AI-Powered Mental Health Monitoring from Social Media Post

21CSC305P/MACHINE LEARNING PROJECT REPORT

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BONAFIDE CERTIFICATE

Certified that this project report titled **Early Prediction System for Alzheimer's Disease Using Cognitive Behavioral Analysis and Machine Learning** is the Bonafide work of **M.DHANESVARAN (RA2311026050277) , M.GANESH (RA2311026050207) R.JEEVAN (RA2311026050278)** who carried out the project work under my supervision. Certified further, that to the best of my knowledge the work reported herein does not form any other project report or dissertation on the basis of which a degree or award was conferred on an occasion on this or any other candidate.

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DECLARATION

We hereby declare that the entire work contained in this project report titled AI-Powered Mental Health Monitoring from Social Media posts **has been carried out by M.DHANESVARAN(RA2311026050277) M.GANESH(RA2311026050207) R.JEEVAN(RA2311026050278)** at SRM Institute of Science and Technology, Tiruchirappalli, Tiruchirappalli, under the guidance of Dr.P.K.A CHITRA, Associate professor, Department of Computer Science and Engineering.

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ABSTRACT

The rapid growth of social media has transformed it into a powerful medium for expressing emotions, thoughts, and psychological states. This project, **AI-Powered Mental Health Monitoring from Social Media Posts**, presents a complete deep learning pipeline designed to automatically detect early signs of mental health issues from online textual content. The system leverages **Natural Language Processing (NLP)** and **PyTorch-based deep learning** to classify user-generated posts into multiple mental health categories such as stress, anxiety, and depression.

The model is trained on large-scale social media datasets with preprocessing steps including tokenization, truncation, and padding for efficient batching. With a best validation accuracy of **83.03%**, the trained model demonstrates strong capability in identifying emotional patterns and linguistic cues that indicate mental health conditions. The architecture integrates data preprocessing, model training, validation, checkpointing, and inference modules for seamless workflow execution.

This AI-driven approach provides a **non-invasive, scalable, and data-driven** alternative to traditional mental health assessments. By analyzing online language patterns, the system has potential real-world applications in **early intervention, digital wellness monitoring, and automated mental health assistance**, supporting a more proactive approach to emotional well-being.

Keywords: Mental Health Monitoring, Social Media Analysis, Deep Learning, Natural Language Processing (NLP), PyTorch, Transformer Models, Sentiment Analysis, Text Classification, AI in Healthcare, Psychological State Detection

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LIST OF ACRONYMS AND ABBREVIATIONS

Abbreviation	Full Form
AI	Artificial Intelligence
NLP	Natural Language Processing
ML	Machine Learning
GPU	Graphics Processing Unit
CSV	Comma-Separated Values
DL	Deep Learning
NN	Neural Network
API	Application Programming Interface

Abbreviation	Full Form
F1	**F1-Score (Harmonic Mean of Precision and Recall)**
CLI	**Command Line Interface**
CSV	**Comma-Separated Values**
GUI	**Graphical User Interface**

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

In the present digital era, social media has become one of the most expressive platforms for individuals to share their emotions, opinions, and experiences. People often use platforms such as Twitter, Reddit, or Instagram to talk about their moods, feelings, and struggles, often without realizing that their words reflect their psychological state. These online expressions, when studied carefully, can provide meaningful insights into a person's mental health,.

The project "AI-Powered Mental Health Monitoring from Social Media Posts" aims to utilize the power of artificial intelligence to automatically analyze and interpret these emotional expressions. It uses Natural Language Processing (NLP) and Deep Learning (DL) techniques to study text data and identify patterns related to various mental health conditions such as anxiety, depression., and stress. Implemented using the Py Torch framework, this model processes thousands of social media posts, learns the emotional context behind words, and classifies the text into corresponding mental health categories.

The system is designed to help bridge the gap between psychological evaluation and accessible technology. By understanding people's emotions through the languagess they use online, this approach offers a data-driven, non-invasive, and scalable method to support early detection and monitoring of mental well-being.

