

AI as a new Psychotherapist-To Learn and Fight Mental Illness

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Abstract— Artificial intelligence is used in finding more and more applications in areas such as cancer treatment, internal medicine.

However, the implementation of Artificial intelligence in mental health care and neurobiological research has been bounded. In regard to the future of mental healthcare, it can serve as a bridge between mental illness and treatment plans. Mental health is a critical issue in today's world with a rising number of individuals working from home and away from friends and family, the mental health and medical situation has started to deteriorate. As a direct consequence, it is crucial to recognize and deal with any problems before they become too serious. The aim of the project is to understand the mental illness by evaluating and monitoring the user's responses gathered during a close ended question. A session will take place between the customer where set of questions that would pose regarding their symptoms and the response would be the severity level of the symptom scaling 0 to 4. While being constantly questioned, our model will store all the responses and use SVM Algorithm to display the exact illness the user is suffering from either Depression, Anxiety, Psychoticism, Phobic-Anxiety, Obsessive Compulsion, Anger-Hostility or No Illness. After finding the illness user can check the severity level of the illness by attending different set of question which will disclose if the user has Illness with high severity level or low severity level.

Keywords-Mental Illness, Machine Learning, SCL-90R.

I. INTRODUCTION

There is no doubt that mental health is an essential part of our daily lives. Mental illnesses are medical conditions that affect a person's thinking, feelings, mood, ability to relate to others, and daily functioning. Just as diabetes is a disorder of the pancreas, mental illnesses are medical conditions that often result in a diminished ability to cope with the normal demands of life. Children and adolescents are more likely to be vulnerable to mental illness. Mental illnesses are not the result of personal weakness, a lack of character, or a poor upbringing, but rather due to over-thinking, frustration, lack of confidence, getting annoyed and angry for small reasons, isolation, joblessness, loss of money, and many more thoughts that revolve in our minds and that impact our mental health. The project focuses on Mental illnesses such as depression, obsessive-compulsive, Anxiety, Phobic-Anxiety, Anger-Hostility and Psychoticism. Usually, people are afraid to talk openly about their mental health for fear of being judged and teased. This can be solved by creating a patient-centered model that will help to reduce their suffering by asking them their symptoms as questionnaire and then map the exact illness they are undergoing. In order to do so questions are collected from SCL-90R which is a Symptom Checklist and various supervised algorithms like SVM, KNN, Decision Tree and Naïve Bayes are tested and trained to collect the response from user and give proper class of illness.

II. RELATED WORK

Kopelovich SL, Monroe-DeVita M, et al. [1] in “Transforming mental health for all” observed that during COVID-19, digital care options through telephonic and all manner of new applications saw explosive growth and online services reach the high remote regions and circumvent fears of stigma for making the decision to seek treatment. Young people, their families, and those dealing with mental illness have come to trust organisations like UCLA STAND and 7 Cups, Together All, Reach Out, which are frequently co-designed and advised by peers in the community. In this type of treatment, they used to know their situation and health based on what they used for treating, but this is not a suggested way for a large number of patients in similar circumstances.

Stevie Chancellor, Michael L Birnbaum, et al. [2] in "A Taxonomy of Ethical Tensions in Inferring Mental Health States from Social Media " have proposed that social media provides great information about individual behaviours, emotions, and psychological states. This paper has successfully employed the data from social media to predict the mental health states of individuals, ranging from the presence and severity of mental disorders like depression to the risk of suicide and even others. These algorithmic inferences hold great potential for supporting the early detection and treatment of mental disorders and the design of interventions. At the same time, the outcomes of this research can pose great risks to individuals, such as issues with incorrect, opaque algorithmic predictions, the involvement of bad or unaccountable actors, and potential biases from intentional or inadvertent misuse of insights by posting weird, unnecessary, or sad photos that will showcase their mindset based on how they have been treated recently.

Marcel Trozsek, Sven Koitka, et al. [3] have proposed that depression is ranked as the largest contributor to global disability and is also a major reason for suicide. Still, many individuals, especially young and adults suffering from forms of depression are not treated for various reasons. Depression also has an effect on language usage, and many depressed individuals use social media platforms to collect data of the patient or the internet in general to get information or discuss their problems. This paper addresses the early detection of illness using machine learning models based on messages on a social platform and even other activities. In particular, a convolutional neural network based on different word embeddings is evaluated and compared to a classification based on user-level linguistic metadata.

