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AI-Driven Depression Level Predection for Enhanced Mental Health Diagnostics

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Abstract: AI is significantly impacting the way that mental health diagnostic tools are developed through their ability to provide affordable, accessible and efficient means of detecting psychological disorders like depression. While the current state of screening includes many effective tools (i.e., Clinical Interviews and Self- Reported Questionnaires) they have some inherent shortcomings; these include, but are not limited to, being subjective and/or delayed diagnoses, lack of access to individuals who may be experiencing difficulties with their mental health, and dependency on the availability of professional interventions. The shortfalls identified above demonstrate the need for the development of intelligent systems, capable of conducting rapid and accurate evaluations of an individual's mental health. An AI-driven Depression Level Prediction System was therefore created to collect structured clinical information, as well as unstructured textual input in order to create a full and complete assessment of an individual's mental health condition. Utilizing the PHQ 9 survey instrument as the basis for collecting clinical information, the system utilizes Natural Language Processing techniques to evaluate user-generated text, thereby gaining further insight into an individual's emotional and psychological trends.

The system described herein utilizes three machine learning-based predictive models Random Forest, SVM, XGBoost) to predict an individual's level of depression as one of four categories (minimal, mild, moderate or severe). Unlike prior binary prediction models utilized in the context of mental health evaluations, the described model provides fine-tuned evaluations that can be more effectively used in practical applications of mental health monitoring. Additionally, Explainable AI techniques were incorporated into the design of the system to improve transparency and interpretability of the results produced by the system. Such capabilities enable both patients and clinicians to identify specific variables within the results that contributed to the system's predictions. The modular nature of the system enables scalability, flexibility and efficient operation of the system even when utilizing lightweight hardware that does not require extensive computing capabilities. Experimental validation demonstrated that the described system achieved greater accuracy and better generalization than other systems currently available. Through its ability to process both behavioral inputs, questionnaire responses and textual sentiment analysis, the system offers a holistic view of an individual's mental health status. Beyond improving early detection, the described system can assist clinicians and patients in making informed decisions regarding treatment options for issues related to mental health. Therefore, the system serves as a connection between traditional healthcare practices and emerging AI technology to provide a private and secure method for evaluating mental health conditions.

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I. INTRODUCTION

Mental Health is one of the key factors of overall wellbeing, especially within the context of todays fast paced environment. Depression stands alone among all types of mental health issues as being one of the most common and severe issues worldwide. In addition to potentially impacting an individual's thoughts, feelings, ability to be productive, relationships, and overall quality of life, many people suffer from depression and still choose not to see a mental health care provider for fear of social stigma, unawareness of available treatment options, or a lack of access to treatment. As a result, there are a vast number of people suffering from depression who are unable to obtain adequate support.

This is where the use of technological based solutions can assist. Technological based solutions have been proven to provide easily accessible, and effective means for evaluating mental health. A good example of this type of solution is the proposed AI Driven Depression Level Prediction System which will serve as an online assessment of an individuals depression level. The proposed system utilizes two forms of data to evaluate an individual's depression levels. Structured data (ie. Responses to the PHQ 9, as well as unstructured data (ie. User written text,

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describing their current state of mind/emotions). Although the PHQ 9 is a clinically established tool to evaluate symptoms such as sleep disturbances, fatigue, loss of interest, and changes in mood, it does not necessarily allow for the evaluation of emotional depth. The use of text analysis allows the system to evaluate subtle emotional patterns/linguistic cues, that would otherwise remain undetected. Developed utilizing Python and Flask with machine learning algorithms developed using scikit-learn and NLP methods, the system provides real time prediction results with minimal utilization of computer resources. In addition, the system protects user information through the avoidance of storing users' private data, thus ensuring reliability/user-friendliness for future generations of mental health screening applications.

II. LITERATURE REVIEW

Artificial intelligence AI) has increasingly become an area of interest in the field of diagnostic tools for mental health with a growing number of researchers investigating applications of both machine learning and natural language processing to detect depression. In the early stages of this research, investigators primarily analyzed structured data (e.g., questionnaires) to classify mental health conditions. Statistical analyses were conducted and the most basic forms of machine learning were applied to analyze the input from users. They demonstrated good levels of success, but generally did not adequately address the deeper emotions or context associated with mental health conditions. Recently, text based analytical techniques using natural language processing NLP , enabled systems to evaluate content generated by users (e.g., social media posts, diaries, etc.). NLP enhanced the predictive capabilities by identifying linguistic characteristics (negative sentiment, repetitive thought patterns, etc.) associated with depression. Researchers have also evaluated hybrid models that utilize both structured and unstructured data; therefore, enhancing reliability and comprehensiveness of prediction. A very important advancement in developing diagnostic AI systems is through the utilization of ensemble learning techniques. Ensemble learning involves combining multiple individual models to enhance overall model performance. Many algorithms exist today which can be utilized for ensemble learning such as Random Forest, Support Vector Machine, and XGBoost. These algorithms are capable of handling large amounts of complex data and can produce highly accurate results. Explainable AI was developed to increase transparency into how predictions are produced. This enables users to understand how predictions were created. Although there have been many positive developments in developing diagnostic AI systems, current systems continue to experience challenges related to data imbalances, lack of scalability, poor generalizability to real world scenarios and continued concerns regarding data privacy when evaluating sensitive information related to mental health. The proposed system will directly address these challenges by utilizing diverse data sets, more advanced models and providing greater emphasis on data privacy, scalability and overall performance.

