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Early Risk Identification and Support System for Mental Health Using Artificial Intelligence

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***Abstract:** The burden of mental illnesses, especially depression and anxiety, is high in the world, and in most cases, it results in severe losses of quality-adjusted life years. This paper describes advancements and initial estimates for an artificial intelligence (AI) system expected to diagnose mental health risks early and provide individual-level support. The technique impacts Natural Language Processing (NLP) and emotion analysis to identify emotional structures in user-posted text, such as daily diaries and mood journals. An emotional tone Bidirectional Encoder Representations from Transformers (BERT) model is fine-tuned, and the system suggests self-care options (e.g., mindfulness exercises, breathing) in response to the context, towards an adaptive recommendation engine. One notable aspect is a user-friendly visual dashboard that enables users to monitor their mood patterns over time. More importantly, the system is entirely offline, and the user's privacy is guaranteed, as all data is processed locally on the machine. The data simulation tests the system's functionality for sentiment classification and recommendation delivery. The results indicate that this platform may be a promising, ethics-driven, proactive mental health support tool and may be applied in educational, workplace, and personal contexts. The next phase of work will be long-term real-world validation and efficacy studies.*

***Keywords:** Mental Health, Artificial Intelligence, Natural Language Processing, Sentiment Analysis, Early Intervention, Digital Health, BERT Model.*

Nomenclature:
MDD: Major Depressive Disorder
NLP: Natural Language Processing
BERT: Bidirectional Encoder Representations from Transformers
AI: Artificial Intelligence

I. INTRODUCTION

The increased worldwide cases of mental health disorders are one of the current endemic issues of public health. Anxiety disorders and major depressive disorder (MDD) are common enough, and according to the Wellcome Global Monitor [1], about every fifth adult has reported at least some clinically significant symptoms that have affected their functioning daily at least twice in a period of two weeks. The implications are not only limited to the individual suffering but also impose a substantial economic burden on the health institutions and society, with the cost of lost productivity and treatment accruing every year [2]. This is particularly true of the effect on the youth; depression has become a significant disability-inducing factor in adolescence and adulthood [3-5]. The long-term effects are severe, and this has been proven by a longitudinal study in the United States of America that has estimated a loss of 29 quality-adjusted life years of an 18-year-old person diagnosed with depression as opposed to a non-infected counterpart [6]. The close linkage between depression and suicide is another factor that emphasises the importance of effective intervention strategies, which are accessible [7].

Although there is an obvious need, access to traditional mental health services is hampered by substantial challenges. The significant number of people who cannot get encouragement is attributed to stigma, economic limitations, and mental health providers' inadequacies. In this regard, the most critical aspect is the early identification of emerging mental well-being dilemmas, as timely intervention can significantly enhance prognosis and prevent their development. Nevertheless, there are many reasons to be aware of issues before they arise: the signs are usually very minor. Individuals or the surrounding community might not notice them. Another instinctive response to emotional distress is to write, either in the form of personal entries or mood notes, or through emails and messaging. These written products represent a fertile, unexploited source of information about a person's cognitive and affective state. They may contain linguistic signs of health degradation before one is consciously aware of it.

Current advances in artificial intelligence, focused primarily on Natural Language Processing (NLP), offer unprecedented prospects for analysing large quantities of personal text data and understanding it in subtle ways. Nonetheless, numerous digital mental health apps are cloud-based, raising valid concerns about data privacy, security, and user autonomy. The lack of intelligent systems capable of delivering personalised, proactive support while clearly prioritising user privacy is apparent.

The proposed study aims to fill this gap by presenting a new, innovative, and privately inherent AI-driven mental health monitoring platform. The system is programmed to process text provided by the user to recognise emotive trends and offer supportive responses, without the user having to send any information to the device. The main contributions made by this work are:

A. A fully offline, privacy-focused AI system of continuous mental health monitoring through textual analysis.

B. The introduction and validation of a fine-tuned BERT model to perform

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accurate, contextual sentiment analysis of personal journaling-style text.

C. The development of a dynamic recommendation system that provides self-care, evidence-based measures of individualized self-care based on identified emotional patterns.

D. Their combination with other elements into a visual dashboard that would be user-friendly and focus on enhancing emotional self-awareness and encouraging proactive self-management.

II. LITERATURE REVIEW

The application of Natural Language Processing (NLP) has developed into a subspecialty of computational linguistics and has become a pillar of contemporary data analysis across various contexts. Earlier pioneering research, including that by [8], investigated the potential of NLP to close the gap between human language and computer programming and showed that it can decode the semantic meaning for use in technical applications. In the business world, [9] conducted an in-depth survey in which NLP played a significant role in analysing textual corpora from annual reports and social media to gain insights into business strategy, marketing, and financial aspects. They mentioned the benefits of scalability and reduced analyst bias, but did not exclude the issues of model interpretability and the necessity of domain-specific modifications.