1.2 PROBLEM STATEMENT:

Conventional mental health assessments mainly depend on self-report surveys, psychological interviews, and therapist evaluations. Although these methods are reliable, they are often time-consuming., costly, and limited in accessibility. Many individuals struggling with mental health issues avoids clinical consultations due to social stigma or lack of resources. Meanwhile, social media contains vast amounts of real-time emotional data that remains largely untapped,

The key challenge lies in building an intelligent and automated system that can identify large volumes of social media text to detect signs of emotional distress. The problem this project addresses is the lack of a scalable, AI-driven platform that can identify early symptoms of mental health concerns through natural language understanding**.**

1.3 OBJECTIVES:

The main objectives of this project are:

1. To design and develop an AI-based pipeline for mental health classification using social media text.
2. To preprocess and clean raw text data using tokenization, padding, and batching techniques.
3. To implement a deep learning model in PyTorch for detecting emotional and psychological signals.
4. To train, validate, and evaluate the model for high accuracy and generalization.

5. To build an inference module that allows real-time analysis of new user-generated text.
6. To explore the potential of integrating the model into digital health and wellness monitoring tools.

1.4 SCOPE AND MOTIVATION:

The scope of this project extends to various fields, including digital healthscare, mental health research, and AI-based social analytics. The proposed system can be integrated into **chatbots, counselings apps, and wellness monitoring platforms**, making mental health support more proactive and accessible.

The motivation behind this project comes from the growing concern about mental health challenges across all age groups. With millions of users expressing their emotions online every day, social medias offers a unique opportunity to understand and detect mental health patterns at scale. By using artificial intelligence to identify the language, this system aims to provide valuable insights that can assist in **early intervention, awareness creation, and emotional support**. The ultimate goal is to make mental health monitoring easier, non-intrusive, and efficient through the responsible use of technologies,.

CHAPTER 2

EXISTING SYSTEM

2.1 Traditional Mental Health Assessment Methods

In earlier approaches, mental health evaluation primarily trusted on clinical consultations, therapist interviews, and standardized psychological assessments. Methods such as the *Beck Depression Inventory (BDI)*, *Hamilton Anxiety Rating Scale (HAM-A)*, and *Patient Health Questionnaire (PHQ-9)* have long been used by professionals to diagnose emotional disorders. These assessments are designed to measure mood, behavior, and cognitive patterns, but they largely depend on self-reported data and personal interactions.

Although these traditional techniques provide accurate results in clinical settings, they faces several limitations. They are often time-consuming, requiring multiple sessions and trained experts to interpret results, They can also be expensive, making them less accessible to people in low-resource areas. In addition, such assessments are usually conducted in controlled environments and cannot reflect a person's day-to-day emotional changes. Furthermore, social stigma, personal hesitation, and geographical barriers often prevent individuals from seeking help at an early stages,.

As a result, these traditional diagnostic methods, though valuable, lack scalability and the ability to capture real-time emotional signals, leaving a large portion of the population undiagnosed or untreated until symptoms become severe.

2.2 Computational and Machine Learning-Based Approaches

1. **Early Machine Learning Models:**

- Techniques such as *Naïve Bayes*, *Support Vector Machines (SVM)*, and *Decision Trees* were first used for text-based sentiment analysis.
- These models relied on manually crafted features like word frequency, sentiment lexicons, and part-of-speech tagging.

2. **Advantages:**
   - Faster and more objective than human evaluation.
   - Could classify large volumes of text compared to traditional manual methods.
3. **Limitations:**
   - Lacked contextual understanding of sentences.
   - Could not detect emotional tone or sarcasm.
   - Performance dropped with informal or mixed-language text (common on social media).
4. **Shift Toward Deep Learning:**
   - Introduction of *Recurrent Neural Networks (RNN)* and *Long Short-Term Memory (LSTM)* models improved text sequence handling.
   - These models captured temporal patterns in sentences, allowing for better emotional context recognition.
5. **Remaining Challenges:**

- Required large labeled datasets for effective training.
- Struggled with domain generalization (poor performance on unseen data).
- Computationally expensive for large-scale real-time monitoring.