Breeksema JJ, Niemeijer AR, et al. [4] have stated that depression is the most common cause of disability globally and a major contributing factor to suicide. However, many people who suffer from depression do not obtain therapy for a variety of reasons. Previous studies have shown that language use is affected by depression and that a lot of depressed people use social networking sites or the

internet in general to get information or chat about their problems. This study investigates the use of social media communications to diagnose depression in its early phases using machine learning algorithms. In particular, a convolutional neural network based on different word embeddings is contrasted with a classification based on user level linguistic data which is not available easily.

Karen Hilyard, David Broniatowski, et al. [5] have proposed that studies using WEIRD (Western, educated, industrialised, wealthy, and democratic) study participants i.e., average U.S. college students are not as representative of our global population as studies using cell phones and wearables. By gathering real-world, "ecologically valid" information from individuals in their normal day-to-day lives rather than in the artificial setting of a standard lab, such data have already proven beneficial in bridging dozens, if not hundreds, of research gaps. Furthermore, the knowledge can assist us in providing psychology and psychiatric researchers with objective, quantifiable data.

Hatoon S. AlSagri, Mourad Ykhlef, et al. [6] have proposed that the leading cause of disability worldwide and a significant factor in suicide is depression. However, for a variety of reasons, many people with depression do not receive treatment. Previous research has indicated that language usage is impacted by depression, and that many sad people use social networking sites or the internet in general to acquire information or talk about their issues. This study examines the use of machine learning models to identify depression in its early stages using communications from social media platforms. In specifically, a classification based on user-level linguistic information is compared to a convolutional neural network based on various word embeddings.

Karol Chlasta et al. [7] have proposed Early detection and treatment of Mental Illness are essential for promoting remission, preventing relapse, and reducing the emotional burden of the disease. These diagnoses are primarily subjective, inconsistent across professionals, and expensive for individuals who may be in urgent need of help. The study automated illness detection in speech using a convolutional neural network (CNN) and multipart interactive training. The model was tested using 2568 voice samples obtained from 77 non-depressed and 30 depressed individuals. In experiments conducted, data were applied to residual CNNs in the form of spectrograms images auto-generated from audio samples. The experimental results obtained using different ResNet architectures gave a promising baseline accuracy of 77%.

Marcel Trozsek Sven Koitka et al. [8] have proposed that the leading cause of disability worldwide and a significant factor in suicide is depression. However, for a variety of reasons, many people with depression do not receive treatment. Previous research has indicated that language usage is impacted by depression, and that many sad people use social networking sites or the internet in general to acquire information or talk about their issues. This study examines the use of machine learning models to

identify depression in its early stages using communications from social media platforms. Specifically, a classification based on user-level linguistic information is compared to a convolutional neural network based on various word embeddings.

Karol Chlasta, Krzysztof Wołk et.al. “automated speech-based screening of depression using deep convolutional neural networks” [9] describes about Artificial companions and intelligent virtual worlds like Virtual reality simulation is another AI application that is gaining popularity. An example of human-computer interaction is virtual reality, which enables users to interact with a computer-generated virtual environment while immersed in it. Clinical virtual reality is the use of virtual reality for clinical assessment and therapy. It has also been used to treat a variety of psychological disorders. Artificial intelligence (AI) is already being used in virtual environments to create intelligent entities that can interact with and learn from users, improving their versatility and realism. Additionally, these artificially intelligent beings can now communicate with humans and show emotion. Virtual dogs for the house and other “biologically inspired” virtual companions may also improve mental health by reducing loneliness and boosting mental well-being.

Sven Koitka, Marcel Trotzek et al., “Utilizing Neural Networks and Linguistic Metadata for Early Detection of Depression Indications in Text Sequences” [10] briefs about Artificial intelligence (AI) integration into clinical tools used by experts in mental health and other areas of medicine can improve efficiency, accuracy, and convenience. Speech recognition technology has been used for medical dictation for a long time. Eighty five percent of American doctors utilise electronic health/medical records in their offices, according to the National Centre for Health Statistics. However, there are now EMR software options that use AI and Boolean logic to automate patient data entry by recalling elements from earlier cases that are identical to or similar to the present case, improving accuracy and cutting down on time. As an illustration, any document written by mental health professionals may unintentionally or purposely be made public to all linked and disconnected providers and administrators due to the fact that other health providers and administrators have access to client information.

Martin, A., Johnson, R., & Williams, S “A Review on Voice and Emotion Analysis for Mental Health Detection”(2019) [11] provides a comprehensive overview of the application of speech processing and emotion analysis techniques in detecting mental health issues in patients. The authors systematically review various methods, including traditional acoustic feature extraction, machine learning approaches, and deep learning techniques, to assess their effectiveness in identifying mental health disorders from speech data. highlights several speech processing and emotion analysis techniques commonly employed in mental health detection, such as pitch and intensity analysis, spectral feature extraction, and

prosodic feature analysis. The authors explore their applications in different scenarios, such as detecting depression from patients' speech, identifying anxiety levels from vocal patterns, and assessing stress and other emotional states that may be indicative of mental health issues.