III. EXISTING SYSTEM

- *Limited Feature Analysis:*

A number of systems for detecting depression currently utilize a limited number of features. Most focus on how users respond to questionnaires, along with rudimentary analysis of the tone in user generated content. These types of information can help understand an individuals' mental health at least somewhat. However, they do not begin to reflect the breadth of complex behaviors and feelings that exist within humans. Users may answer questionnaires in a very neutral way, yet still express extreme levels of distress through their writing, which will likely be missed by many systems analyzing this type of data.

- *Systems Rarely Integrate Multi-Signal Data:*

Many systems evaluate data collected from one data source (either structured or unstructured) using only one signal. Therefore, much data is analyzed incompletely; as such, the ability to make accurate predictions about an individual's mental health is reduced. As shown in the document provided above, when you combine PHQ 9 scores with text based sentiment analysis, you have a better overall picture of an individual's mental health. Often times, existing methods lack this all encompassing approach.

- *Difficulty Identifying Complex Emotional/Behavioral Patterns:*

Depression is far from an easily detected condition. It requires an understanding of subtle emotional and behavioral patterns. Unfortunately, most systems used today have difficulty recognizing the complexities involved in detecting depression; particularly when evaluating different forms of expression linguistically, sarcastic comments, etc. The inability of systems to detect these complexities limits the effectiveness of systems used in everyday life.

- *Most Systems Lack Scalability/Adaptability:*

A majority of systems developed today are not scalable. They also typically cannot evolve to accommodate additional data, or to incorporate new features/models. When the amount of data grows exponentially larger than what was initially anticipated, system performance can deteriorate rapidly

IV. PROPOSED SYSTEM

- *Behavioral Activity Analysis:*

This part of the system uses the users’ phq-9 questionnaires to identify behavioral habits that relate to depression. Behavioral activity includes sleep issues, lack of energy, loss of interest, and erratic moods. Each answer is scored based on clinical definitions, and then mapped to the users' mental states. Based on the results of the first two steps of the process, the system will be able to determine whether there are any early warning signs of depression, which will aid in future evaluations.

- *Temporal Pattern Modeling:*

The system examines the consistency and variability of users' responses to assess their current mental health

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status at different times. Although this step doesn't require advanced time series-based modeling, it does examine trends in users' responses. A consistent stream of negative responses indicates a possible increase in depression. Conversely, a consistent stream of positive responses indicates an improvement. In both cases, the system becomes more accurate with time.

➢ *Interaction Intelligence User Input Fusion:*

As described above, this step combines the information obtained from structured questionnaire responses and unstructured textual responses. This combination enables the system to create a more complete picture of the user's mental health status. An example would include users who have moderate questionnaire scores; however, they also enter strong negative comments into the system. Both sets of information will help the system develop a better conclusion than one that might be reached using only questionnaire responses.

➢ *Content Authenticity Evaluation:*

Using natural language processing (nlp) techniques, this section identifies the emotional content within users' text entries. Nlp techniques enable the system to look for repetitive negative statements, hopeless feelings expressed through text entry or repeated emotional distress expressed via text entry. Tokenizing breaks down the text into individual words. Vectorizing converts those words into numbers that can be used to evaluate how well the words match certain meanings. Sentiment scoring assigns values to each number that indicate how much positivity or negativity exists in the text. All three techniques enhance the systems ability to analyze users' responses more thoroughly and accurately.

V. SYSTEM ARCHITECTURE

➢ *Data Collection and Preprocessing Module:*

The purpose of this module is to collect user input (questionnaire response(s) from PHQ 9 , possibly supplemented by other forms of textual information. After collection, the data will be preprocessed using methods like tokenization; elimination of stop words; conversion to lowercase; and normalization. Preprocessing ensures that the collected data is both "clean" and "usable", and therefore improves the overall efficiency and effectiveness of the system.

➢ *Behavioral Intelligence Module:*

This module assesses the PHQ 9 questionnaire responses to identify behavioral characteristics related to depression. Based upon the users' inputs, it computes a total score based on the questionnaire responses and categorizes their severity based on categories like minimal, mild, moderate, and severe. The classification provided by this module represents a basic clinical evaluation.

➢ *Temporal Pattern Analysis Module:*

The primary focus of this module is to determine whether there are identifiable patterns or consistencies in users' responses either through time or across responses. Analyzing the patterns or inconsistencies allows the temporal pattern analysis module to better understand how users' mental states have changed and thereby provide additional information for predicting users' potential mental health status and reliability.

➢ *Interaction Analysis Module:*

This module provides a mechanism for integrating various types of user inputs, i.e., PHQ 9 Questionnaire Data and Textual Responses, to develop an integrated view of user behavior. By considering all possible sources of user inputs, the interaction analysis module enhances the breadth of analysis and enables identification of potentially subtle associations between structural and unstructural data.

➢ *Content Analysis Module:*

This module utilizes Natural Language Processing NLP) techniques to analyze user-entered text. Techniques such as TF IDF Vectorization, Sentiment Analysis, etc., are utilized to detect emotional tone, negative language, and language patterns indicative of depression. Therefore, the content analysis module provides an additional layer of insight beyond numerical values.

