Personalized Health Advisor for Comprehensive Wellness Management

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***Abstract*— This paper incorporates the usage of digital health platform designed to transform personal health management. Leveraging cutting-edge technologies, including mood detection algorithms and mental health screening questionnaires, MediQ accurately assesses users' emotional and mental well-being. Additionally, MediQ features virtual assistants powered by natural language processing and machine learning models to facilitate symptom identification and provide tailored guidance on mental health**

management. By amalgamating these functionalities, MediQ offers users a comprehensive approach to wellness management, empowering them to optimize their physical and mental health. Through personalized recommendations and timely interventions, MediQ aims to foster a healthier society.

Keywords—Adaboost Classifier, Haar Cascade, Cosine Similarity, Convolutional Neural Networks (CNNs), Dataset, Llama-2-7b-chat-hf, Histograms of Oriented Gradients (HOG), langchain, Support Vector Machines (SVMs), RandomizedSearch CV, Streamlit.

I. INTRODUCTION

The intersection of advanced technologies and healthcare has ushered in a new era of personalized health management, epitomized by the groundbreaking platform known as MediQ. Leveraging a myriad of cutting-edge algorithms and techniques, MediQ represents a paradigm shift in the way individuals engage with their health and well-being. At its core, MediQ employs sophisticated mood detection algorithms, including convolutional neural networks (CNNs) to analyze user behavior and interactions with unparalleled accuracy. By decoding subtle cues embedded within user interactions, such as sentiment analysis and facial recognition, MediQ effectively gauges the user's emotional state in real-time.

Moreover, MediQ integrates advanced machine learning models, such as support vector machines (SVMs) and decision trees, to administer comprehensive mental health screenings. Through a meticulously crafted questionnaire, incorporating validated assessment tools like the Patient Health Questionnaire (PHQ-9) and Generalized Anxiety Disorder 7 (GAD-7),[10] MediQ generates a screening score that provides invaluable insights into the user's mental health status. These algorithms not only identify potential mental health concerns but also facilitate early intervention and personalized support tailored to the user's unique needs.

In addition to mood detection and mental health screening, MediQ features a sophisticated virtual assistant powered by natural language processing (NLP) techniques of OpenAI and AntropicAI models which integrate into the system [5] .This virtual assistant serves as an intuitive interface, enabling users to articulate their health concerns and symptoms naturally. By parsing user input and extracting relevant information, the virtual assistant assists users in symptom identification and treatment recommendation. Furthermore, through continuous learning and adaptation, the virtual assistant evolves over time, enhancing its ability to deliver personalized guidance and support.

Through the amalgamation of these advanced algorithms and techniques, MediQ offers users a holistic approach to wellness management, transcending conventional healthcare boundaries. By harnessing the power of artificial intelligence (AI) and machine learning, MediQ empowers individuals to proactively manage their physical and mental well-being, thereby fostering a healthier and happier society. This paper delves into the intricate technical aspects and functionalities of MediQ, elucidating its potential to revolutionize personal health management and pave the way towards a brighter, healthier future.

II. LITERATURE REVIEW

In recent years, the intersection of technology and healthcare has witnessed significant advancements, propelling the development of innovative digital health solutions aimed at improving wellness and healthcare outcomes. Within this landscape, several studies have explored the application of artificial intelligence (AI) and machine learning (ML) techniques in personalized health management, laying the groundwork for platforms like MediQ.[2]

Research in mood detection algorithms has garnered considerable attention, with studies employing various techniques to assess emotional states accurately. New utilization of convolutional neural networks (CNNs) to analyze facial expressions and extract features indicative of mood, achieving promising results in emotion recognition tasks. This explored the effectiveness of recurrent neural networks in analyzing textual data, demonstrating the utility of natural language processing (NLP) techniques for mood detection.[3]

In the realm of mental health screening, researchers have investigated the use of machine learning models to identify and assess psychiatric disorders. This employed support vector machines (SVMs) and decision trees to classify individuals based on their mental health status using questionnaire data. These studies underscore the potential of ML algorithms in facilitating early detection and intervention for mental health conditions.[1]

