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AI Powered Virtual Assistance for Mental Health Support

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Abstract:

Mental health issues, such as anxiety, depression, and other psychological disturbances, have become a significant public health concern globally. Identifying individuals at risk of these conditions early on can lead to timely interventions and improved outcomes. With the rise of technology and the increasing use of smartphones and wearable devices, there is an opportunity to develop an innovative system that can monitor emotional health in real-time, helping to detect potential psychological disturbances before they escalate. Traditionally, mental health assessments relied on self-reporting and periodic check-ins with mental health professionals. These approaches often had limitations, as individuals may not always accurately report their emotional state, and there could be significant delays between assessments. Additionally, access to mental health services was not always readily available, leading to potential delays in diagnosis and treatment. Therefore, the need for an innovative system for monitoring emotional health arises from the desire to overcome the limitations of traditional approaches. By leveraging technology, such as machine learning, natural language processing, we can create a continuous and unobtrusive monitoring system. Such a system could gather real-time data on an individual's emotional state, behavior, and physiological responses. Early detection of emotional disturbances can lead to timely intervention and support, improving the overall mental well-being of individuals and reducing the burden on mental health services. This innovative monitoring system has the potential to significantly improve mental health outcomes on a broader scale. It offers a proactive approach to emotional well-being, empowering individuals to take control of their mental health and providing an invaluable tool for mental health professionals in identifying and supporting those at risk of psychological disturbances.

Keywords: Mental health, psychological disturbances, Natural Language Processing, Machine Learning.

1.INTRODUCTION

Mental illness is a health problem that undoubtedly impacts emotions, reasoning, and social interaction of a person. These issues have shown that mental illness gives serious consequences across societies and demands new strategies for prevention and intervention. To accomplish these strategies, early detection of mental health is an essential procedure. Medical predictive analytics will reform the healthcare field broadly as discussed by Miner et al. Mental illness is usually diagnosed based on the individual self-report that requires questionnaires designed for the detection of the specific patterns of feeling or social interactions. With proper care and treatment, many individuals will hopefully be able to recover from mental illness or emotional disorder. Machine learning is a technique that aims to construct systems that can improve through experience by using advanced statistical and probabilistic techniques. It is believed to be a significantly useful tool to help in predicting mental health. It is allowing many researchers to acquire important information from the data, provide personalized experiences, and develop automated intelligent systems. The widely used algorithms in the field of machine learning such as support vector machine, random forest, and artificial neural networks have been utilized to forecast and categorize the future events.Supervised learning in machine learning is the most widely applied approach in many types of research, studies, and experiments, especially in predicting illness in the medical field. In supervised learning, the terms, attributes, and values should be reflected in all data instances. More precisely, supervised learning is a classification technique using structured training data. Meanwhile, unsupervised learning does not need supervision to predict. The main goal of unsupervised learning is handling data without supervision. It is very limited for the researchers to apply unsupervised learning methods in the clinical field.The World Health Organization (WHO) reports the region-wise status of different barriers in diagnosing mental health problems and encourages researchers to be equipped with the scientific knowledge to address the issue of mental health. Now, there are various techniques to predict the state of mental health due to advancement of technology. Research in the field of mental health has increased recently and contributed to the information and publications about different features of mental health, which can be applied in a wide range of problems. Many steps are involved in diagnosing mental health problems, and it is not a straightforward process that can be done quickly. Generally, the diagnosis will begin with a specific interview that is filled with questions about symptoms, medical history, and physical examination. Besides that, psychological tests and assessment tools are also available and are used to diagnose a person for mental health problems. There are several types of research carried out to investigate and examine the movements of the face to identify certain mental disorders. The increase of research in the mental health field has led to the rise of information in the form of finding suitable solutions to reduce mental health problems. However, the precise reasons for mental illnesses are still unclear and uncertain.

2. LITERATURE SURVEY

According to the paper by Greenstein et.al., classification of childhood-onset schizophrenia has been performed. The data consist of genetic information, clinical information, and brain magnetic resonance imaging. The authors use a random forest method to calculate the probability of mental disorder. Random forest is being used in this paper because it has lower error rates compared with other methods. The accuracy of 73.7% is obtained after the classification.