Patel, N., Kumar, V., & Lee, J. "Assessing Mental Health using the Symptom Checklist-90 (SCL-90): A Comprehensive Review"(2018) [12] provides an extensive analysis of the Symptom Checklist-90 (SCL-90), a widely-used self-report questionnaire designed to evaluate a broad range of psychological symptoms and assess mental health in clinical and research settings. The authors systematically review the history, development, and validation of the SCL-90, discussing its structure, which consists of 90 items rated on a five-point Likert scale. The questionnaire covers nine symptom dimensions: somatization, obsessive-compulsive, interpersonal sensitivity, depression, anxiety, hostility, phobic anxiety, paranoid ideation, and psychoticism.

II. METHODOLOGY

An overview of how the system operates is shown in Fig-1, which explains the flow of data where the process will start from the dashboard, namely the access dashboard which collects the data from the user which is required for the operations to be performed

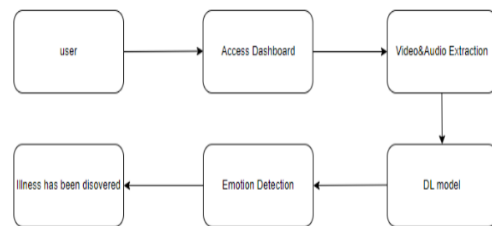


Fig 1. Flow Diagram of Working

After collecting all the details from the user there will be a certain operation to be performed, Initially the user has to undergo Mental Assessment where a user has to answer 59 questions in order to identify which type of illness particular user is suffering from it can be either Depression, Anxiety, Phobic-Anxiety, Anger-Hostility, Psychoticism, OCD or no Illness detected. After that user can click on illness which will be displayed on the screen to check the severity of the illness by answering questions related to it. Once the user completed the session, user's severity level will be displayed on the screen. The steps in order to identify the user which illness they have, they have to go through various questions, the questions are framed from Symptom Checklist-90-Revised (SCL-90-R). It is a 90-item self-report symptom survey created to reflect the psychological symptom patterns of respondents from their responses. Symptoms of the diseases are considered as questions and the response are considered as scores. Scores are as follows: If the user give response as “Not at all”, “no” it is considered as 0, indicating the user doesn't have the symptoms.

If the user give response as “use to be” “rarely” it is considered as 1, indicating the user has the symptoms but it does not bother them much.

If the user give response as “Frequently” “sometimes” it is considered as 2, indicating the user has mild symptoms.

If the user give response as “Occasionally” “Most often” it is considered as 3, indicating the user had extreme symptom.

If the user give response as “Always” “yes” it is considered as 4, indicating user suffers from it and the symptoms bother them a lot.

After answering with appropriate responses, disease will be displayed either Depression, Anxiety, Phobic-Anxiety, Anger-Hostility, Psychoticism, OCD, or no Illness is detected.

IV. IMPLEMENTATION

In order to predict the illness, 4 Machine Learning Algorithms namely KNN, Decision tree, Naïve bayes and SVM is compared to get the highest accuracy. Let’s understand each Algorithm.

KNN

KNN stands for "k-nearest neighbors" and is a kind of machine learning method used classification. In our system we first plotted testing and validation graph, there we found when considering k=9, model has the highest Accuracy. Confusion Matrix of the KNN can be seen below and gives 86% accurate result.

Decision Tree

Decision tree is another approach for testing our model where each leaf node represents a class label or a numerical value, each internal node represents a test on an attribute, and each branch reflects the test's result. First, we plotted the accuracy for testing and validation, there we got when the depth is 3, decision tree shows the highest Accuracy for our dataset. Confusion Matrix can be seen below which gives 73% accurate result.

SVM

A supervised machine learning approach called a Support Vector Machine (SVM) can be applied to classification or regression tasks. SVMs are especially helpful for handling datasets with several features when there are many more characteristics than samples. Finding a hyperplane that best divides the data into various classes is the underlying premise of SVMs. When plotted the graph between Testing and Validation, we got 100% accurate result when the penalty parameter is 2

Naive Bayes

Naive Bayes is a classification technique that divides data into various groups or classes and is based on the Bayes theorem. The Naive Bayes classifier makes the erroneous assumption that a feature's presence in a class is unrelated to the presence of other features giving accuracy of 92%.