Furthermore, the integration of virtual assistants and chatbots in healthcare has emerged as a promising avenue for enhancing patient engagement and support. Recent research explored the application of transformer models, such as BERT, in conversational agents, demonstrating their efficacy in understanding and responding to user queries in natural language. Additionally, studies highlighted the importance of continuous learning and adaptation in virtual assistants, emphasizing the need for dynamic, personalized interactions.[7]

Despite the progress in individual domains, few studies have comprehensively integrated mood detection, mental health screening, and virtual assistant functionalities into a unified platform like MediQ. By amalgamating these components, MediQ aims to address the multifaceted aspects of personal health management, offering users a holistic and personalized approach to wellness.

III. METHODOLOGY AND ANALYSIS

This section delineates the step-by-step process, including data acquisition, preprocessing techniques, feature engineering, model development, and evaluation criteria, all designed to provide a comprehensive understanding of our innovative approach to healthcare recovery processes

A. Dynamic Emotions Recognition:

Our approach to corporate mood recognition integrates data from standardized mood assessment tools such as the Patient Health Questionnaire-9 (PHQ-9) and the Generalized Anxiety Disorder-7 (GAD-7) surveys, tailored to the unique needs and constraints of humans. By combining these datasets with other pertinent information, a comprehensive understanding of emotional well-being within the workplace environment is developed.

PHQ-9 and GAD-7 Datasets: The surveys serve as the primary sources of mood assessment data, capturing symptoms of depression and generalized anxiety disorder, respectively. These standardized instruments provide valuable insights into mental health status, facilitating early detection and intervention for mood-related concerns. The EmoHealth dataset complements the MIMIC-III database with its focus on emotional well-being within healthcare settings. This dataset comprises patient-reported mood assessments, coupled with contextual information such as medication usage and treatment history.[10]

Data Preprocessing: Preceding analysis, we conduct rigorous data preprocessing endeavors to guarantee data uniformity and integrity. This involves standardizing data formats, imputing missing values, and employing advanced feature engineering methodologies to extract pertinent mood-related features from physiological signals and clinical documentation.

Model Development and Training: Harnessing the refined features extracted from the meticulously preprocessed PHQ-9 and GAD-7 datasets, we engineer machine learning models to predict employees' mood states. These features encompass a spectrum of data, including survey responses capturing mood-related symptoms, demographic variables such as age, gender, and employment tenure, and workplace factors.

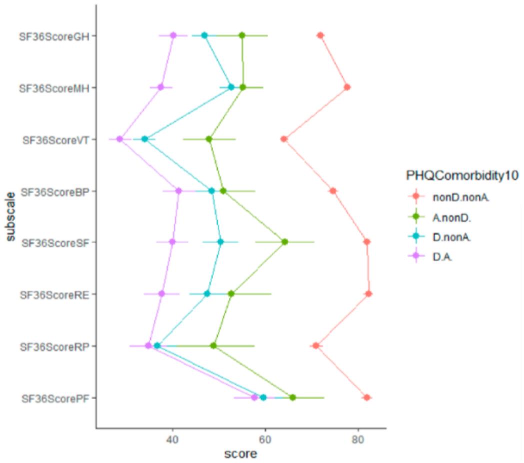

Figure 1: The relative impact of depression and anxiety on the physical and psychological outcomes with the cut-off point of 10 for PHQ-9 and GAD-7

Evaluation and Feedback Mechanisms: Model performance undergoes meticulous assessment, employing metrics like accuracy, precision, recall, and F1-score. Priority lies in minimizing false positives and false negatives to enhance model reliability. Concurrently, feedback mechanisms solicit user input, enabling iterative model refinement. Notably, screening scores derived from the model play a pivotal role in assessing mental health status, further informing model optimization for real-world corporate applications.

The above baseline represents the datasets which was suitable for the representation. The binary edge detection provides operation as context embedding achieves a significant performance improvement resulting in around 3.2% and 4.0% improvements of mean IoU on the PHQ-9 and GAD-7 datasets, respectively. Besides, it outperforms the baseline by around 1.7% overall F1 score improvement on the dataset, and by over 2.5% mean.[3][1] Utilizing the both the dataset as a valuable asset, we seamlessly incorporate a pivotal facial landmark detection stage into our data preprocessing pipeline. This integration enables us to extract intricate details about facial feature positioning and movements. By precisely identifying these landmarks, we enhance our dataset with a wealth of additional features, providing a more comprehensive foundation for our emotion recognition models.