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In one of the research works conducted by Jo et.al., they used network analysis and machine learning approaches to identify 48 schizophrenia patients and 24 healthy controls. The network properties were rebuilt using the probabilistic brain tractography. After that, machine learning is being applied to label schizophrenia patients and health controls. Based on the result, the highest accuracy is achieved by the random forest model with an accuracy of 68.6% followed by the multinomial naive Bayes with an accuracy of 66.9%. Then, the XGBoost accuracy score is 66.3% and the support vector machine shows an accuracy of 58.2%. Most of the machine learning algorithms show promising levels of performance in predicting schizophrenia patients and healthy controls.

The support vector machine, which is a machine learning model, has been implemented to classify schizophrenia patients. The data set is obtained from the 20 schizophrenia patients and 20 healthy controls. Then, the support vector machine algorithm is used for classification with the help of functional magnetic resonance imaging and single nucleotide polymorphism. After the classification, an accuracy of 0.82 is achieved with the functional magnetic resonance imaging. For the single nucleotide polymorphism, an accuracy of 74% is obtained.

Srinivasagopalan et.al. used a deep learning model to diagnose schizophrenia. The National Institute of Health provides the data set for the experiments. The accuracy of each machine learning algorithm is obtained and recorded. The results obtained from the experiment show that deep learning showed the highest accuracy with 94.44%. The random forest recorded an accuracy of 83.33% followed by logistic regression with an accuracy of 82.77%. Then, the support vector machine showed an accuracy of 82.68% in this experiment.

In another study conducted by Pla¨schke et al., the schizophrenia patients were distinguished from the matched health controls based on the resting-state functional connectivity. Resting-state functional connectivity could be used as a spot of functional dysregulation in specific networks that are affected in schizophrenia.

The authors have used support vector machine classification and achieved 68% accuracy.
Pinaya et.al. applied the deep belief network to interpret features from neuromorphometry data that consist of 83 healthy controls and 143 schizophrenia patients. The model can achieve an accuracy of 73.6%; meanwhile, the support vector machine obtains an accuracy of 68.1%. The model can detect the massive difference between classes involving cerebrum components. In 2018, Pinaya et.al. proposed a practical approach to examine the brain-based disorders that do not require a variety of cases. The authors used a deep autoencoder and can produce different values and patterns of neuroanatomical deviations.

A machine learning algorithm is developed to predict the clinical remission from a 12-week course of citalopram. Data are collected from the 1949 patients that experience depression of level 1. A total of 25 variables from the data set are selected to make a better prediction outcome. Then, the gradient boosting method is being deployed for the prediction because of its characteristics that combine the weak predictive models when built. An accuracy of 64.6% is obtained by using the gradient boosting method.

In order to identify depression and anxiety at an early age, a model has been proposed by Ahmed et.al.. The model involves psychological testing, and machine learning algorithms such as convolutional neural network, support vector machine, linear discriminant analysis, and K-nearest neighbour have been used to classify the intensity level of the anxiety and depression, which consists of two data sets. Based on the results obtained, the convolutional neural network achieved the highest accuracy of 96% for anxiety and 96.8% for depression. The support vector machine showed a great result and was able to obtain an accuracy of 95% for anxiety and 95.8% for depression. Besides that, the linear discriminant analysis reached the accuracy of 93% for anxiety and 87.9% for depression. Meanwhile, the K-nearest neighbour obtained the lowest accuracy among the models with 70.96% for anxiety and 81.82% for depression. Hence the convolutional neural network can be a helpful model to assist psychologists and counsellors for making the treatments efficient.

3. PROPOSED METHODOLOGY

An "Innovative System for Monitoring Emotional Health to Identify Individuals at Risk of Psychological Disturbances" is a conceptual framework or technological solution designed to address the critical issue of mental health monitoring and early identification of individuals who may be at risk of psychological disturbances. The primary objective of this innovative system is to proactively monitor the emotional well-being of individuals and identify signs or patterns that suggest they may be at risk of psychological disturbances or mental health issues. It aims to provide timely support and intervention to those in need.