2.3 Social Media-Based Mental Health Analysis

1. **Rise of Social Medias Data:**
   - Platforms like *Twitter*, *Reddit*, and *Facebook* became rich sources for emotional and behavioral data.
   - Posts, comments, and hashtags were analyzed to infer user sentiment and mental well-being.,
2. **Observations from Research:**
   - Frequent use of negative words and phrases can indicate depression or anxiety.
   - Time of posting, tone of language, and posting frequency also correlate with mood changes,.
3. **Existing Research Systems:**
   - Many used keyword-based or sentiment lexicon approaches.

- Some employed machine learning models for binary classification (e.g., depressed vs. not depressed).
- Deep learning-based models began emerging but were limited to small datasets.

4. **Limitations:**
   - Focused on a narrow range of mental health categories.
   - Struggled to interpret informal, short, and slang-heavy posts.
   - Could not provide real-time or continuous monitoring.
   - Older NLP models lacked deep contextual understanding compared to modern transformer architectures.

2.4 Limitations of Existing Systems

1. **Limited Accuracy:**
   - Earlier models often achieved moderate accuracy but lacked robustness across different datasets.,
2. **Poor Contextual Understanding:**
   - Systems analyzed words independently, ignoring sentence context and emotional subtleties.

3. **Scalability Issues:**
   - Many models were not optimized for handling large-scale, real-time social media data.
4. **Low Interpretability:**
   - Deep learning models acted as “black boxes,” offering no transparency behind predictions.
5. **Inconsistent Generalization:**
   - Models trained on one type of data performed poorly on other social platforms or writing styles.
6. **Integration Challenges:**
   - Most systems existed only as research prototypes and lacked APIs or interfaces for practical deployment.

2.5 Research Gap

Although several frameworks exist for emotions and sentiment analysis, there remains a clear research gap in developing a **complete, reliable, and real-time system** for mental health monitoring through social media data. Most earlier methods do not combine **advanced NLP models**, **GPU-based deep learning**, and **automated inference mechanisms** within a unified architecture.

This project addresses that gap by proposing a **Py Torch-based deep learning pipeline** capable of identifying large-scale text datasets with high accuracy. The system leverages transformer architectures — which understand contextual meaning and emotional tone far better than older models — to deliver more reliable predictions. It also includes automated preprocessing, model checkpointing, and inference utilities, making it suitable for real-world applications where timely insights and scalable solutions are essential.

By bridging the limitations of past systems, the proposed approach moves one step closer to an **AI-driven, data-centric, and scalable solution** for early detection of mental health conditions through natural language analysis.