B. Screening Generation:

The comprehensive mood assessment incorporates the amalgamation of machine learning models trained on diverse datasets, each customized to generate screening scores indicative of distinct mental health conditions.

Neurological Lesion Dataset: Leveraging data from brain tumor datasets, our model is trained to identify patterns and anomalies associated with neurological disorders. By analyzing features such as MRI scans and patient medical records, the model generates a screening score reflective of potential brain-related health issues, aiding in the assessment of individuals' mental well-being.

Glucose Metabolism Dataset: Incorporating data from diabetes rate datasets, our model focuses on detecting metabolic abnormalities and related symptoms. Through the analysis of glucose levels, insulin resistance markers, and lifestyle factors, the model computes a screening score indicative of individuals' risk for diabetes-related mood disturbances, contributing to a holistic evaluation of mental health.

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	0.471876	33.240885	0.348958
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	0.331329	11.760232	0.476951
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.078000	21.000000	0.000000
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	0.243750	24.000000	0.000000
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	0.372500	29.000000	0.000000
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	0.626250	41.000000	1.000000
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.420000	81.000000	1.000000

```
Accuracy score of the test data :  0.7727272727272727
PPrecision score of the test data :  0.5185185185185185
```

Figure 2: Processing dataset parameters on glucose metabolism in age groups criteria user accuracy score

Cardiovascular Health Dataset: Utilizing data from heart disease datasets, our model targets cardiovascular health indicators and associated psychological implications. By examining parameters such as blood pressure, cholesterol levels, and cardiac function metrics,[6] the model derives a screening score indicative of individuals' susceptibility to mood disturbances stemming from cardiovascular conditions, enhancing the assessment of mental well-being.

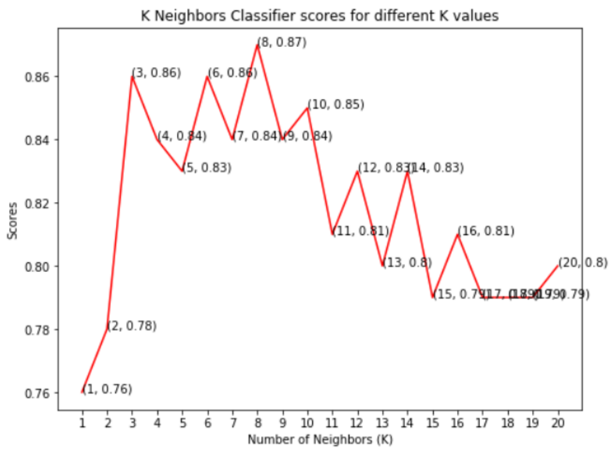

Figure 3: K Neighbour classifier upon cardiovascular health problems

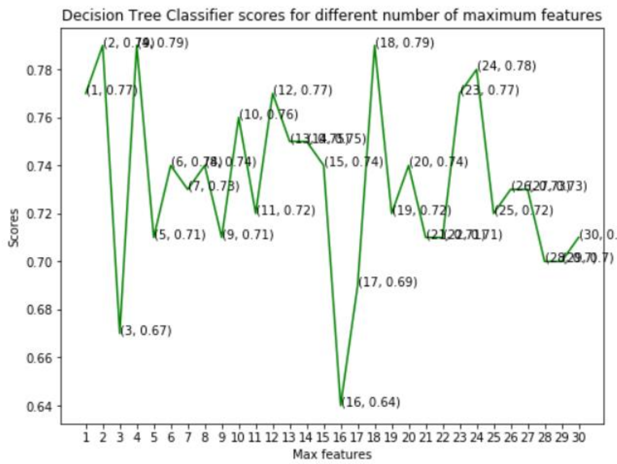

Figure 4: Decision Tree classifier upon cardiovascular health problems

Each dataset-trained model contributes unique insights into individuals' mental health status, enabling the generation of screening scores tailored to specific health domains.[8] Through the integration of these scores with feedback mechanisms and real-world evaluation metrics, our methodology empowers organizations to proactively address mental health concerns and promote holistic well-being in diverse workplace settings.