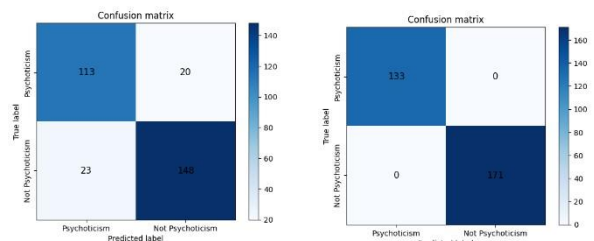
Table 1. Comparison of Models

Sl No.	Model Name	Percentage Accuracy
1	KNN	86%
2	SVM	100%
3	Decision Tree	73%
4	Naive Bayes	92%

From the above Table 1 we can say that the percentage accuracy of SVM is 100% and it is greater compared to KNN, Decision Tree, Naïve Bayes which gives us 86%, 73% and 92%.

Confusion Matrix

Considering the symptoms that the patient has psychoticism and the patient that doesn't have psychoticism, while testing the KNN model we get 86% accuracy as the confusion matrix itself says when we take 133 values for testing it has produced 113 True positive and 20 false positive, meanwhile when 171 values have considered for not psychoticism it has tested 148 true negative and 23 false positive



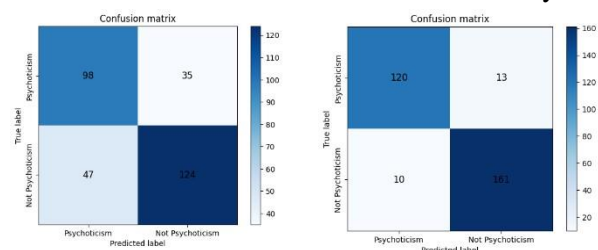
KNN

SVM

Here for SVM it is showing 100 accuracies when it reads the data, when 133 values are taken into testing it has predicted 113 true positive and 0 false positive. Meanwhile when 171 values are considered for not psychoticism it has tested 171 true positive and 0 false positive.

Decision Tree

Naive Bayes



In the confusion matrix of decision tree, when 133 values are being used for testing it has predicted 98 true positive and 35 false positive, Meanwhile when 171 values are considered for not Psychoticism it has tested 121 true negative and 47 false negative resulting 73% accuracy value

In the confusion matrix of Naïve bayes, when 133 values are being used for testing it has predicted 120 true positive and 13 false positive, meanwhile when 171 values are considered for not Psychoticism it has tested 161 true negative and 10 false negative resulting 73% accuracy value

IV. RESULT AND DISCUSSION

Once the Accurate Algorithm is been selected, as we know it's SVM. Now let's deploy the project with SVM as model. We have set of questions prepared to analyse particular type of diseases. It will redirect to the page where questions will be asked as shown in below figure.

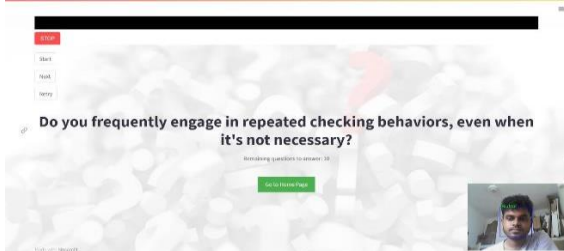


Fig 2. Questionnaire Page

The Fig 2. shows the working of services which uses user response as voice input and also shows the user expression to detect whether a person is undergoing that illness or not.



Fig 3. Result Page

The above figure shows the disease detected after going through the question answer session.

V. CONCLUSION

In this project we have successfully developed an architecture that utilizes video and audio inputs to detect the emotional state of an individual., The model is trained to recognize five distinct emotional states: neutral, happy, sad, surprised, and anger and along with emotion, speech is recognized using speech recognition. Taking questionnaire from SLC-90 R symptom checklist, we can frame the questions. Through a video teleconference and question- answering process, our system calculates the

mean of the scores obtained and compares it against predefined threshold values which will map the illness.

Project also discuss about various algorithms such as K-Nearest Neighbor, Naïve Bayes, SVM and Decision Tree Algorithms to classify different types of illness. After building this project, the machine gives more accuracy in SVM with 100% and hence we built a frontend system using Django and Streamlit. User has undergone through questionnaire page and answer all the question meanwhile the scores are counted which is fed as an input to the model to give the result in the end of questions and classify the illness such as, depression, anxiety, phobic anxiety, psychoticism, anger issues or OCD. Once users know the illness they are suffering from, they can proceed to another page where the severity of the illness can be detected, either mild or extreme.

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