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DEPRESSION DETECTION SYSTEM USING ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

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Abstract: In a state of natural psychic equilibrium, tension may be viewed as a disturbance in general. A person's mental health will be put under stress if they cannot balance the expectations placed on themwith their ability to cope with them. There are many different kinds of challenges. Psychological equilibrium disruption is a broad description of depression. Depression detection is one of the main areas of biomedical engineering study because it may be simple to avoid depression with the right measures. There are many bio signals accessible, including Mri, Rgb, oxygenation, and Frs. which can be used to determine depression levels because they show unique changes in depression induction. Due to the readily available recording, we use ECG as the top candidate in this endeavor. Multiple SVM model types have been examined by changing the function number and kernel type**.**

Keywords: Preprocessing, Segmentation, SVM Algorithm, Machine Learning. Feature Extraction,Classification CNN Algorithm.

1. INTRODUCTION

Disorders like depression and worry are very common everywhere. It has been justified to pay attentionto the negative impacts of depression on patient health as well as the associated financial burden. To support objective depression assessment, the affective computing community engaged in signal processing, computer vision,and machine learning approaches for analyzing verbal and non-verbal behavior of depressed patients [1] and made predictions about what patterns should be indicative of a depressed state [2] [3]. For the purpose of automaticdepression evaluation, these studies have examined the relationship between objective measurements of voice, speech, and nonverbal behavior and clinically subjective ratings of depression severity. Despite significant progress in recent years, there are still a number of unresolved scientific questions in the field of depression: • Audio and video features from individuals only concern the paralinguistic information, such as speaking rate, facial action units (AUs), rather than the linguistic information from the speaking content, which can reflect the sleep status, emotional status, feeling and another life status of the individual. Designing a multi-modal fusion paradigm and investigating more efficient audio, visual, linguistic, and other multi-modal features are crucial for depression recognition.

Only a small number of depression datasets and hardly any pre-training models are presently available due to privacy concerns. Additionally, there is a dearth of consistency in these widely used depressiondatasets. They are difficult to combine to increase the number of samples, which makes it difficult to benefit from deep models. They have various languages, durations, data types, and goals. To expand the number of samples and enhance the model performance, some data augmentation techniques must be used.

2. LITERATURE REVIEW

I.Paper Name: Clinical Depression Detection in Adolescents by Face

Author: Prajakta Bhalchandra Kulkarni, Minakshee M . Patil

Description: Depression is a serious issue that can have numerous effects on individuals. There are many treatments available to help those who are depressed, but the problem is identifying those who aren't even aware that they are depressed. As a result, various models are created to predict depression in individuals, and this articleprovides an overview

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of three main models: using imaging and machine learning techniques, using risk variables,and using machine learning classifiers and WEKA. People with depressive disorders are physiologically and psychologically unfit. It affects people's quality of living in a variety of ways. In addition, depression need not be severe to have an impact on a person's existence. There are numerous studies being done on how to predict depression, and from those earlier studies, the three main techniques have been examined to see which is the mosteffective. After researching machine learning classifiers, feature reduction methods, cross-validation methods, andrisk factors, the Bayesnet Classifier for Percentage Split testing choice proved to be the most reliable and accuratetechnique. To evaluate the predictive model's success, various data sets can be used. Future research into alternative techniques for this depression prediction could lead to increased precision

II. Paper Name: Multimodal Spatiotemporal Representation for Automatic Depression Level Detection

Author: Mingyue Niu, Student Member, IEEE, Jianhua Tao, Senior Member, IEEE, Bin Liu, Member, IEEE, Jian Huang, Student Member, IEEE, and Zheng Lian

Description: Physiological studies have shown that there are some differences in speech and facial activities between depressive and healthy individuals. Based on this fact, we propose a novel spatiotemporal Attention (STA) network and a Multimodal Attention Feature Fusion (MAFF) strategy to obtain the multimodal representation of depression cues for predicting the individual depression level. Specifically, we first divide the speech amplitude spectrum/video into fixed-length segments and input these segments into the STA network, which not only integrates the spatial and temporal information through the attention mechanism but also emphasizes the audio/video frames related to depression detection. The audio/video segment-level feature is obtained from the output of the last full connection layer of the STA network. Secondly, this paper employs the eigen evolution pooling method to summarize the changes in each dimension of the audio/video segment-level features to aggregate them into the audio/video level feature. Thirdly, the multimodal representation with modal complementary information is generated using the MAFF and inputs into the support vector regression predictor for estimating depression severity. Experimental results on the AVEC2013 and AVEC2014 depression databases illustrate the effectiveness of our method