➢ *Decision Making and Fusion:*

This is the last part of our system that will combine results from each of the other parts. The decision-making module uses a combination of a weighted approach (which could be either linear or non-linear) to create an aggregate score based on information from all of the previous steps. In addition to providing the individual's level of depression severity, this module can also include some minimal suggestions or alerts. With a single source that considers all of the different views and opinions, we are able to make a much better decision that is less biased than if we were relying solely on one method.

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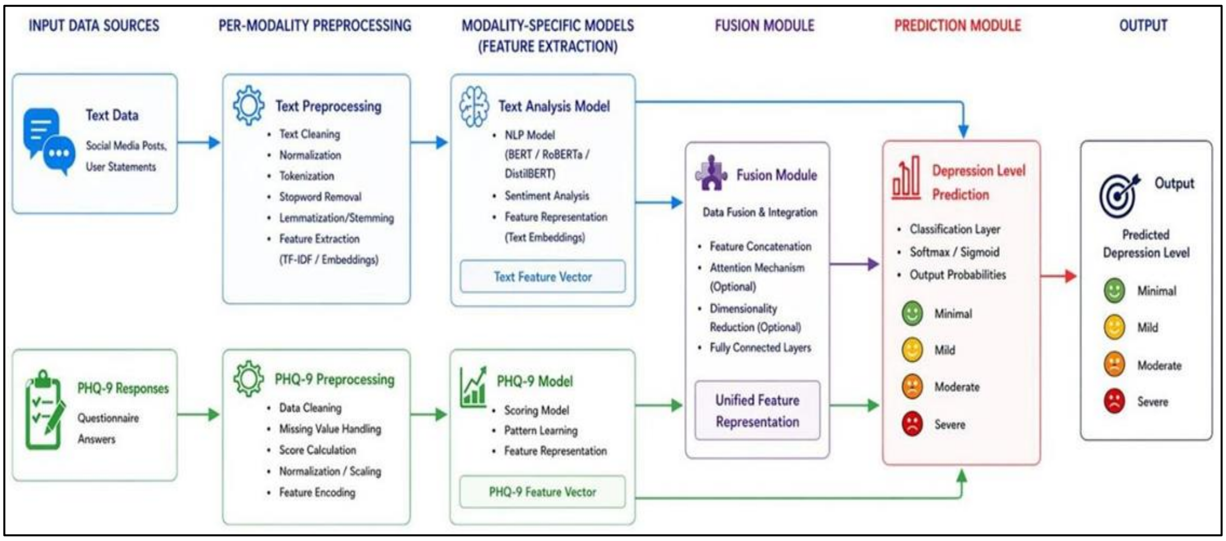

