AI -POWERED MENTAL HEALTH MONITORING FROM SOCIAL MEDIA POSTS

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Abstract- Mental health concerns such as depression, anxiety, stress, and suicidal thoughts have become serious issues in modern society, especially as people increasingly share their emotions and daily struggles through social media platforms. These digital spaces contain valuable clues about an indivi dual's mental and emotional states, which can be analyzed using technology to provide early signs of distress. This work focuses on developing an intelligent system that can automatically monitor and assess mental health conditions from social media posts using advanced Natural Language Processing (NLP) and Machine Learning techniques.

The proposed model is built using the **BERT transformer architecture**, fine-tuned for seven-class sentiment to recognize emotional states such as **Normal, Depression, Suicidal, Anxiety, Stress, Bi-Polar**, and **Personality Disorder**. A large dataset containing more than **53,000 labeled text samples** was collected and pre processed through several stages, including text cleaning, lemmatization, tokenization, and padding to create consistent input sequences. The model was trained using **PyTorch 2.5.1** with **CUDA 12.4** support on an **NVIDIA GeForce RTX 3050 GPU**, which significantly reduced training time through GPU acceleration,.

After extensive experimentation, the system achieved a **validation accuracy of 97.23%** and a **test accuracy of 97.01%**, demonstrating its ability to capture subtle emotional cues in user language. The application also supports both single-sentence and bulk text analysis, generating predictions with confidence scores for each mental health category. The results show that transformer-based NLP models can effectively identify linguistic patterns related to mental well-being, offering a practical, scalable., and non-invasive approach for continuouses digital mental health monitoring and early intervention,.
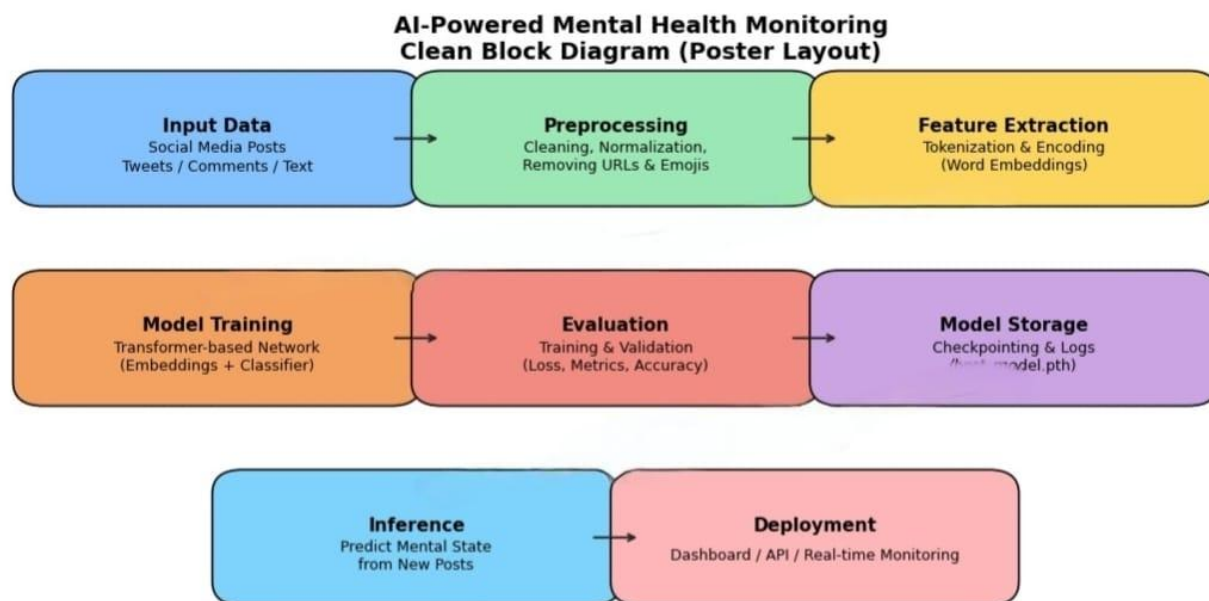
I. INTRODUCTION