NLP utility has ample documentation in the field of healthcare. Article [10] reviewed in systematic order the effect of NLP methods on converting unstructured medical scripts to structured data, e.g. doctor observations and discharge summaries, to improve medical decision support and operational efficiency. A more recent systematic review by [11] affirmed the effectiveness of NLP systems for extracting specific clinically relevant information, e.g., activities of daily living, from electronic health records, highlighting its usefulness in patient monitoring and outcomes research.

The intersection of NLP and mental health has generated sufficient research interest, especially in early detection and risk stratification. Research has been done on examining social media sites to determine linguistic correlates of depression, anxiety and other diseases. In particular, the concept of using AI to assist in social media exploration to identify mental wellness status promptly was investigated in [12], which states that screening individuals based on their digital footprints is feasible. Nonetheless, these methods are prone to ethical concerns, such as consent and information ownership.

In addition to detection, the design of effective intervention systems is becoming an issue. Notably, Article [13] highlighted the urgent need to integrate emotional intelligence with efficient security models in healthcare IoT and the importance of trust in digital health solutions. It is also essential how feedback is presented; a study by [14] found that empathetic design features, such as avatars, can help increase user interaction with self-measuring devices compared to conventional dashboard designs.

One of the new trends is the shift towards more context-sensitive and customized systems. Article [15] claimed that dropout rates are high with fixed mental health applications and that adaptive systems that can learn over time through user interaction are necessary to maintain user engagement. Moreover, the ethical call for privacy in online psychiatry has been strongly expressed by [16], who argued that on-device processing should be the standard for sensitive health applications, as it is less risky in the event of data breaches and unauthorised access.

Although the available literature offers a solid foundation, a gap remains in integrating high-level, contextual NLP analysis with real privacy-by-design and adaptive personalisation to support individual mental health. Our project aims to address this gap by creating an independent system that runs locally on a user's device and maintains confidentiality while still providing thoughtful, active feedback.

III. METHODOLOGY

A. Data Collection and Preprocessing

The logic behind the creation and preliminary testing of our sentiment analysis model was based on an extensive dataset obtained from Kaggle, containing 469,854 text comments with emotional labels. The range of textual genres presented in this corpus was quite broad (including simulated personal journal entries, two-person conversations, and social media posts). It guaranteed the representation of a broad spectrum of linguistic styles and emotional expression. This is essential to ensure that a model is trained in a way that can generalise across user writing of various types.

To ensure data accuracy and model performance, a comprehensive data-preprocessing pipeline was implemented. To reduce noise, all non-textual features, such as emojis, URLs, and numeric characters, were removed in the initial step of the process. The text was then converted to lowercase, and common English stop words were removed, after which terms were reduced to their dictionary or base forms via lemmatisation. After the text was cleaned and normalised, it was tokenised for use as input to a neural network model. To improve the model's capacity to identify significant linguistic patterns associated with emotion, this thorough preprocessing is crucial.

B. NLP Model and Sentiment Analysis

To perform the main sentiment analysis task, we chose a BERT model, which is famous for its deep bidirectional design, allowing it to capture complex relationships in context. We have used the bert-base-uncased model as a reference because it has been shown to perform well on a variety of NLP tasks. This was refined on our labelled sentiment dataset to enable it to specialise in capturing emotional nuances in personal text.

The technical implementation consisted of 1) tokenising every input text sequence with the BERT tokeniser, which includes special tokens such as [CLS] at the start. These tokenised sequences were then input into the BERT model, which produced high-dimensional contextual embeddings for each token. The feature vector used for classification was the embedding of the [CLS] token, which aggregates sequence-level information. A fully connected dense layer was used on this vector with a softmax activation, yielding probability distributions over the target sentiment classes. The model

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was first trained to recognise emotional tone across major categories, such as positive, negative, and neutral, and this foundation can be refined to finer states, such as anxiety, sadness, or anger. To prevent overfitting, part of the data was held out to validate the model whilst the model was trained over multiple epochs, using the AdamW optimiser and cross-entropy loss function.