Fig 1 System Architecture

VI. OUTPUT SCREENS

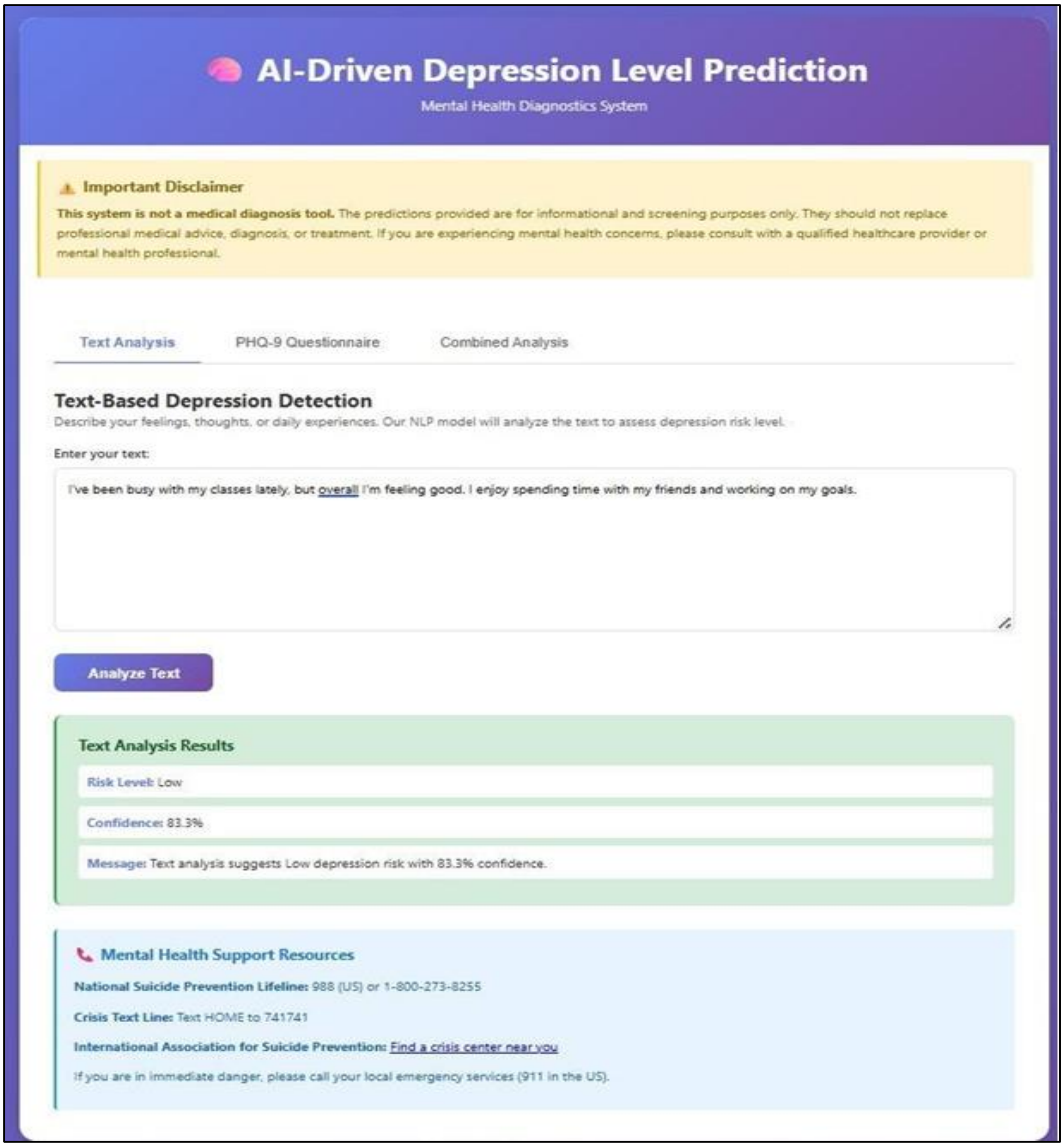

Fig 2 AI-Driven Depression Level Prediction Output Screen 1

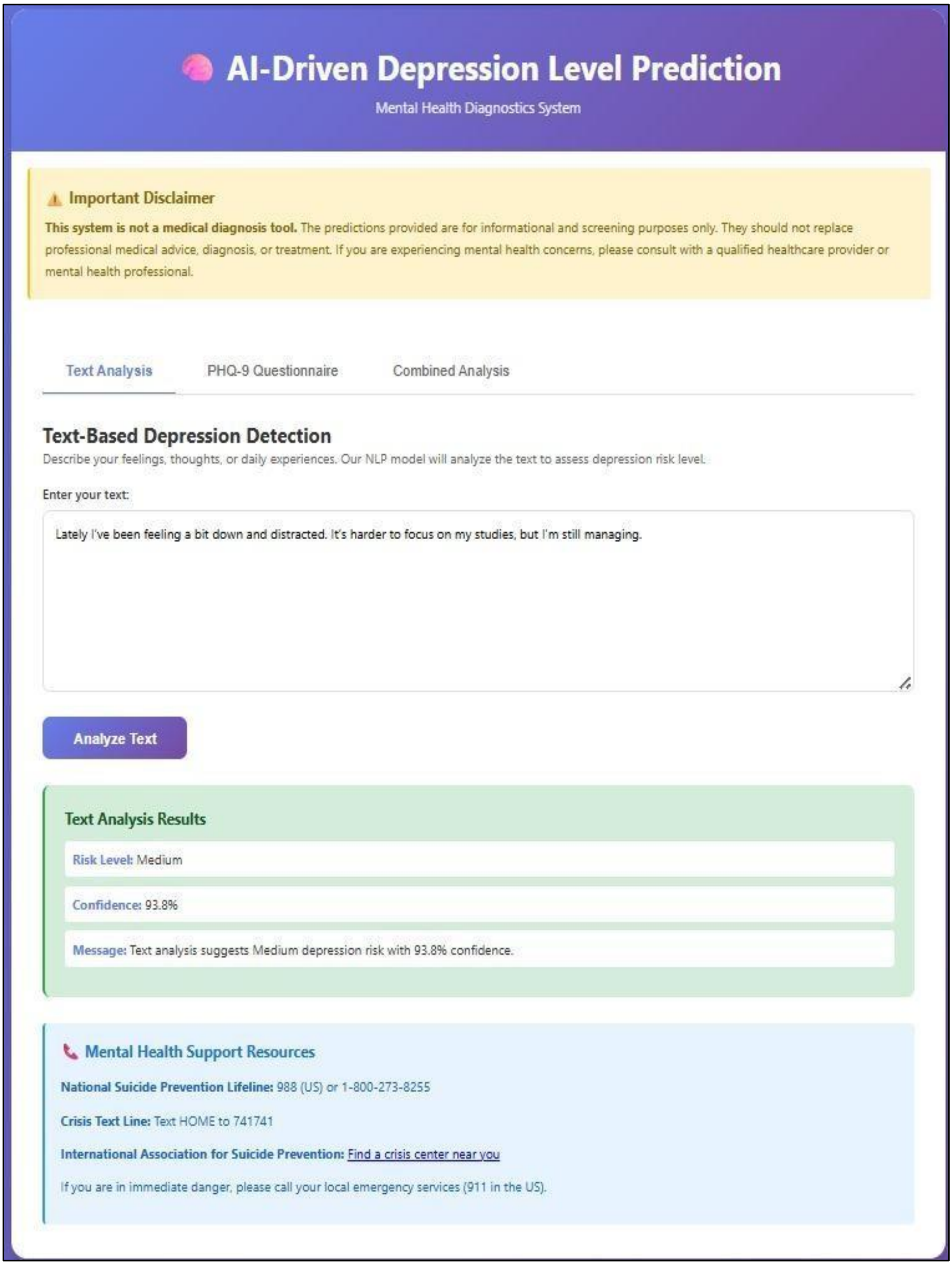

