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Ai-Powered Depression Detection Using Chatbot and Live Video Facial Analysis

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ABSTRACT:
A mental health problem that affects millions of individuals worldwide is depression. Each person experiences depression in a different way, but common symptoms include feelings of hopelessness, emptiness, or sadness that last for a long time; loss of interest in or enjoyment from once-enjoyed activities; changes in appetite and sleep patterns; exhaustion; trouble focusing; and thoughts of self-harm or suicide In order to effectively assist and care for those with depression, early identification and prompt intervention are essential. With the use of chatbot technology, live video face analysis, and supervised machine learning algorithms trained on a depression dataset, this study suggests a cutting-edge AI-powered depression diagnosis system.The principal aim of the system is to ascertain the user's degree of sadness by use of a real-time facial expression analysis captured by a web camera. Additionally, the system will employ a chatbot interface to have natural language chats with users so they may express their feelings.

INTRODUCTION:
In a time when technology and healthcare are combining, mental health support is going through a revolutionary change. The "AI-POWERED DEPRESSION DETECTION USING CHATBOT AND LIVE VIDEO FACIAL ANALYSIS" project is an innovative attempt at the nexus of machine learning, artificial intelligence, and mental health services. As a worldwide mental health issue, depression necessitates creative approaches to early identification and prompt treatment. The goal of this initiative is to use cutting-edge technologies to give depressed people easily accessible, non-intrusive, and effective support. A common and frequently crippling mental illness, depression affects millions of individuals globally. Early detection of depression is essential for enhancing results and lessening the strain on healthcare services. Real-time data analysis combined with AI and machine learning gives a promising path in this regard. This research aims to develop a sensitive and all-encompassing depression detection system by combining natural language interactions through chatbot interfaces with facial expression analysis via live video streaming. The way we provide mental health support could be completely changed by this system. In addition, the initiative expands on a solid data base by utilizing insights from the vast amount of social media data, especially depression-related posts on Twitter. With the help of this varied dataset, the system will create a strong and accurate depression detection model by using a variety of

supervised machine learning techniques, such as support vector machines, decision trees, and neural networks. This initiative emphasizes the significance of ethics and user privacy, as well as the ability to increase the effectiveness and accessibility of mental health support, as technology continues to transform the landscape of healthcare. The "AI-POWERED DEPRESSION DETECTION USING CHATBOT AND LIVE VIDEO FACIAL ANALYSIS" project is a ray of hope for a better future in mental health care as it navigates the frontier between technology and mental health.

LITERATURE SURVEY:

Timely intervention can be facilitated by early identification of depression. The efficacy of automatic depression identification has been hampered by its reliance on variables that may be too coarse for individual-level data extraction. Interview questions often employed in the assessment of clinical depression have been mostly ignored by existing detection methods. In order to diagnose sadness, this study suggests a two-layered multi-modal model that can both identify the semantic categories of interview questions and extract characteristics from replies at the level of individual questions. The evaluation's findings show that the suggested model works better at detecting depression than the most advanced techniques. The study's conclusions have wide-ranging, interdisciplinary effects.

EXISTING SYSTEMS:

Existing framework for wretchedness location basically depend on customary techniques like self-managed polls and studies, which have limits in exactness and promptness. Fundamental facial examination might be incorporated however needs profundity and constant capacities. Moreover, information assortment from virtual entertainment stages like Twitter is as often as possible done physically, which can be tedious and wasteful. These frameworks by and large don't offer ongoing association with clients, which is significant for ideal mediation and backing. Moreover, the mix of AI models in existing frameworks is restricted and dependence on abstract self-reports can prompt errors. Generally current framework needs for an encompassing methodology coordinating ongoing facial investigation, chatbot connections, and AI for exact and open method for distinguishing and supporting people in danger of melancholy.

PROBLEM STATEMENT:

Due to the subjectivity of self-reports and their frequent inability to accurately reflect an individual's emotional state in the moment, delayed treatments and possible misdiagnoses may result. Although it lacks depth and real-time capabilities, basic facial analysis may be added. The efficacy of these technologies is further restricted by the lack of integration with sophisticated machine learning models and real-time interactivity. As a result, there is an urgent need for a more comprehensive and technologically sophisticated strategy to quickly and reliably identify and assist people who may be depressed. Thus, to provide a real-time evaluation of a person's emotional state, our suggested method makes use of cutting-edge AI and machine learning technology. The technology attempts to provide a comprehensive approach to mental health monitoring by mixing live video facial analysis with NLP through chatbot conversations.

PROPOSED SYSTEM:

The suggested depression detection technique is a major improvement over current practices. Real-time facial analysis, machine learning algorithms trained on a dataset of tweets about depression, and natural language processing via a chatbot interface are all included. It provides real-time interaction by continuously evaluating a webcam's live video feed and holding meaningful chats with users. Reliance on subjective self-reports is decreased when machine learning models are integrated, improving the accuracy of depression detection. No matter where they live, people at risk of depression can be identified and supported with its help thanks to its scalability and accessibility. A substantial step toward a more efficient and generally available method of providing mental health support is represented by this suggested system.

