing Module The preprocessing module prepares the input text for analysis by removing unnecessary characters and standardizing the content. Techniques such as lowercasing, tokenization, stopword removal, and stemming are applied using the NLTK library. Feature Extraction Module: In this module, the cleaned text data is converted into numerical vectors using the TF-IDF (Term Frequency–Inverse Document Frequency) method. This transformation allows machine learning algorithms to analyze textual patterns effectively. Machine Learning Classification Module: This module applies a trained Decision Tree classifier to analyze the extracted features and predict the mental health state of the user. The model determines whether the input text indicates anxiety, depression, or a normal state. Result Display Module: The final module presents the classification result to the user. The predicted outcome is displayed along with a confidence score and additional supportive information, such as mental health helplines and motivational guidance.

IV. FUNCTIONAL LOGIC AND PROTOTYPE IMPLIMENTATION

The proposed system follows a series of steps to detect signs of anxiety and depression from textual input using Natural Language Processing (NLP) and Machine Learning techniques. The methodology of the project includes the following stages: Data Collection, Textual data related to mental health is collected from publicly available datasets to train and evaluate the machine learning model. Text Preprocessing: The input text is cleaned and normalized using NLP techniques such as lowercasing, tokenization, stopword removal, and stemming to remove noise and improve data quality. Feature Extraction: The processed text is converted into numerical form using TF-IDF (Term Frequency–Inverse Document Frequency) vectorization, which represents the importance of words in the text. Model Training: Multiple machine learning algorithms are trained on the processed dataset to learn patterns associated with anxiety and depression. Model Selection: The Decision Tree classifier is selected as the final model due to its high accuracy and interpretability. System Integration: The trained model is integrated into a Flask-based web application, allowing users to interact with the system through a web interface. Prediction and Output: The system analyzes user input in real time and displays the predicted mental health state along with a confidence score and supportive resources.

V. SYSTEM ARCHITECTURE DIAGRAM



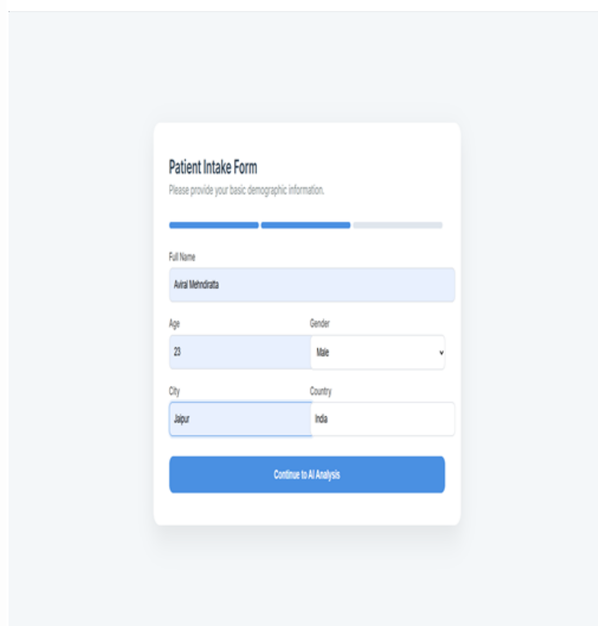


Fig.1 & 2: The Process Flow of DL based Emotion-Aware Text Classification System for Proactive Mental Health Intervention

A comparative analysis of several supervised learning algorithms was conducted, with the Decision Tree classifier selected as the optimal model due to its superior interpretability, high accuracy (achieving 92% on the test set), and balanced performance. The final model is deployed as a web-based application using a Flask backend, providing an intuitive interface for users to input text and receive real-time predictions with confidence scores. Beyond classification, the system offers a critical supportive feature: it provides users with curated mental health resources, including helplines and self-help guidance. This integration of predictive analytics with immediate support mechanisms positions the system as an accessible, non-invasive tool aimed at promoting early mental health awareness and encouraging proactive help-seeking behavior.