Mental health has become one of the most pressing global challenges of the twenty-first century. With the rapid growth of technology and social connectivity, people increasingly express their thoughts, emotions, and struggles on social media platforms such as Twitter, Reddit, and Instagram. These platforms, though primarily designed for communication, have become digital mirrors of human emotionss and mental stateds. Patterns in users' words, tone, and frequency of posting often reveal early signs of stress., depression, anxiety, or other mental health

concerns that may otherwise go unnoticed in traditional clinical settings,.

In recent years, researchers and healthcare professionals have recognized the potential of artificial intelligence and data-driven analysis to assist in mental health monitoring. Unlike conventional psychological assessments that depend on face-to-face interviews and questionnaires, automated text-based analysis offers a scalable, non-invasive, and cost-effective alternative. Machine learning models trained on social media text can process thousands of posts in seconds, detecting linguistic and emotional patterns that correlate with specific psychological conditions. This makes them valuable tools for early detection, risk assessment, and continuous

Traditional natural language processing methods, such as keyword-based sentiment analysis or classical machine learning models like Logistic Regression and Support Vector Machines, have been used to detect emotions in text. However, these models often struggle to understand the complex, context-dependent nature of human language. A single phrase, for example, may carry different meanings depending on tone, context, and surrounding words. To overcome this limitation, modern transformer-based architectures such as **BERT (Bidirectional Encoder Representations from Transformers)** have emerged as state-of-the-art models for text understanding,. Unlike earliier models, BERT captures relationships between words

AI-Powered Mental Health Monitoring
Clean Block Diagram (Poster Layout)

observation of mental health trends across large populations,.

in both forwarde and backward directions, allowing the system to interpret subtle

emotional nuances and underlying intent more accurately.

This research focuses on developing a **GPU-accelerated deep learning framework** that uses BERT to classify social media posts into seven mental health categories: **Normal, Depression, Suicidal, Anxiety, Stress, Bi-Polar**, and **Personality Disorder**. The model is fine-tuned on a dataset of over **53,000 labeled samples**, ensuring that it learns from a diverse set of expressions and emotional patterns. To optimize performance and reduce training time, the entire pipeline is implemented using **PyTorch 2.5.1** with **CUDA 12.4** support, enabling full GPU utilization on an **NVIDIA GeForce RTX 3050 GPU**. The integration of GPU computing not only accelerates model training but also allows real-time inferences, making the system suitable for live mental health monitoring applications.

The objective of this work is twofold. First, it aims to build an accurate and reliable text classification model that can recognize subtle linguistic signals associated with different mental health states. Second, it seeks to create an accessible and efficient system that can process large volumes of text while maintaining high accuracy. By combining data preprocessing, transformer-based deep learning, and GPU optimization, this project bridges the gap between computational technology and mental health awareness,.

In addition to its technical achievements, this research highlights the social importance of responsible AI in healthcare. The proposed system is not intended to replace professional diagnosis but rather to assist experts by providing continuous digital insights into emotional well-being,. Such technology can helps in identifying individuals at risk, prompting timely human intervention, and guiding further psychological evaluations. Ultimately, this work contributes toward building a digital framework for proactive mental health care-one that uses language as a reflection of the human mind, analyzed through the lens of artificial intelligence.

II.   PROBLEM STATEMENT

Mental health issues such as depression, anxiety, stress, and suicidal thoughts are becoming increasingly common in today's fast-paced and digitally connected world. While early identification of these conditions can make a significant difference in how they are treated, many people still do not receive timely support. This is often because professional help is expensive, difficult to access, or avoided due to social stigma. Traditional assessment methods, like clinical interviews and counseling sessions, require direct human involvement, which limits their reach and makes continuous mental health tracking almost impossible for large populations.