C. System Architecture and Personalization

The integrated system is designed around three connected, locally hosted modules, ensuring a smooth user experience.

i. *Sentiment Analysis Engine:* This engine is the primary data input and interpretation engine. The fine-tuned BERT model processes each user-entered text entry in real time. The result, which is one of the sentiment classifications (e.g., negative) and the confidence score (e.g., 0.85), is time-stamped and saved in a secure local database on the user's computing device. This provides a chronological discourse of emotional conditions.

ii. *Trend Analysis Module:* This module works based on the historic accumulated data and is used to conduct longitudinal analysis to extract meaningful patterns. It uses statistical methods to identify meaningful patterns, such as a decrease in the sentiment score over two weeks, which may indicate mood deterioration. It is also able to bring to attention recurring trends, such as negative sentiment on Sunday evenings, or to identify statistical outliers that reflect sudden periods of acute emotional responses. This time-travel analysis is essential for moving beyond the reactive analysis of a single entry to a proactive interpretation of the user's emotional pattern.

iii. *Recommendation Engine*: It is the part that converts analytical knowledge into practical assistance. It is essentially a rule system that pairs certain emotional states and patterns with a set of evidence-based coping mechanisms. Anxiety symptoms or patterns, e.g., may lead to the recommendation of diaphragmatic breathing, a guided grounding exercise, and sustained sadness may lead to the behavioural activation suggestion, e.g., a schedule of pleasant activities or gratitude journaling. One of the innovative elements that is essential to implement is the use of a feedback loop. The system records the user's emotional entries after a recommendation is provided. When a steady increase in sentiment scores precedes a proposed activity, the engine will acquire the habit of focusing on similar strategies with that user in similar circumstances, thus, adding a level of adaptive customization as time progresses.

D. Privacy and Ethical Considerations

This system is not driven by secondary features such as user privacy or ethical design, but rather by the principles. As a direct response to concerns about data misuse in digital health [16], all data processing is performed locally on the user's machine. None of the personal texts, sentiment scores, and usage data is sent to third-party servers. The local database has been encrypted using industry-standard tools, such as AES-256, ensuring data protection even if the device is stolen. Users also have complete access to and control over their data and can clearly see, export, or permanently destroy all their history. The application has a rigid opt-in model, with informed consent received upfront. The way the system works and how it manages the data is clearly outlined. As a protective measure against algorithmic bias, the original model was trained on a diverse set, and the methods of the new fairness systems in AI will support future training [17].

E. Evaluation Strategy

System evaluation was carried out in two main stages. First, the classification model of the sentiment was quantitatively evaluated based on standard machine learning measures, which included Precision, Recall, F1-Score, and total Accuracy, on a stratified test set, which was not known in any way during the training and validation stages. This provided a strong gauge of the model's fundamental linguistic ability.

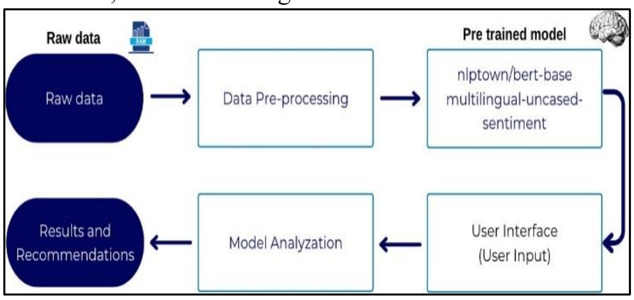
Second, the end-to-end functionality of the entire system was tested with a series of scenario tests using journal entries. The team of researchers created scenarios of storylines that included a range of emotional trajectories, from stable well-being trajectories through decline and recovery, and acute stress events. This testing confirmed the incorporation of all elements: proper sentiment detection, effective trend determination and the suitable elicitation of context-dependent suggestions. The second important evaluation step to be incorporated into future work is user studies to assess real-world usability, perceived usefulness, and emotional acceptability.

IV. RESULTS AND DISCUSSION

A. System Performance

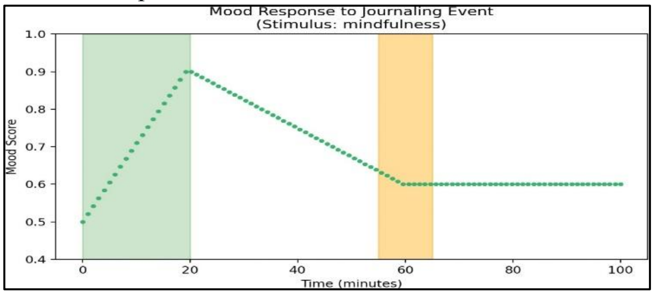
When the optimised BERT model is evaluated on the held-out test set, the average precision is also relatively high (92). The model's accuracy and recall for the negative emotion category (F1-score of 0.89) were 0.91 and 0.87, respectively. This good performance implies that the model is highly qualified to accurately recognise and describe emotional language, reducing both false negatives and false positives, which are essential for promoting user confidence.