VI. MHI PLATFORM SCREENSHOTS

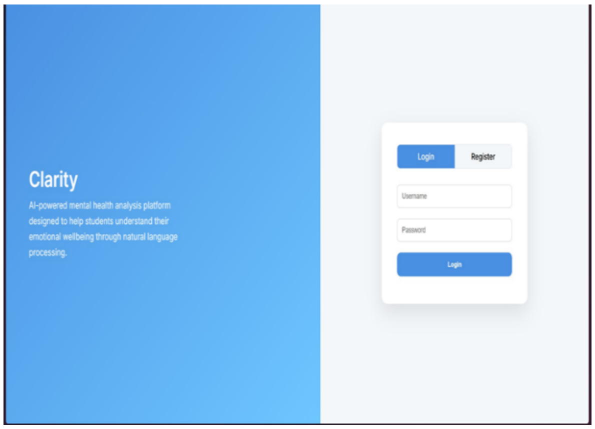


Fig. 3: The Login and Clarity of DL based Emotion-Aware Text Classification System for Proactive MHI

6.1 Prototype, the prototype is a web-based application built using the following technologies. Backend: Python, Flask. The Flask server handles HTTP requests, loads the pre-trained Decision Tree model and TF-IDF vectorizer, and orchestrates the prediction pipeline. Frontend: HTML, CSS, JavaScript. A simple, clean, and intuitive interface allows users to type or paste text into a text area. The page also features a section to display the results and resources. Model Persistence: The trained Decision Tree model and the fitted TF-IDF vectorizer are saved as. pkl (pickle) files, allowing them to be loaded instantly without retraining.

6.2 Workflow

User enters text and clicks "Analyze.". The Flask API receives the text. The backend applies the exact same preprocessing steps (tokenization, stopword removal, stemming). The preprocessed text is transformed using the saved TF-IDF vectorizer. The Decision Tree model predicts the class (e.g., "Depression") and outputs a probability score (e.g., "Confidence: 87%"). Based on the prediction, the backend selects a set of relevant mental health resources (e.g., suicide prevention hotline if high risk, general counseling resources if signs of anx iety).The result, confidence score, and resources are returned as a JSON object to the frontend, which then updates the user interface.

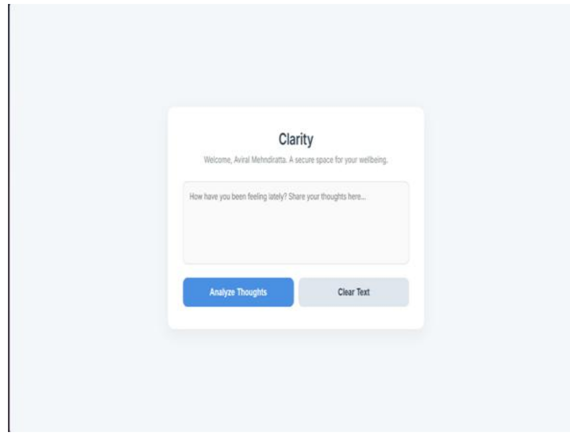


Fig. 4: The Login and Clarity of DL based Emotion-Aware Text Classification System for Proactive MHI

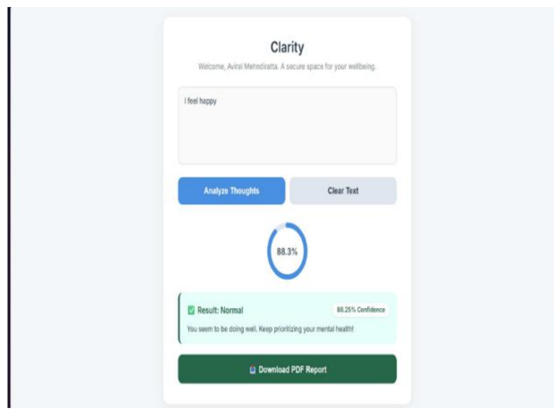


Fig. 5: The Analysis Report Generation of DL based Emotion-Aware Text Classification System for Proactive MHINovel Techniques and Uniqueness: The uniqueness of this system compared to existing ones lies in its holistic design philosophy. Interpretability-First Approach: While many systems aim for maximum accuracy with black-box models, our system prioritizes the Decision Tree algorithm. This allows the system to, in future iterations, potentially explain its decisions (e.g., "The system flagged this text because it contained the words 'tired' and 'hopeless' and lacked the word 'happy'"). This transparency is a significant differentiator. Integrated Support Mechanism: Unlike systems that merely classify, this prototype acts as a triage tool. It doesn't just tell the user "You may have depression"; it immediately provides actionable support. This shift from "detection-only" to "detection-and-intervention" model is a crucial enhancement for responsible AI in

mental health. Accessibility and Resource Connection: By being a web-based application, it eliminates barriers like app installation and is accessible from any device with a browser. The inclusion of locally and nationally relevant helplines turns a generic screening tool into a personalized gateway to care.