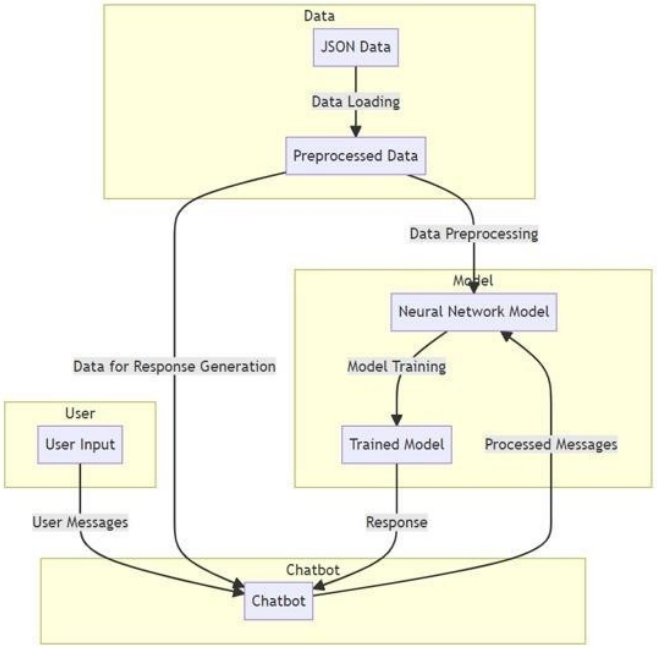

Figure 1: Overall design of proposed system.

Below are the main components and features:

- Chatbot Interface: The system often utilizes a chatbot as its user interface. Users can interact with the chatbot through text-based messages, providing them with a comfortable and non-judgmental platform to express their feelings and emotions.
- Data Collection: The system collects and analyses user data, specifically their text- based input. This data can include conversations, responses to predefined prompts, or free-form text input. The key is to gather textual information that reflects the user's emotional state.
- Natural Language Processing (NLP): The system employs NLP techniques to understand and interpret the user's text

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input. This involves sentiment analysis, emotion recognition, and context understanding to gauge the user's emotional state and identify potential concerns.

4. EXPERIMENTAL ANALYSIS

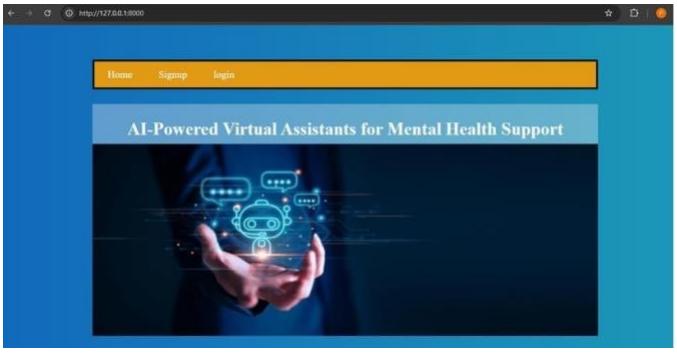

Figure 1: Home Page

The page prominently features a navigation bar at the top, containing three key action buttons: "Home," "Signup," and "Login." The "Home" button likely serves to refresh or return the user to this main page. The "Signup" button is crucial for new users, taking them to a registration page where they can create an account to access the mental health support services. The "Login" button caters to existing users, enabling them to enter their credentials and access their personalized accounts.