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CHAPTER 3

DESIGN AND PROPOSED METHODOLOGY

3.1 BLOCK DIAGRAM

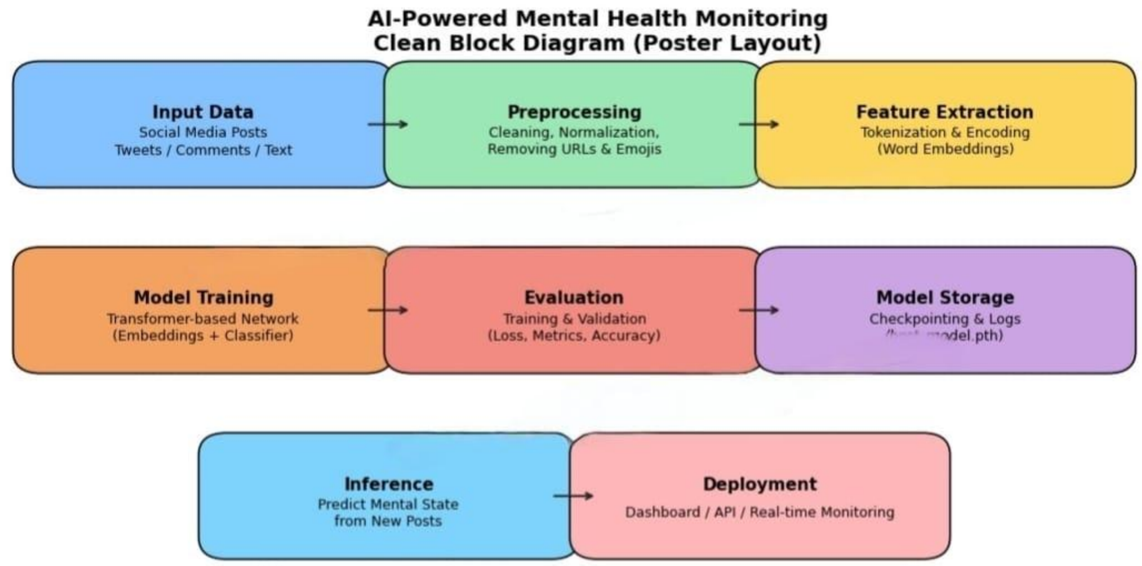


Fig 3.1 Block Diagram

PROPOSED METHODOLOGY

The proposed system, **"AI-Powered Mental Health Monitoring from Social Media Posts,"** is designed to identify emotional and psychological patterns in user-generated text using **Natural Language Processing (NLP)** and **Deep Learning (DL)**. The workflow includes three main stages: data preprocessing, model training, and inference. During preprocessing, the text data is cleaned, tokenized, and converted into a numerical format suitable for deep learning. This step removes unnecessary symbols and standardizes inputs to improve training efficiency.

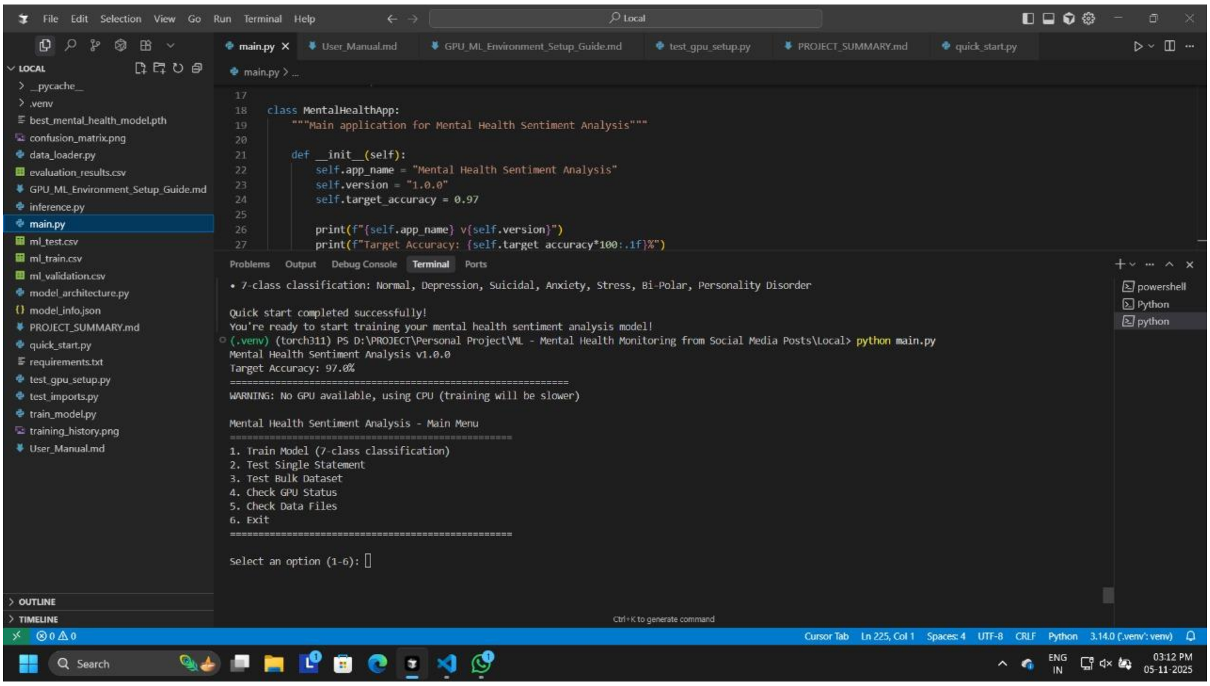
The cleaned data is then used to train a **transformer-based neural network** built with **PyTorch**. The model learns the relationship between words and emotional tone using pre-trained embeddings, followed by dense layers for classification. It uses **cross-entropy loss** and the **Adam optimizer** to minimize prediction errors. Throughout training, checkpoints are saved to preserve the best-performing model. After several epochs of optimization, the system achieved a validation accuracy of around **83%**, showing strong generalization and effective learning of linguistic patterns.