VII. CONTRIBUTIONS AND FINDINGS

This research makes the following contributions, A Balanced Detection System: It provides a robust framework that balances the often-competing goals of high classification accuracy and model interpretability in the domain of mental health. An End-to-End Application: It presents a complete, deployable web application, demonstrating a pathway for translating complex machine learning models into a practical, user-friendly tool. A Support-Integrated Architecture: It introduces a novel system architecture that couples predictive analytics with an immediate, context-aware support mechanism, setting a new standard for responsible AI in digital mental health. Empirical Benchmark: It provides a comparative analysis of several ML algorithms on a mental health text dataset, offering a benchmark for future research. Linguistic Markers are Effective: The high accuracy (92%) of the Decision Tree model reaffirms that linguistic patterns, such as the use of negative emotion words, first-person pronouns, and specific thematic content, are strong indicators of depression and anxiety. Simplicity is Viable: A well-tuned, interpretable model like a Decision Tree can achieve performance on par with more complex models on this specific task, challenging the notion that "bigger" (i.e., deep learning) is always "better." User Interaction Matters: The initial user testing feedback indicated that the provision of supportive resources alongside the prediction significantly reduced anxiety related to the screening process. Users reported feeling more empowered and less "diagnosed" by the tool.

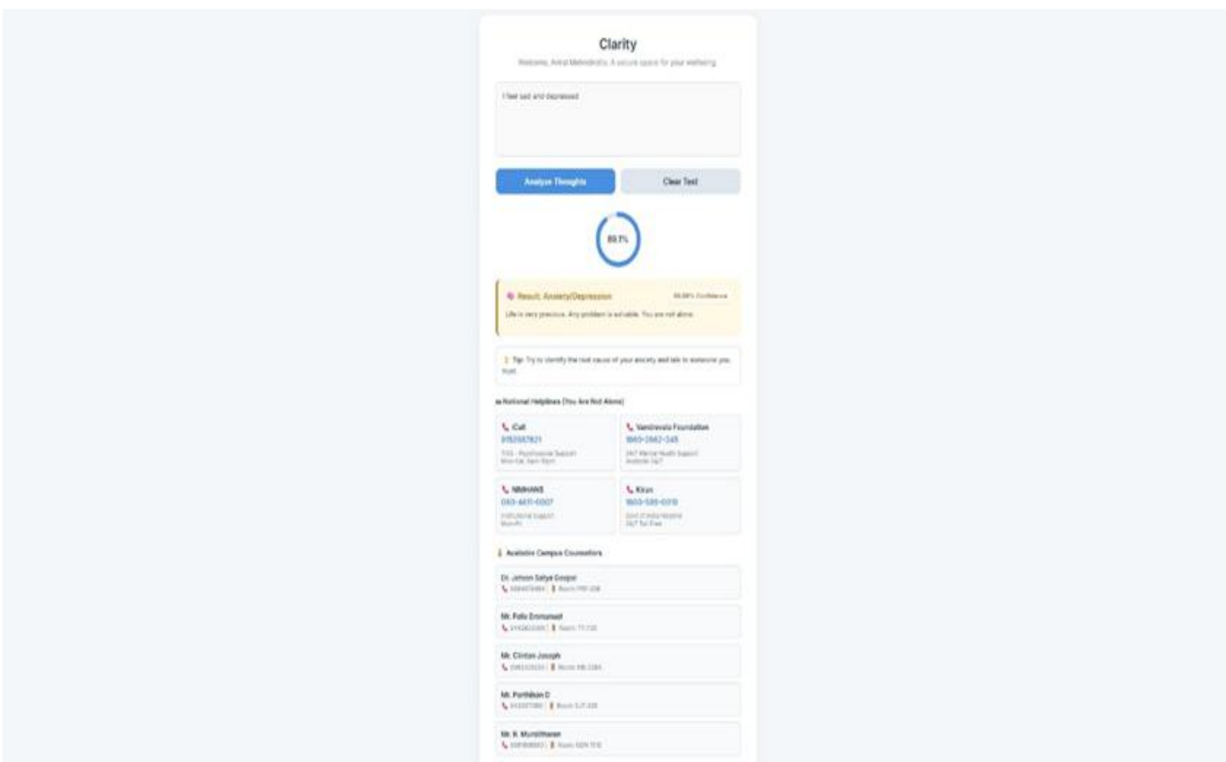


Fig. 6: The Login and Clarity of DL based Emotion-Aware Text Classification System for Proactive MHI