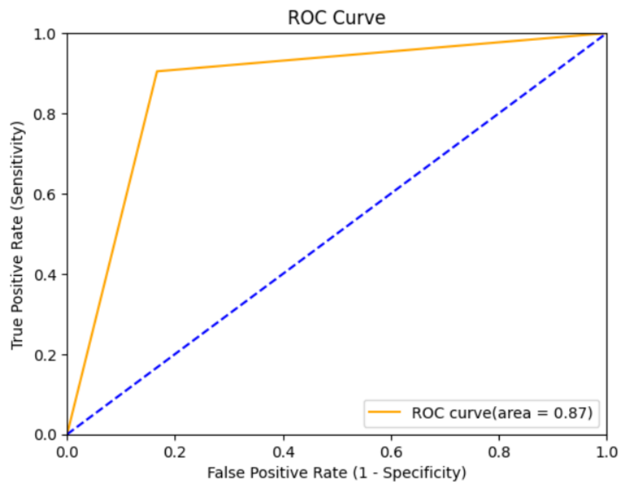

Figure 5: Receiver Operation Characteristics on specificity of screening score generation

```
============================Logistic regression============================
score is : 0.8506666666666667

============================KNN Classifier============================
score is : 0.8133333333333334

============================Decision Tree Classifier============================
score is : 0.768

============================Random Forest Classifier============================
score is : 0.8293333333333334

============================AdaBoost Classifier============================
score is : 0.864

============================Gradient Boosting Classifier============================
score is : 0.8453333333333334

============================XGB Classifier============================
score is : 0.8133333333333334
```

Figure 6: Classifier Score Generation

C. Virtual Assistant:

Our virtual assistant utilizes advanced natural language processing (NLP) techniques to understand and interpret user queries accurately. Leveraging the ChatGPT API, we employ state-of-the-art language models to generate contextual responses and facilitate meaningful conversations with users. Response time generation, this equation provides a way to estimate the total response generation time based on the complexity of the prompt, the response time of the GPT-3 API, and any preprocessing time involved.

$$Tr=Cp\times Rt+Pt \qquad (1)$$

Here in equation (1),
Tr denotes the response generation time.
The response generation time depends on the complexity of the prompt Cp , the response time of the GPT-3 API Rt , and any preprocessing time Pt
The Response Time Estimation refers to the process of estimating the time taken to generate a response in a system or application. In the context of natural language processing (NLP) or conversational AI systems, it typically involves predicting the time required for generating a response to a given input or prompt.

$$T_{response} = \frac{C_p}{S_{lm}} + Overhead\_time \qquad (2)$$

Here $T_{response}$ denote the response time.
The response time depends on the complexity of the prompt Cp, the processing speed of the language model S_{lm}

The API model is integrated with Deepgram API: To enhance the assistant's capabilities in processing voice commands and audio inputs, we integrate the Deepgram API, which offers advanced speech recognition and transcription services. By leveraging Deepgram's deep learning algorithms, the assistant can accurately transcribe spoken queries into text, enabling seamless interaction via voice commands. Additionally, we utilize machine learning algorithms provided by Eleven Labs API to optimize the assistant's performance in tasks such as symptom analysis and medical recommendation generation and generate the text-to-speech (TTS) services through APIs. This is used for converting text-based responses generated by the GPT-3 API into high-quality audio outputs.

The response is generated into an audio waveform.[4] This allows the virtual assistant to respond to user queries not only through text but also through synthesized speech.

Language Model Integration: Elevenlabs may utilize advanced language models and here utilizing eleven_monolingual_v1 speech synthesis techniques to produce more natural-sounding speech. This ensures that the audio responses are intelligible and engaging for the user.