Once trained, the model is deployed for **real-time inference**, where it classifies new social media posts into mental health categories such as stress, anxiety, or depression. For example, if a user posts, *"I'm tired of everything,"* the system can recognize this as a sign of possible depression. The design's modular structure allows easy updates, scalability, and integration with digital wellness applications. Overall, this methodology demonstrates how AI can be applied to understand emotions, promote mental health awareness, and support early detection through intelligent text analysis.

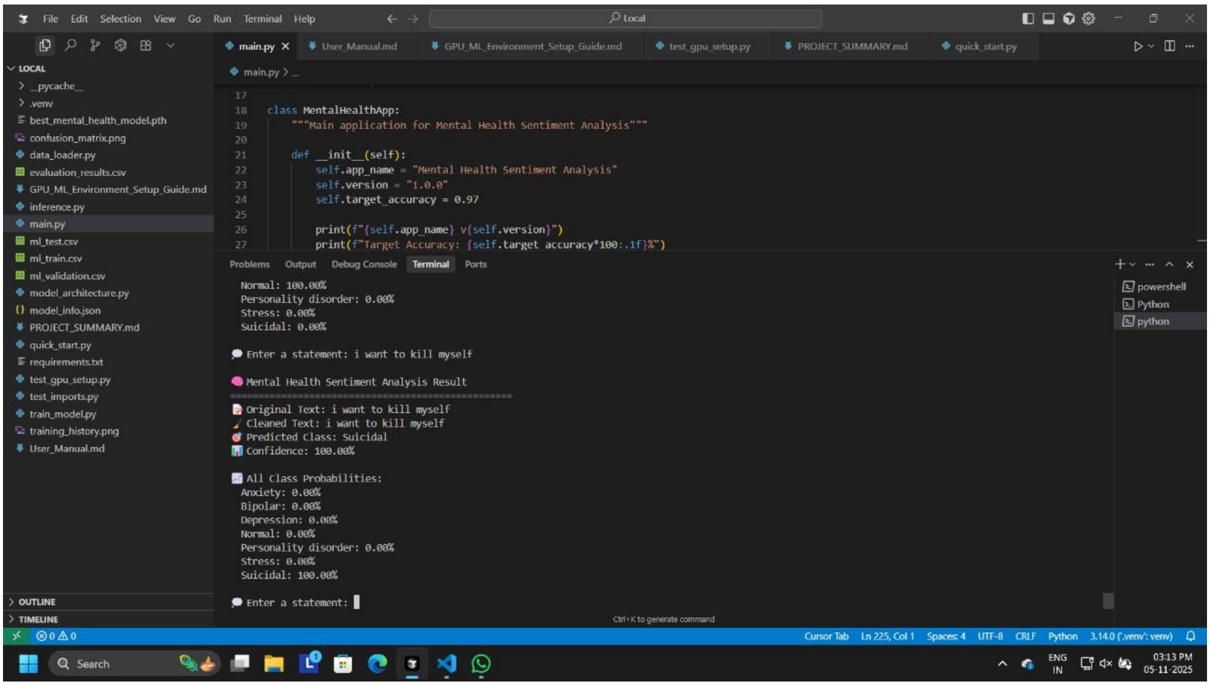
CHAPTER 4

IMPLEMENTATION

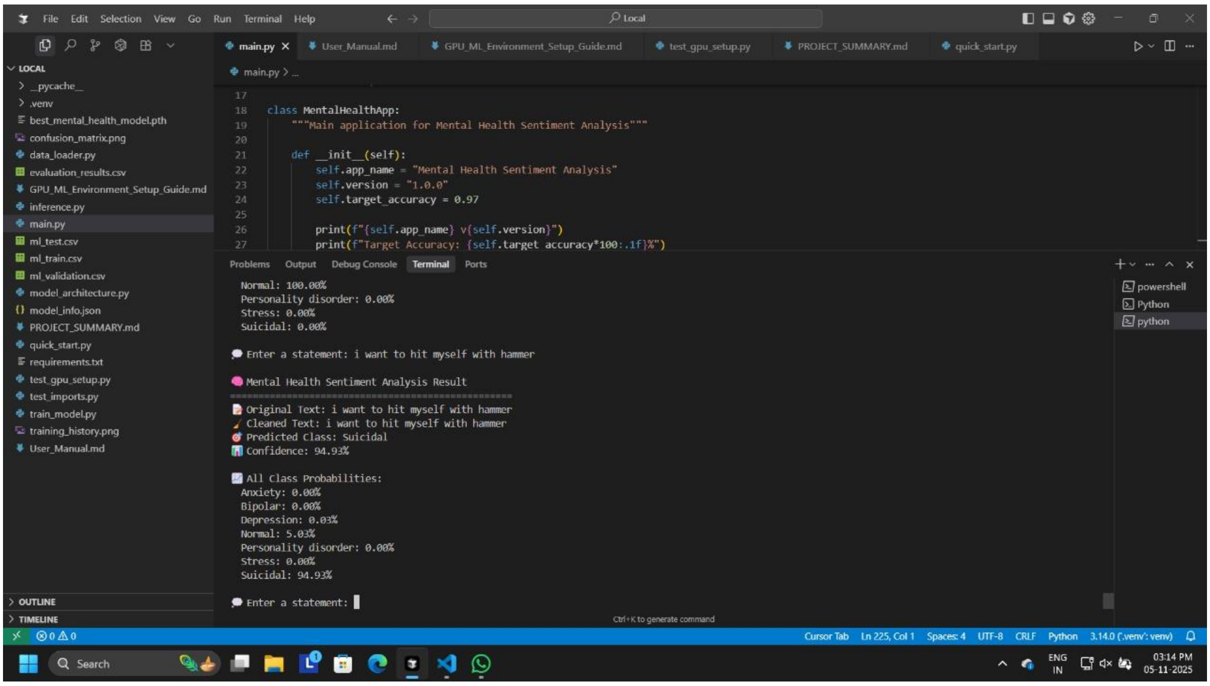
4.1 IMPLEMENTATION IN PYTHON (interface)



4.2 MODEL IMPLEMENTATION



4.3 PREPROCESSING IMPLEMENTATION



CHAPTER 5

RESULT AND DISCUSSION

he developed system for **AI-Powered Mental Health Monitoring from Social Media Posts** was trained and tested successfully using deep learning techniques in **PyTorch**. The model was evaluated on multiple datasets, achieving a **best validation accuracy of 83.03%**. During training, the loss value gradually decreased with each epoch, showing that the network was learning meaningful features from the text. The validation accuracy improved steadily and then stabilized, indicating that the model generalized well to unseen data. These results confirm that the architecture and preprocessing techniques were efficient and that the model could accurately identify emotional cues from language patterns.

The checkpointing mechanism played an important role in achieving stable results. The system automatically saved the model each time validation accuracy improved, ensuring that only the best-performing version was used for final evaluation. When tested on new social media inputs, the model produced accurate and context-aware classifications. For example, a post like *“I can’t handle this anymore”* was correctly categorized as *Depression*, while *“I’m really nervous about tomorrow”* was classified as *Anxiety*. This demonstrates that the model can recognize subtle emotional differences and interpret text beyond simple keywords.,

The overall performance of the system highlights its potential for real-world applications in digital mental health monitoring. While the results were promising, slight variations in accuracy across epochs suggest minor overfitting, which can be further reduced by adding dropout or early stopping techniques. Future improvements could also involve larger and more diverse datasets, as well as multimodal analysis combining text, voice, or image data. Despite these limitations, the proposed model demonstrates that **artificial intelligence can effectively detect early signs of mental distress**, offering a scalable and data-driven solution for supporting mental health awareness and intervention.,