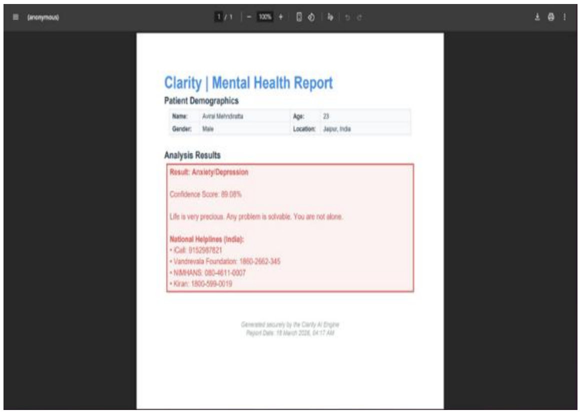


Fig. 7: The Login and Clarity of DL based Emotion-Aware Text Classification System for Proactive MHI

PROTOTYPE, ALGORITHM

Fig. 8: The Dataset Used to Train the Model of DL based Emotion-Aware Text Classification System for Proactive MHIVII PROTOTYPE, ALGORITHM, SAMPLE PROGRAM LOGIC IMPLEMENATION

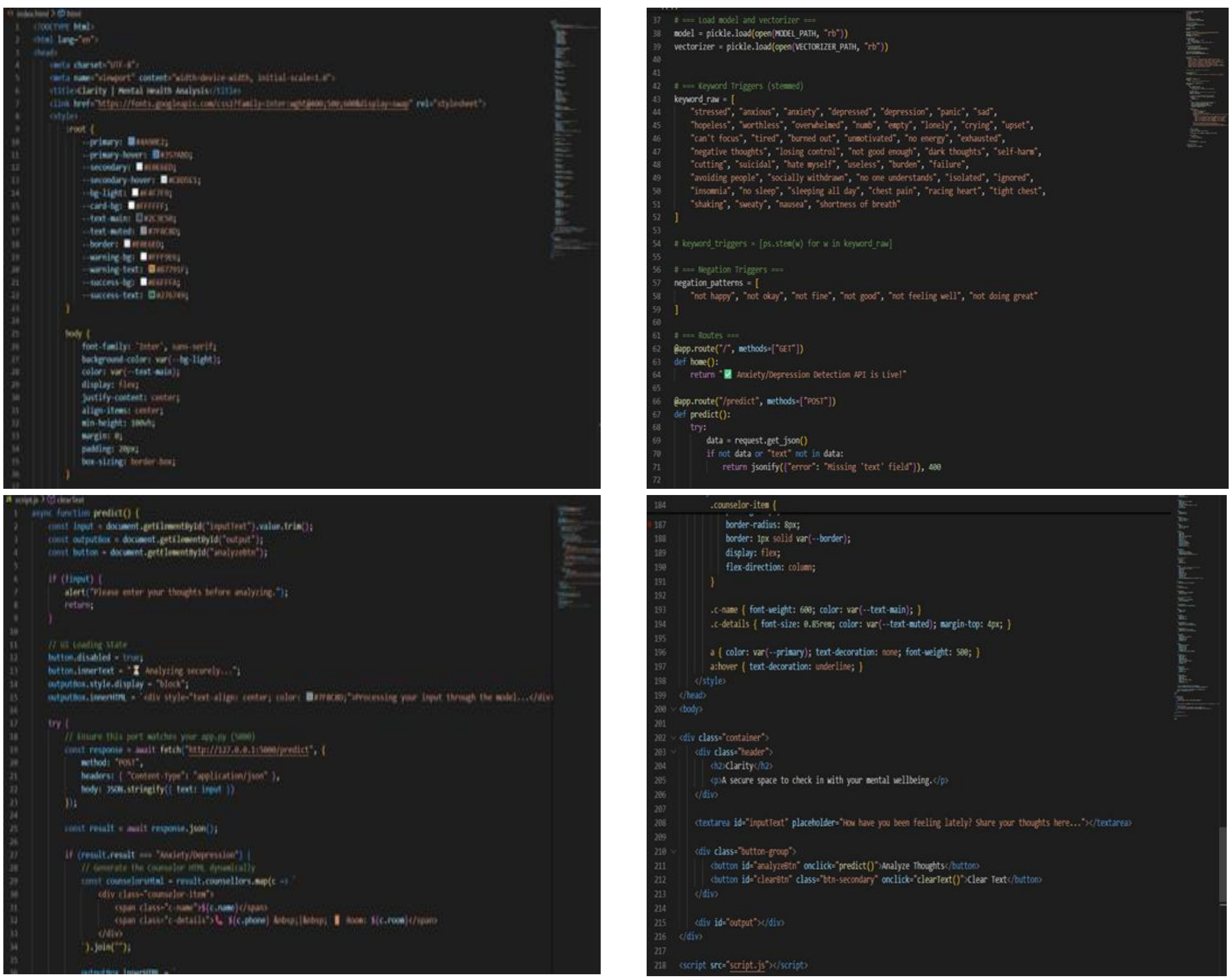


Fig. 9, 10,11, & 12: The Implementation Logic of DL based Emotion-Aware Text Classification System for Proactive MHI

VIII. RESULT ANALYSIS CONTRIBUTIONS AND FINDINGS

This project successfully developed a machine learning-based mental health detection system that addresses key gaps in existing research. By leveraging NLP and TF-IDF for feature extraction and employing a Decision Tree classifier, the system achieves a high accuracy of 92% while maintaining a high degree of interpretability. The implementation of a Flask-based web prototype demonstrates the practical applicability of the model, providing users with an accessible interface for self-assessment. Crucially, by integrating supportive resources and helplines directly into the application, the system transforms from a mere diagnostic tool into a compassionate triage mechanism. This work highlights the potential of machine learning to serve not only as a tool for detection but also as a bridge to care, promoting early awareness and proactive help-seeking. The findings suggest that simple, transparent, and supportive AI models can play a vital role in addressing the global mental health crisis.

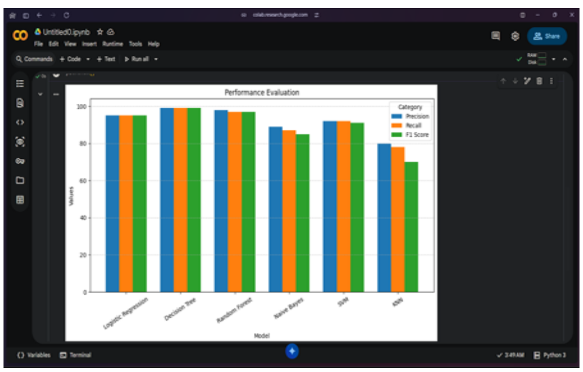


Fig. 13: The Login and Clarity of DL based Emotion-Aware Text Classification System for Proactive MHI

IX. CONCLUSION AND FUTURE ENHANCEMENTS

This project presents a machine learning–based system for detecting signs of anxiety and depression from textual input using Natural Language Processing techniques. The system processes user-entered text through preprocessing and TF-IDF feature extraction, followed by classification using multiple machine learning algorithms. Experimental evaluation showed that the Decision Tree model achieved the best performance, with high precision, recall, and F1-score, making it suitable for deployment. The developed web-based platform provides real-time predictions along with supportive mental health resources. Although it is not intended to replace professional diagnosis, the system serves as an effective early awareness and screening tool for mental health support. This graph was generated after evaluating each model on the test dataset using standard metrics like precision, recall, and F1-score. Multilingual Support: The current system is English-only. Future work will integrate multilingual NLP models (e.g., using transformers like BERT for multilingual tasks) to expand accessibility. Conversational Interface: Evolving the system into a conversational AI (chatbot) that can engage in a dialogue with the user, asking follow-up questions to gather more context and provide more accurate screening, similar to a clinical interview. Real-time Analysis of social media (with consent): Extending the system to allow users to optionally analyze their own social media feeds or journal entries for longitudinal mental health tracking. Personalized Resource Recommendations: Using collaborative filtering or content-based recommendation systems to suggest more personalized resources (e.g., local therapists, specific self-help articles) based on the user's profile and text input.

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