These analytical results were effectively translated into a usable dashboard. It continuously read in textual input, updated the user's mood history, and created explicit visual representations of sentiment patterns by day, week, and month. The dashboard layout was made to be easy to use and understand, as shown in Figure 1.



[Fig.1: The System's Dashboard Interface, showing a Timeline of Mood Entries (Left), a Trend Graph of Sentiment Over Time (Top Right), and a Context-Aware Self-Care Recommendation Triggered by a Period of Negative Emotion (Bottom Right)]

The recommendation engine responded effectively to the simulated scenarios. In one representative test case, a sequence of entries simulating a period of mounting work-related stress was input. The trend analysis module detected a significant negative trend, and the recommendation engine subsequently suggested a progressive muscle relaxation exercise. The following simulated entry, reflecting a user who had completed the exercise, showed a marked positive shift in the sentiment score. This interaction, depicted in Figure 2, illustrates the system's potential to facilitate a positive feedback loop.



[Fig.2: A Simulated Case Study Showing the System's Response. A Period of High Negative Emotion (1) Triggers A Recommendation for Mindfulness. The Subsequent Journal Entry (2) Reflects A Positive Mood Shift Following the Intervention]

B. Discussion

The outcomes of the functional testing period confirm the technical feasibility and robustness of the proposed system. The outstanding performance of the sentiment analysis model aligns with results from other authors who use transformer-based models on psychological text [18], strengthening confidence in the methodological approach. The functionality of the analytical engine, combined with a convenient user dashboard and a viable recommendation engine, has enabled the integration to achieve significant milestones toward a holistic digital mental health tool.

The significant advantage of this system, relative to the state of the art in mental health-related mobile apps, is its proactive, longitudinal design. It can analyse data over time, so it can diagnose even the slightest change that might not be evident in a cross-sectional study. Early detection, or the ability to examine data before a problem becomes acute, is the foundation of preventive medicine, particularly in mental health. Moreover, the shift from general content and a fixed model to a dynamic model that focuses on personal data can address several limitations identified in the literature regarding user engagement with similar apps, such as the proposed system's relation to concern for mental health [15]. The privacy-preserving, offline system addresses the ethical issues that have hampered the development of many health-related apps, such as the proposed system, by prioritising user privacy and autonomy, even if the app lacks direct medical functionality [16].

Nonetheless, the first set of findings must be treated with great caution. The simulated data, although essential for initial validation, is a serious limiting factor. The simulated data cannot capture the complexity, spontaneity, or emotional elements typically found in a personal journal. The success that the recommendations can achieve in a simulated setting does not necessarily translate to their success or usability with a real user experiencing genuine emotional pain.

C. Limitations

This research has some limitations that should be acknowledged. First, the model's training corpus, although vast and varied, consisted of general emotive text that may not fully capture the distinct linguistic patterns of the self-reflective practice of journaling. This needs to be addressed in future research by training and testing the model on authentic diary entries. Second, as pointed out, this current assessment does not involve real-world user responses. Its practical usability, the user experience of the empathetic value of the suggestions, and the overall effectiveness of the eventual influence on mental health outcomes are yet to be validated. Third, the current suggestion model, although involving a feedback system, is more rule-based at present. Integration of a more advanced reinforcement learning model for the personalisation aspect could be the aim of future improvements. Lastly, this current model, being a prototype, needs optimisation to improve its performance in mobile environments with resource constraints.

V. CONCLUSION AND FUTURE WORK

In the context of the current study, this project has successfully established the development and functional validation of the prototype AI system model for early risk identification of mental health and support provision. In this case, the model has properly integrated the sophisticated sentiment model with the adaptation support model within the offline privacy model. From the preliminary study, the model's technical soundness and capacity to perform its functions are confirmed.

The positive findings of this initial stage set the stage for the broader research agenda. The next step would be to move from the laboratory testing phase into the real-life testing phase. This would include conducting usability testing with participants with varying levels of mental health literacy and from diverse cultural backgrounds. Such testing would be highly informative for improving the end-user interface to maximise user engagement.

However, usability optimization needs to be followed by field tests. It would be essential to deploy the system with a group of users for a period of time to evaluate its effectiveness on various outcomes such as resilience, emotional self-awareness, and symptoms of depression and anxiety. These outcomes would be measured with a control group using the conventional mood-tracking diary. Moreover, future research would examine the incorporation of additional modalities, such as typing speed and rhythm, which have been shown to correlate with cognitive load and emotion [19], to improve the model's specificity. The incorporation of NLP modules for languages such as Arabic would also be essential to ensure global appropriateness. Lastly, interaction with mental health professionals would be crucial to ensuring the system's recommendations remain therapeutically sound.

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