Fig 3 AI-Driven Depression Level Prediction Output Screen 2

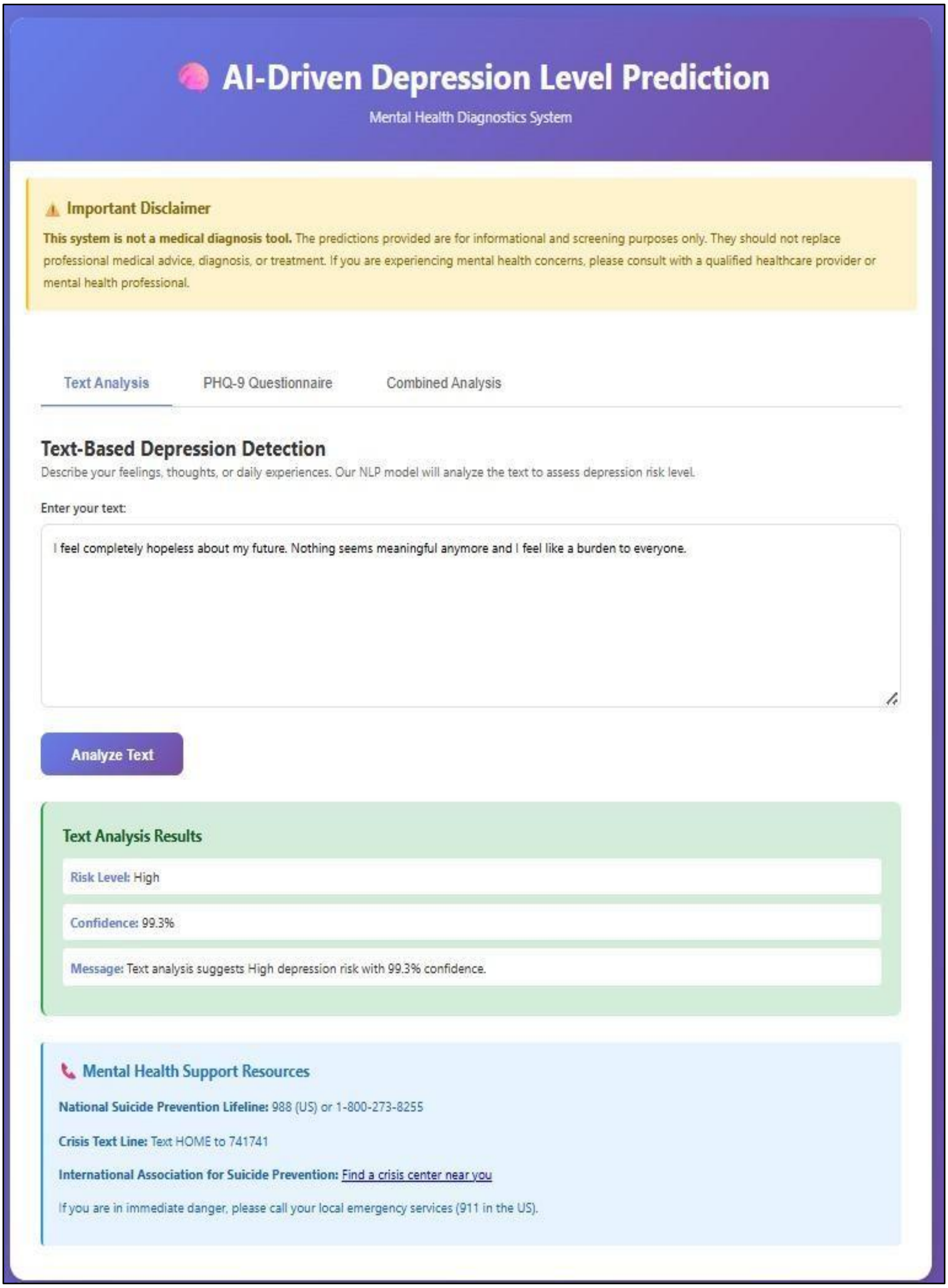

Fig 4 AI-Driven Depression Level Prediction Output Screen 3