PREPROCESSING:

Preprocessing live video for face analysis in depression detection entails numerous key procedures to achieve accurate and dependable results. These methods prepare the raw video data for further analysis by improving its quality and extracting essential information. The primary preprocessing processes are:

DEEP FACE:

DeepFace computer based intelligence is the most lightweight face acknowledgment and facial trait investigation library for Python. The publicly released DeepFace library incorporates all driving edge simulated intelligence models for current face acknowledgment and consequently handles all systems for facial acknowledgment behind the scenes.

Face Verification: The process of comparing two faces to determine if they match is known as face verification. As a result, face verification is frequently employed to match one candidate's face to another. This may be used to verify if a person's face corresponds to the one on an identification paper.

Face Recognition: Finding a face in an image database is the task of face recognition. facial verification must be conducted several times in order to perform facial recognition.

Facial Attribute Analysis: This work involves characterizing the visual characteristics of face pictures. Consequently, features including age, gender categorization, mood analysis, and race/ethnicity prediction are extracted through the study of face traits.

Real Time Facial Analysis: Tests for facial recognition and facial attribute analysis with the real time video feed of your webcam are included in the Real-Time Face Analysis module.

In this facial analysis Specific facial features, such as the lips and eyes, are identified and used as facial markers for analysis. In order to spot depressive symptoms (such as melancholy or lack of emotion), facial expressions are also examined.

Fig 1: Face Detect Model

OPEN CV:

The lightest face detector is OpenCV. The widely used image processing tool employs an algorithm called haar-cascade, which is not grounded in deep learning methodologies. Because of this, it operates at a

comparatively modest speed. OpenCV needs front facing images in order to function effectively. Its eye detection performance is also mediocre. It throws off the alignment. Remarkably, OpenCV is used by DeepFace as its default detector.
haar-cascade algorithm**:** Haar Cascade is a machine learning strategy that uses a large number of positive and negative images to train the classifier.

Depression Dataset:
Depression-related tweets were gathered from Twitter. The tweet data is preprocessed to extract relevant characteristics (such as sentiment and keywords) for training the model.

Fig 2: Depression Dataset

Machine learning algorithms are unable to directly interpret raw text. In order to turn text into a matrix or vector of features

Natural Language Processing:
Elementary feature extraction approaches in natural language processing (NLP) are utilized to analyze the resemblances between textual segments. Natural Language Processing (NLP) is a field within computer science and machine learning that focuses on teaching computers to analyze and understand vast quantities of human language data. In essence, Natural Language Processing (NLP) refers to the capacity of computers to comprehend human language. Importance of feature extraction methods Machine Learning algorithms utilize a predetermined set of features from the training data to generate output for the test data. It is necessary to employ feature extraction techniques:

TF-IDF Vectorizer:
TF-IDF, short for Term Frequency-Inverse Document Frequency, is a statistical metric employed in tasks related to information retrieval and natural language processing. The TF-IDF Vectorizer is a tool used to convert a collection of text documents into a numerical representation, based on the importance of each word in the documents.The TF-IDF Vectorizer draws attention to a particular problem that is significant even if it may not occur frequently in our corpus(data-set).
It is divided into two smaller portions, which are:
1. Term Frequency (TF)
2. Inverse Document Frequency (IDF)

Logistic Regression Classifier:
Logistic regression is a statistical method for binary classification issues that can also be applied to multi-class classification. When used in text classification, the purpose is to predict the category or class of a gi-

ven text based on its characteristics.

a) Text Representation: Text data needs to be text vectorized a process that turns text into numerical features before using logistic regression.

Term Frequency-Inverse Document Frequency (TF-IDF), Bag of Words (BoW), and other methods are frequently used for text vectorization.

b) Extracting Features: Once data has been quantitatively represented, the representations can be utilized as model features.

Word counts in BoW, weighted values in TF-IDF, and numerical vectors in embeddings are examples of features.

c) Model of Logistic Regression: Using the logistic function, logistic regression models the relationship between the features and the likelihood of belonging to a specific class.

Any real-valued number can be mapped into the range [0, 1] by the logistic function, commonly known as the sigmoid function, and this range is appropriate for describing probabilities. To determine the likelihood of being in the positive class, the logistic regression model applies the logistic function to a weighted sum of the input features.

Navie Bayes Classifier:

In this instance, text cannot be directly fed into our classifier. Because texts are long and contain numerous words in different combinations, we utilize the number of times a word appears in a single text (term frequency, tf) and the number of times it appears in all text (inverse document frequency, idf) to create feature vectors.