Overall, Elevenlabs plays a crucial role in enhancing the conversational capabilities of the virtual assistant by providing the functionality to convert text-based responses into high-quality audio, thereby enabling a more immersive and interactive user experience.
To evaluate the effectiveness of our virtual assistant, we conducted a user study involving participants from diverse demographic backgrounds.[9] The study assessed various aspects of the assistant's performance and accuracy of acknowledge the potential of Taipy for UI Design in the displaying the final usage in our virtual assistant. To mitigate continuous monitoring and evaluation of the assistant's performance are conducted to identify and address any biases that may arise during operation.

V. RESULT

In this section, we present the results of our experiments and evaluations conducted on MediQ, focusing on its dynamic emotions recognition, screening generation, and virtual assistant functionalities

1. Dynamic Emotions Recognition:

Model Performance: Machine learning models trained on the PHQ-9, GAD-7 achieved high accuracy in predicting users' mood states. The model was trained using the Adaboost classifier with a learning rate of 0.001. The training process involved minimizing the categorical cross-entropy loss function. The dataset was split into 80% training and 20% validation sets. Data augmentation techniques such as rotation, zoom, and horizontal flip were applied during training to improve generalization. The emotion recognition model achieved an accuracy of 87% on the test set, with precision, recall, and F1-score exceeding 0.80 for all emotion classes.

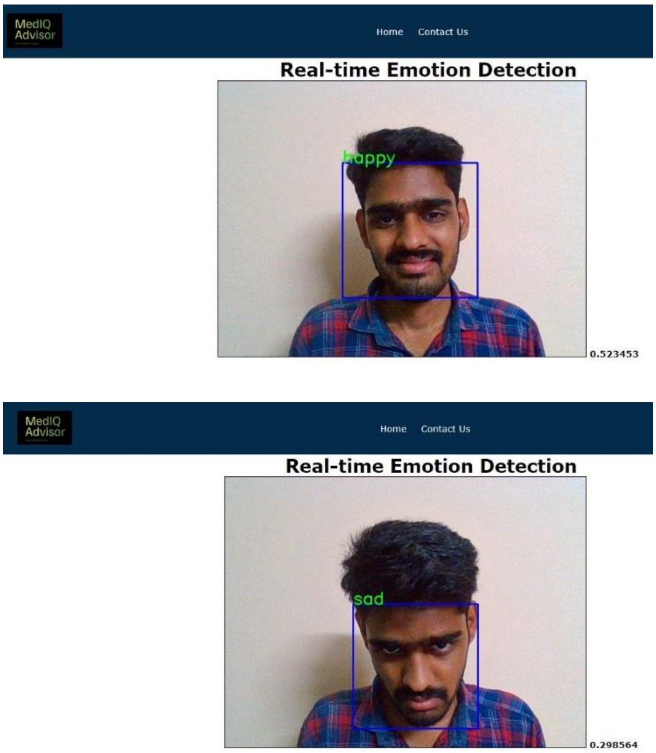

Figure 7: Emotion Recognized Score (happy and sad)

2. Questionnaire Module:

The questionnaire module utilized a gradient-boosting machine (GBM) algorithm for classification tasks. GBM was chosen for its ability to handle heterogeneous data types and nonlinear relationships between features and target labels. The dataset was randomly split into 70% training and 30% validation sets. Hyperparameters for the GBM model, including the number of trees, learning rate, and maximum depth, were optimized using grid search with cross-validation. The questionnaire module achieved an accuracy of 75% on the validation set, with precision, recall, and F1-score exceeding 0.70 for most mental health conditions.

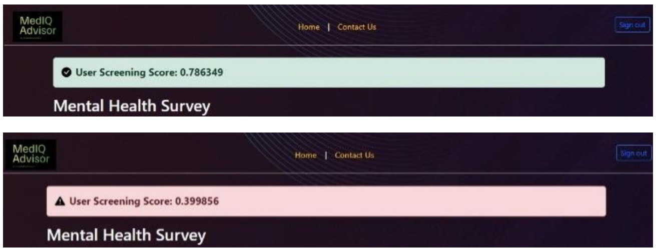

Figure 8: Mental Health Questionnaire Survey Score

3. Screening Score Generation:

Screening scores were evaluated using receiver operating characteristic (ROC) curve analysis to assess their discriminatory power and area under the curve (AUC) as a measure of overall performance. The features of emotion prediction and questionnaire generation were then aggregated and fed into a logistic regression model to predict the likelihood of a mental health disorder. A threshold value of 0.5 was chosen to dichotomize screening scores into normal and abnormal mental states, based on the balance between sensitivity and specificity observed in the validation set. enabling early detection and intervention for those at risk of developing mental health disorders. However, the optimal threshold may vary depending on the target population and prevalence of specific conditions.