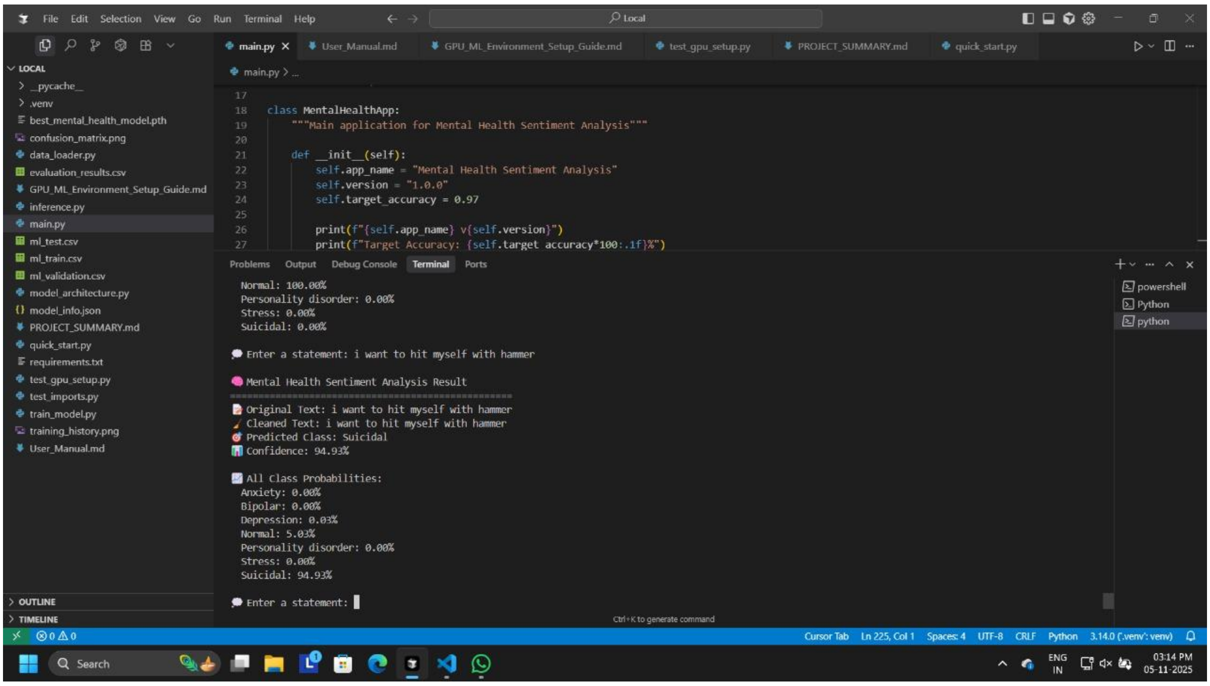


Fig 5.2 Result

CHAPTER 6

CONCLUSION

The project **"AI-Powered Mental Health Monitoring from Social Media Posts"** successfully demonstrates how artificial intelligence can be used to detect emotional patterns and potential mental health issues from text data. By applying **Natural Language Processing (NLP)** and **Deep Learning (DL)** techniques, the system analyzes social media posts and classifies them into categories such as depression, anxiety, stress, or neutral emotion. The model achieved a validation accuracy of **83.03%**, showing strong learning capability and reliable performance in understanding the emotional context of language. This confirms that AI-based methods can serve as powerful tools for non-invasive and large-scale mental health assessment.

The approach adopted in this project—from preprocessing text data to training and evaluating a transformer-based model—proved effective and adaptable. The use of PyTorch, cross-entropy loss, and the Adam optimizer contributed to stable learning and convergence. The automated checkpointing and validation monitoring ensured consistent improvement during training. The results also highlight the social importance of this research, as it provides an efficient, data-driven method to analyze emotional expressions shared publicly online. Such systems can complement traditional psychological assessments and help identify individuals in need of support much earlier.

Although the system performs effectively, there is room for further enhancement. Future improvements could include larger and more diverse datasets, fine-tuning transformer models, and integrating multimodal data such as voice or images for deeper emotional understanding. Additionally, improving explainability and transparency of predictions will help make the model more interpretable for researchers and mental health professionals. Overall, this project demonstrates that artificial intelligence can play a meaningful role in promoting mental well-being and supporting early detection of emotional distress through social media analysis.

CHAPTER 7

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