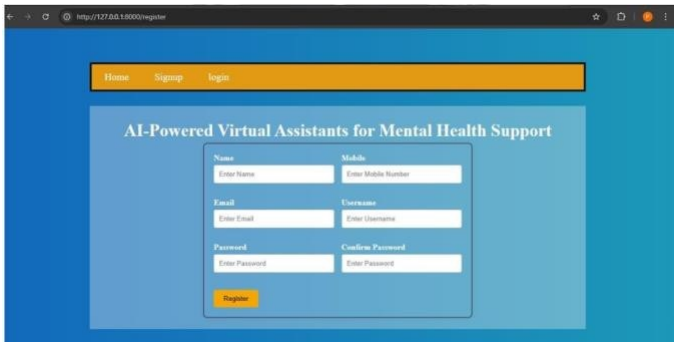

Figure 2: Signup Page

The signup form, accessed by clicking the "Signup" button on the homepage, is clearly structured and user-friendly. It features distinct input fields for essential personal details, including "Name," "Mobile," "Email," "Username," "Password," and "Confirm Password." Each field is accompanied by a descriptive label to guide the user through the registration process. The "Name" and "Mobile" fields allow for the input of a user's full name and mobile phone number, respectively. The "Email" field requires a valid email address, likely for verification and communication purposes. The "Username" field allows the user to create a unique identifier for their account. The "Password" and "Confirm Password" fields ensure secure account creation by requiring users to enter and confirm a password, preventing typos and enhancing security. Finally, a prominent "Register" button at the bottom of the form allows users to submit their information and complete the signup process.

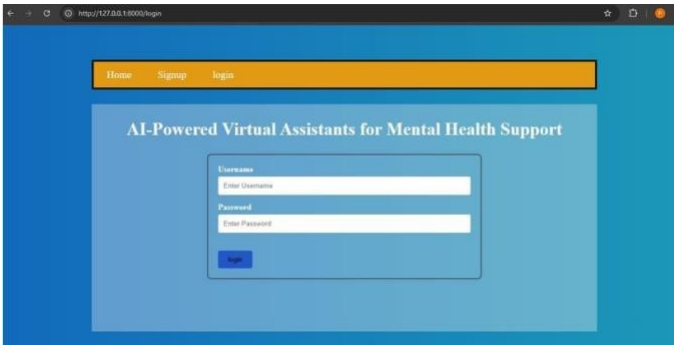

Figure 3: Login Page

The login form, accessible via the "Login" button on the homepage, presents a straightforward and secure interface for returning users. It consists of two primary input fields: "Username" and "Password." The "Username" field prompts users to enter the unique username they created during the signup process. The "Password" field, appropriately masked for security, requires users to input the corresponding password associated with their account. Below these fields, a prominent "login" button allows users to submit their credentials for verification. Upon successful authentication, users are granted access to their personalized accounts and the platform's mental health support services.

Figure 4: Dashboard

The "Home" button likely serves as a return to the main dashboard. The "chatbot" button directs users to the interface for interacting with the AI-powered virtual assistant, enabling them to engage in conversations and receive support. The "Logout" button allows users to securely exit the platform, ensuring the privacy and security of their interactions. This navigation bar streamlines user experience by providing clear and direct access to the platform's core functionalities.

Figure 5: Chatbot for assistance

The chatbot interface, accessed through the "chatbot" button in the navigation bar, is designed for direct interaction with the AI virtual assistant. The main section of the interface houses the chatbox, which

displays the ongoing conversation. User messages are clearly distinguished from the chatbot's responses, facilitating easy readability and comprehension. At the bottom of the chatbox, a text input field allows users to type their messages, and a "Send" button enables them to submit their queries to the AI. his streamlined design focuses on facilitating a natural and intuitive conversation with the AI assistant, making it easy for users to seek mental health support.

5. CONCLUSION

In conclusion, the implementation of an LSTM-based chatbot designed to monitor emotional health and identify individuals at risk of psychological disturbances represents a significant step forward in the utilization of technology for mental health support. This chatbot showcases its ability to effectively engage in conversations with users and provide responses based on patterns learned from the intents.json dataset. This highlights the potential of natural language processing (NLP) techniques to comprehend and address user emotions and concerns, offering a unique avenue for mental health assistance. One of the standout features of this chatbot is its capability to detect individuals at risk of psychological disturbances. By analyzing user input, it can promptly identify potential issues, enabling timely intervention and support. This proactive approach holds the promise of early intervention, which is crucial for preventing the escalation of mental health challenges and ensuring individuals receive the necessary assistance when they need it most. The accessibility offered by chatbots is a key advantage. Users can comfortably express their emotions and seek help through this platform, which can alleviate some of the barriers and stigma associated with discussing mental health concerns. This accessibility aspect is especially valuable in reaching individuals who may be hesitant to seek help through traditional channels. Additionally, the chatbot system has the potential to amass a substantial dataset of user interactions. Analyzing this data can yield valuable insights into user behavior, common mental health issues, and the effectiveness of various interventions. Such data-driven insights can inform the ongoing development and refinement of mental health support systems.

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