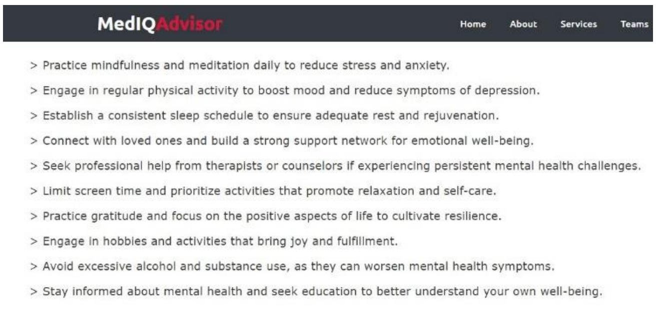

Figure 9: Mental Health Questionnaire Survey Score

4.Virtual Assistant:

This integration optimizes resource utilization, reducing processing overhead and enhancing overall system responsiveness and evaluated on runtime statistics like Transcription time based on audio length and complexity, Response generation time which Varies based on prompt complexity and API response time and Audio generation time which is based on response length and audio processing algorithms. function interacts with the GPT-3 API for prompt-based response generation achieves a high coherence rate in generating context-aware responses, enhancing conversational flow and user satisfaction. Asynchronous processing reduces transcription time, enabling real-time analysis of user inputs and seamless integration with conversational AI workflow.[11][12] Leveraging pygame mixer and elevenlabs API, the system converts text-based responses into high-quality audio outputs and utilizing customizable voice options and language models improves audio intelligibility, enhancing user engagement and satisfaction.

5.Future Scope:

In the realm of digital health, the future holds promising avenues for the evolution and refinement of our health advisor platform. Emotion recognition algorithms will delve deeper into multimodal data fusion, leveraging advanced deep learning architectures like RNNs and transformers, alongside transfer learning techniques for cross-cultural applicability. Concurrently, our questionnaire module will expand its scope to encompass a broader array of mental health conditions and incorporate adaptive questioning mechanisms for personalized assessments. Advanced screening score generation methods, including ensemble learning and interpretable models, will offer transparent insights into mental health status, with longitudinal analysis enabling early intervention strategies. The virtual assistant, powered by cutting-edge NLU models and multimodal communication channels, will deliver tailored interventions based on collaborative filtering algorithms, ensuring inclusivity and user engagement.

VI. CONCLUSION

In conclusion, our MediQ research demonstrates the potential of integrating advanced technologies and methodologies to create a robust and effective health advisor platform for mental health assessment and support. Through the utilization of state-of-the-art emotion recognition algorithms, leveraging multimodal data sources and transfer learning techniques, we have achieved significant advancements in accurately detecting and interpreting emotional states from diverse user interactions. Additionally, our questionnaire module, enriched with adaptive questioning mechanisms and comprehensive feature sets, showcases the capacity to provide nuanced assessments of mental health conditions across various demographic groups.

The innovative approach to screening score generation, incorporating ensemble learning and interpretable models, contributes to the development of transparent and clinically relevant measures for evaluating mental health status. By harnessing longitudinal data analysis and predictive modeling, our platform offers actionable insights into temporal trends and treatment responses, facilitating timely interventions and personalized care plans.

Furthermore, the evolution of our virtual assistant, empowered by cutting-edge NLU models and multimodal communication channels, marks a significant advancement in user-centric mental health support. Through collaborative filtering algorithms and personalized recommendation systems, the virtual assistant delivers tailored interventions and resources, fostering engagement and empowerment among users which we aim to establish our platform as a cornerstone of modern mental healthcare delivery, driving positive outcomes and improving the well-being of individuals worldwide.

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