In order for the algorithm to determine how likely it is that a text belongs in a certain category, feature vectors representing texts contain the probabilities of appearance of the text's words inside texts of that category.

Feature Vector

Document ID	Word 1	Word 2
1	2	0
2	0	1
3	3	1
4	1	3

ID	Class
1	1
2	0
3	0
4	1

1- belongs
0- Does not belong

After determining the likelihoods of each category, we identify the category with the highest likelihood, at which point our text is categorized.

RESULTS:

The aforementioned classifiers are trained and evaluated to identify depression over a dataset of tweets relating to depression. Table 1 represents performance metrics of logistic regression classifier in terms of accuracy, precision and F1 score while Table 2 represents performance metrics of Navie Bayes classifier. The comparison graph of both classifiers is shown in Fig 3.

TABLE 1
Performance Measure Metrics for Logistic Regression Classifier

Performance Measure Metrics	Navie Bayes Classifier
Accuracy	95.375
Precession	95.375
F1-Score	95.375

TABLE 2
Performance Measure Metrics for Navie Bayes Classifier

Performance Measure Metrics	Logistic Regression Classifier
Accuracy	97.986
Precession	98.019
F1-Score	97.986

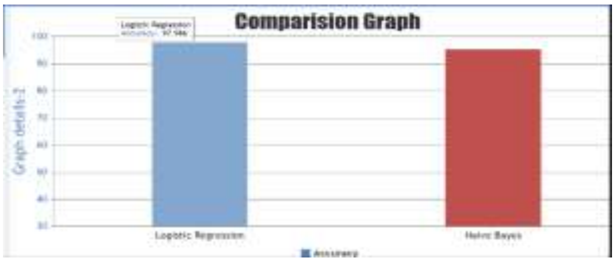

Fig 3: comparison Graph

CHATBOT INTERFACE:

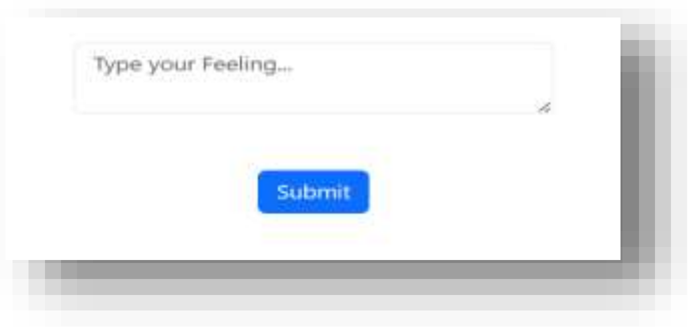

Fig 4: ChatBot

Through a chatbot interface, the system interacts with the user. To do this, start a natural language dialogue with the user in order to learn more about them and gauge their emotional condition.

Text replies from users in the chat session are gathered. Machine learning models are trained on the depression dataset. In the end, the models identify patterns in the text data that point to depression and provide outputs that indicate ‘Depressed’ or ‘Not Depressed.

Fig 5: Depressed

Fig 6: Not Depressed

LIVE VIDEO FACIAL ANALYSIS:

Using live webcam video feeds, the face analysis module recognizes facial expressions in real time. It uses facial expressions and landmarks to determine the user's emotional state. Deep learning and computer vision methods i.e, DeepFace and OpenCv can be used with this curriculum.

The real-time depression detection module integrates chatbot answers with face analysis to continually evaluate user input. It offers instantaneous input on the user's emotional condition.

Fig 7: one of the outcome(Final Result)

FUTURE ENHANCEMENT:

Substantial improvements might be made to the suggested depression detection system in the future. Initially, it has the ability to integrate multimodal data fusion, utilizing physiological sensors such as heart rate monitors to offer a more thorough comprehension of users' emotional states. Machine learning-powered personalized interventions can adjust assistance according to each person's unique profile and preferences. Increasing language support to include more languages and dialects will improve accessibility worldwide. Through time, the system will be able to adapt and get better thanks to continuous learning approaches. When customers require urgent assistance, integration with telehealth systems can put them in direct contact with mental health specialists. The system's usefulness can be increased by features that support mood management, and long-term research can provide insights into the course of depression. By enabling users to get help whenever it is most convenient for them, the system's multi-device accessibility promotes a more comprehensive and user-centered approach to depression identification and intervention.

CONCLUSION:

To sum up, the project "AI-POWERED DEPRESSION DETECTION USING CHATBOT AND LIVE VIDEO FACIAL ANALYSIS" is a major advancement in the fields of technology and mental health. It offers a comprehensive method of identifying depression by utilizing AI, machine learning, and real-time data analysis. Facial analysis combined with chatbot conversations guarantees a thorough evaluation of the user's emotional state. Even though the project shows a lot of promise for early depression detection and support, privacy protection and ethical issues need to stay top priorities. By offering prompt support and enhancing general wellbeing, this creative approach has the potential to significantly impact mental health care with more development and user testing.

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