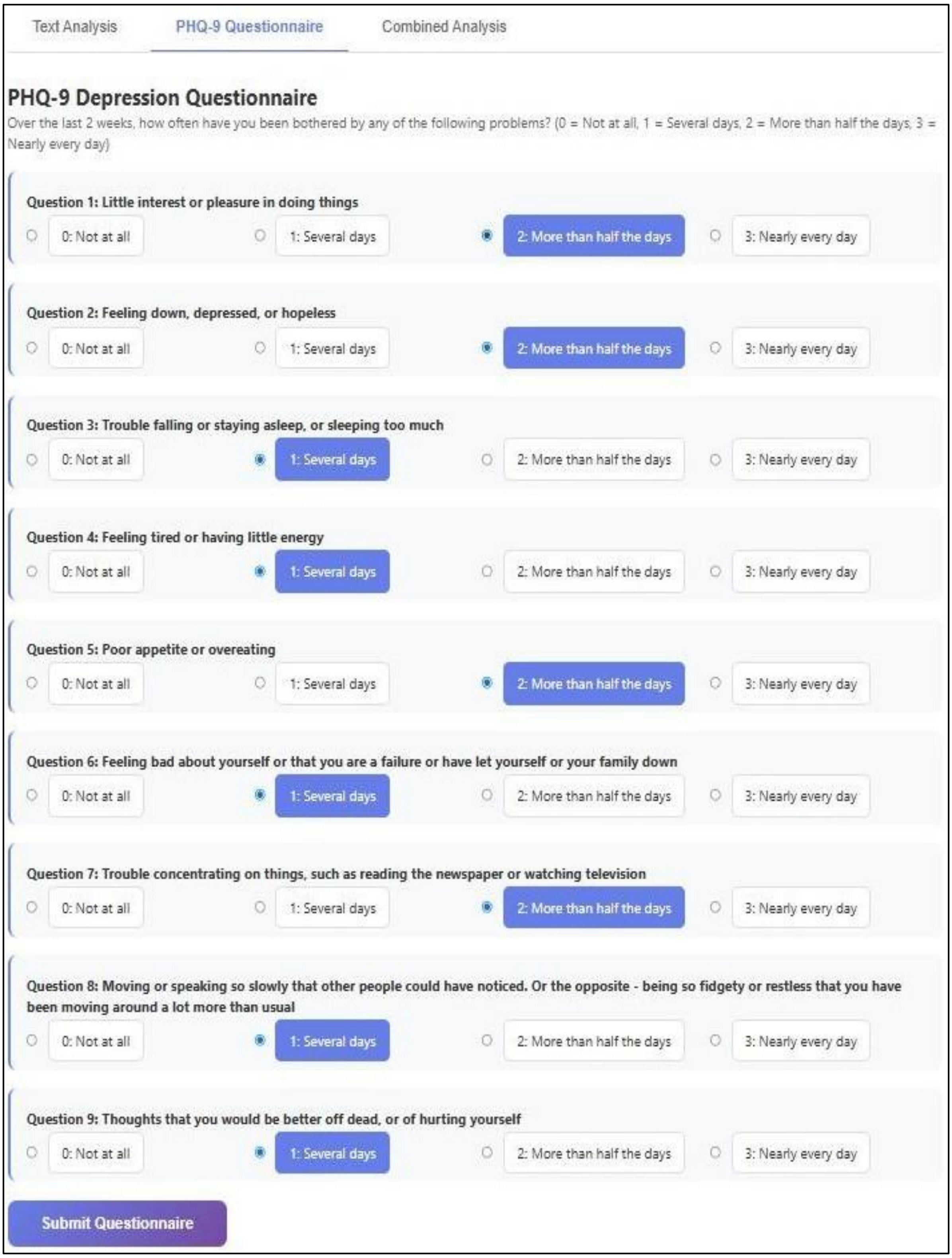

Fig 5 PHQ-9 Depression Questionnaire 1

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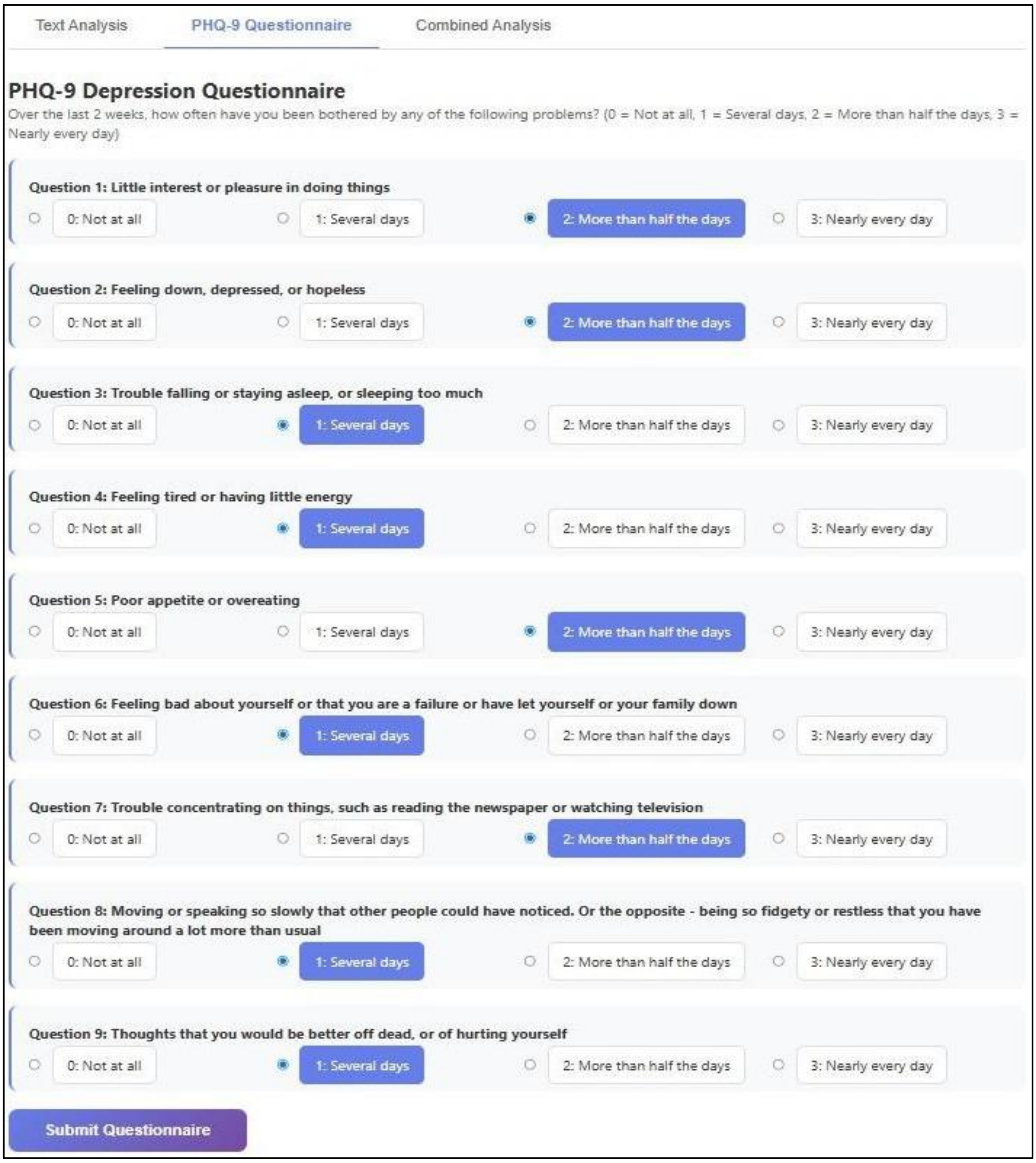