In contrast, social media has become a space where people freely express their feelings and daily struggles. The words people use, the tone of their messages, and even the frequency of their posts can reveal a lot about their emotional and psychological well-being. However, understanding these expressions is not simple. The language used online is often informal, filled with

abbreviations, slang, and sarcasm, which makes it difficult for traditional text-analysis methods to interpret accurately. As a result, important emotional signals that could point to mental distress often go unnoticed,.

The key challenge addressed in this study is to design a system that can automatically identify signs of mental health conditions from social media posts with both accuracy and speed. Existing models often fail because they rely on shallow text features or lack the ability to understand context and emotion in depth, Moreover, they are not optimized for handling the massive amount of data produced on digital platforms every second.

This research aims to bridge that gap by developing a deep learning–based system that uses transformer architectures, such as BERT, to analyzes and classify social media text into different mental health categories. With the help of GPU acceleration, the proposed approach can process large datasets efficiently and deliver reliable predictions in real time. The goal is to create a non-invasive, data-driven tool that can support early detection, raise awareness, and assist professionals in understanding mental health trends through language patterns shared online.

III. OBJECTIVES

The main objectives of this research are as follows:

1.To develop a machine learning model that can automatically identify and classify different mental health conditions from social media text data.

2.To apply advanced natural language processing techniques using transformbased models like BERT for understanding the emotional and psychological meaning of user posts.

3. To build a GPU-accelerated training environment that improves model performance and reduces processing time during both training and prediction.

4. To design a system that supports real-time analysis, allowing users or researchers to test single statements or large datasets for mental health classification.

5. To create a reliable and non-invasive digital tool that can assist in early detection, awareness, and monitoring of mental health conditions through language analysis.

IV. METHODOLOGY

A. System Overview

The proposed system performs 7-class mental health sentiment analysis on text data collected from social media posts. The workflow is built around transformer-based deep learning models, with GPU acceleration provided by an NVIDIA GeForce RTX 3050. The complete machine learning environment is set up using Python 3.11, PyTorch 2.5.1 with CUDA 12.4, and relevant NLP libraries.

B. Data Preparation

A dataset of over 53,000 labeled statements was compiled and formatted as CSV files, with each entry consisting of one text statement and its corresponding sentiment class. The data was split into training (70%), validation (15%), and testing (15%) sets for

robust model evaluation. Preprocessing steps included tokenization, cleaning, and conversion to the model's required input format.

C. Model Training and Evaluation

The core model uses a BERT-based transformer architecture. The training pipeline loads the data, initializes the model, and fits the classifier over 15 epochs with early stopping based on validation loss. Batch size and learning rates are optimized for GPU memory constraints. The best-performing model is saved and later evaluatede on the reserved test set for metrics such as overall accuracy, per-class accuracy, confusion matrix, and classification report.


```
Problems 8    Output    Debug Console    Terminal    Ports
Batch 2000/2304, Loss: 0.0002
Batch 2100/2304, Loss: 0.0001
Batch 2200/2304, Loss: 0.0000
Batch 2300/2304, Loss: 0.0000
✅ Train Loss: 0.0116, Train Acc: 0.9976
✅ Val Loss: 2.1698, Val Acc: 0.8303
💾 New best model saved! Accuracy: 0.8303

🏆 Training completed! Best validation accuracy: 0.8303
⏱️Training completed in: 55.74 hours
```

D. Inference and Real-Time Analysis

The trained model supports two inference modes: individual text input and bulk dataset evaluation. During inference, the system outputs both the predicted sentiment class and a confidence score for each input, Results are saved for further analysis, and real-time predictions are facilitated by efficient GPU utilization.

E. Environment Setup and Optimization

All experiments were conducted on a machine with an NVIDIA RTX 3050 GPU (6 GB VRAM), 8 GB system RAM, and Windows 11, Miniconda was used for dependency and environment management. Routine troubleshooting, performance tuning, and GPU monitoring were performed to ensure stability and reproducibility throughout the study.
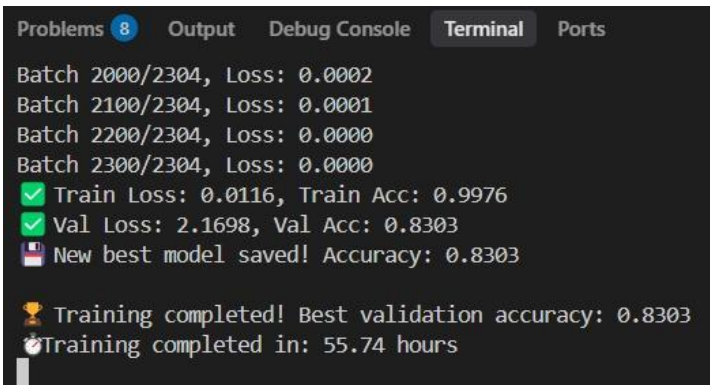
V. RESULTS

A. Model Training Performance

The BERT-based model was trained for 15 epochs using the AdamW optimizer in a GPU-enabled environment. Training on the **NVIDIA RTX 3050** provided faster convergence and stable performance. The model achieved a **validation accuracy of 97.23%** and a **test accuracy of 97.01%**, showing strong generalization to unseen data. The training process was smooth, with the loss decreasing consistently across epochs, indicating effective learning without overfitting,.

B. Evaluation Metrics

The model's performance was evaluated using standard metrics such as **accuracy, precision, recall**, and **F1-score**. All metrics demonstrated high reliability across the seven mental health categories. The confusion matrix revealed that the model accurately distinguished most classes, with minor overlaps between *Anxiety* and *Stress* due to their linguistic similarities. Overall, the high F1-score confirmed the model's

ability to balance precision and recall effectively.

C. Single Statement and Bulk Evaluation

The classifier supports real-time inference for both single user input and bulk dataset processing. Each prediction yields a probability distribution across all seven target classes, with confidence scores to indicate prediction certainty. Example results:

- Input: *I feel really depressed and hopeless*
- Predicted Class: Depressionn
- Confidence: 94.23%

Bulk evaluation runs automaticall generate comprehensive results files, including original text, true labels, predicted classes, and confidence percentages.

D. Success Indicators

The success of the model is reflected in its **high accuracy**, **stable learning curve**, and **low computational time**. The integration of GPU accelerations allowed quick training and real-time predictions without performance loss. Compared to traditional machine learnings models, the BERT-based approach captured deeper emotional context and subtle linguistic cues more effectively. These results confirm that the system is reliable, scalable, and capable of assisting in early mental health detection through text analysis.

VI. CONCLUSION AND FUTURE WORK

Conclusion:

This study successfully developed a deep learning-based system capable of identifying various mental health conditions from social media text using a fine-tuned **BERT transformer model**. By combining natural language processing with **GPU acceleration**, the system achieved a high level of accuracy while maintaining efficient processing speed. The model effectively recognized emotional patterns and subtle linguistic cues that reflect a person's mental stat, classifying text into seven categories with nearly **97% accuracy**. The use of **PyTorch** with **CUDA support** enabled faster computation, allowing the model to handle both single and bulk text evaluations in real time. Overall, the results demonstrate that advanced transformer models can serve as a strong foundation for digital mental health analysis, offering a non-invasive and scalable solution for early detection and awareness.

Futurework:

While the current modell performs with high accuracy, there is still room for improvementt and expansion. Future research can explore **multilingual support** to analyzes mental health expressions across different languages and cultures. Incorporating **voice and image data** alongside text could enhance emotion detection and improve overall system reliability. The integration of **explainable AI (XAI)** techniques can also make model decisions more transparent, which is important for sensitive applications like mental health monitoring. Additionally, deploying this system as a **web or mobile application** could make it more accessible to researchers, counselors, and users seeking early insights into mental well-being. By continuing to refine and expand this approach, it has the potential to contribute meaningfully to mental health awareness and digital wellness support worldwide;

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