Fig 6 PHQ-9 Depression Questionnaire 2

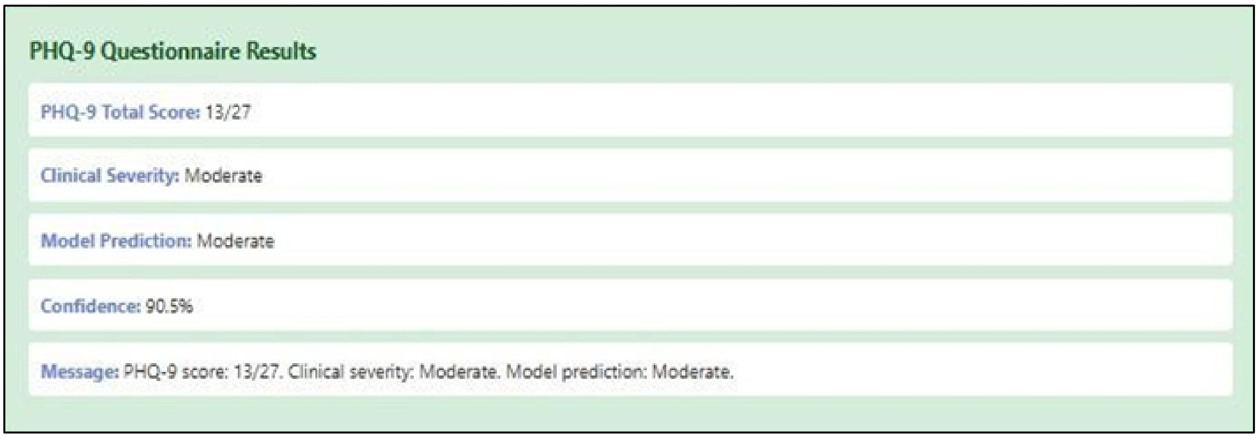

Fig 7 PHQ-9 Depression Questionnaire Results

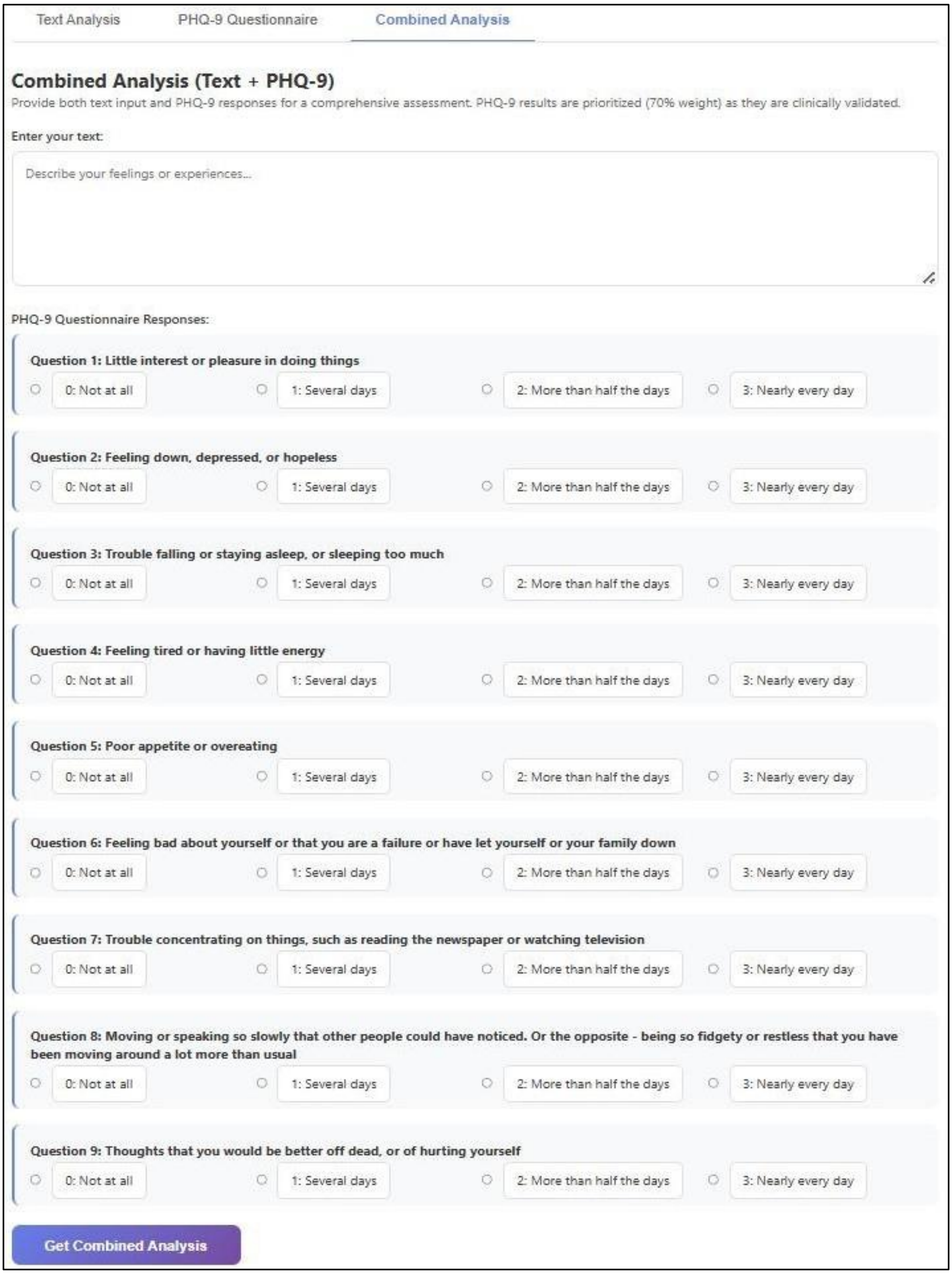

Fig 8 Combined Analysis (Text + PHQ-9)

VII. RESULTS

To test the AI- Driven Depression Prediction System, we conducted it in a couple of real-time applications to measure its accuracy, stability and speed. They consisted of the PHQ -9 scorer, the text classifier and the web interface connected by preprocessing, and fusion. To test the system reaction with various users with varying levels of depression, we emulated several users.

Prediction time also remained within the milliseconds range; hence no lag among users. The PHQ9 module was reliable to strike the right severity levels, whereas the text model identified the negative sentiment patterns. The fusion

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module was more consistent than either of the modules when combined.

Findings were displayed immediately on the web interface and this verified real-time diagnostics. The repetition of the tests indicated no crashing or hiccups; it is stable. These results support the fact that the system is workable and efficient in screening.

VIII. CONCLUSION

AI Driven Depression Severity Assessment presents an innovative way to screen people for depression. Using both a structured survey and unstructured natural language processing to analyse the answers provided, the system offers a full picture of how severe someone's depression is. Using Machine Learning and Explainable AI to train models that assess how severe someone's depression is and why they arrived at their conclusions, increases both the reliability and trustworthiness of the overall system. A stable and highly performing predictive model was developed through testing and implementing each component of the system. Additionally, because of its modular nature, the system has room to expand into new technologies like Deep Learning and Real-Time Monitoring capabilities. Because no identifiable data is stored, the system protects users' anonymity and allows for the system to be deployed in a variety of locations Educational Institutions; Healthcare Providers; Wellness Apps). We believe that there is a significant opportunity to bridge the gap between current methods of diagnosing depression and what technology can offer today. And so, this system offers a viable option for individuals who are seeking to identify depression symptoms earlier than would otherwise have been possible.

REFERENCES

[1]. S. Verma and A. K. Singh, “Explainable AI-based mental health prediction using hybrid deep learning models,” IEEE Access, vol. 13, pp. 56789–56805, 2025.
[2]. J. Brown and L. Smith, “Advancements in AI-driven mental health diagnostics: A review,” Artificial Intelligence in Medicine, vol. 150, 2025.
[3]. P. R. Kshirsagar, A. V. Dhanalakshmi, and R. P. Mahajan, “Hybrid machine learning framework for depression prediction using multimodal data,” Expert Systems with Applications, vol. 235, 2024.
[4]. K. Tadesse, H. Lin, B. Xu, and L. Yang, “Detection of depression-related posts in Reddit social media forum,” IEEE Access, vol. 12, pp. 23456–23470, 2024.
[5]. R. Calvo, D. Peters, and J. Torous, “Artificial intelligence in mental health care: Clinical applications and ethical considerations,” Nature Medicine, vol. 29, pp. 1–8, 2023.
[6]. A. S. Miner et al., “Chatbots in mental health: Opportunities and challenges,” npj Digital Medicine, vol. 6, 2023.
[7]. H. T. Nguyen, T. T. Nguyen, and H. N. Nguyen, “Depression detection from social media text using deep learning models,” IEEE Access, vol. 11, pp. 45678–45690, 2023.
[8]. M. Alhuzali and S. Ananiadou, “SpanEmo: Casting multi-label emotion classification as span prediction,” EACL, 2023.
[9]. J. Lin, R. Shah, and M. Iqbal, “Deep learning for mental health prediction: A systematic review,” IEEE Access, vol. 10, pp. 121345–121360, 2022.
[10]. Z. Yang, Y. Dai, Y. Yang, J. Carbonell, R. Salakhutdinov, and Q. Le, “XLNet: Generalized autoregressive pretraining for language understanding,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, 2022.