III. Paper Name: Multi-Modal Depression Detection and Estimation

Author: Le Yang

Abstract: Depression and anxiety disorders are critical problems in modern society. The WHO studies suggest that roughly 12.8 percent of the world’s population is suffering from a depressive disorder. In this work, we propose several novel approaches toward multi-modal depression detection and estimation. Our previous studies mainly explored the multi-modal features and multi-modal fusion strategies, experimental results showed that the proposed hybrid depression classification and estimation multi-modal fusion framework obtains promising performance. The current work contains two parts: 1) In order to mitigate the impact of lack of data on training depression deep models, we utilize a Generative Adversarial Network (GAN) to augment depression audio features, so as to improve depression severity estimation performance. 2) We propose a novel FACS3DNet to integrate 3D and 2D convolution networks for facial Action Unit (AU) detection. As far as we know, this is the first work to apply 3D CNN to the problem of AU detection. Our future work will 1) focus on combining depression estimation with dimensional affective analysis through the proposed FACS3DNet, and 2) collect the Chinese depression database. When completed, these studies will compose the author’s dissertation. My research mainly focuses on three points: (1) explore effective multi-modal features and the multi-modal fusion strategies for depression recognition; (2) mitigate the influence of lack of data on training the depression deep models; (3) combine depression estimation with dimensional effective analysis. For the first research point, we notice that when depression classification and depression estimation are considered at the same time, better performance could be obtained. Especially, text features (language information) have a good effect on depression classification, while audio and video can be used to build a preliminary depression estimation framework. For the second research point, the DCGAN-based data generation approach effectively improves the performance of depression estimation, which also provides some new insights into depression data augmentation. Also, we have started to collect a Chinese depression database. For the third research point, which will be our future work, we will adopt the current FACS3D-Net to integrate depression estimation and dimensional affective analysis simultaneously. We believe this research could provide a novel perspective on depression recognition.

IV.PROPOSED STSTEM

Depression detection is one of the main areas of biomedical engineering study because it may be simple to avoid depression with the right measures. There are many bio signals accessible, including Mri , Rgb, oxygenation, and Frs. which can be used to determine depression levels because they show unique changes in depression induction. Due to the

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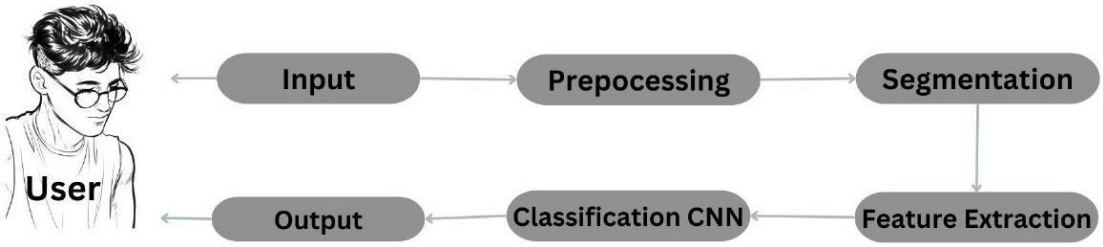
readily available recording, we use ECG as the top candidate in this endeavor. Multiple SVM model types have been examined by changing the function number and kernel type.

System Architecture



4.1 CNN Algorithm :

A CNN is a particular type of network architecture for deep learning algorithms that is used for jobs like image recognition and pixel data processing. Although there are other kinds of neural networks in deep learning, CNNs are the preferred network design for identifying and recognizing objects. A CNN can have multiple layers, each of which learns to detect the different features of an input image. A filter or kernel is applied to each image to produce an output that gets progressively better and more detailed after each layer.

CNN is designed to automatically and adaptively learn spatial hierarchies of features through backpropagation by using multiple building blocks, such as convolution layers, pooling layers, and fully connected layers. Familiarity with the concepts and advantages, as well as limitations, of convolutional neural networks is essential to leverage its potential to improve radiologist performance and, eventually, patient care.

4.2 SVM Algorithm:

A supervised machine learning method called Support Vector Machine (SVM) is used for regression and/or classification. Classification is where it is most frequently used, despite the fact that it can occasionally be very useful for regression.

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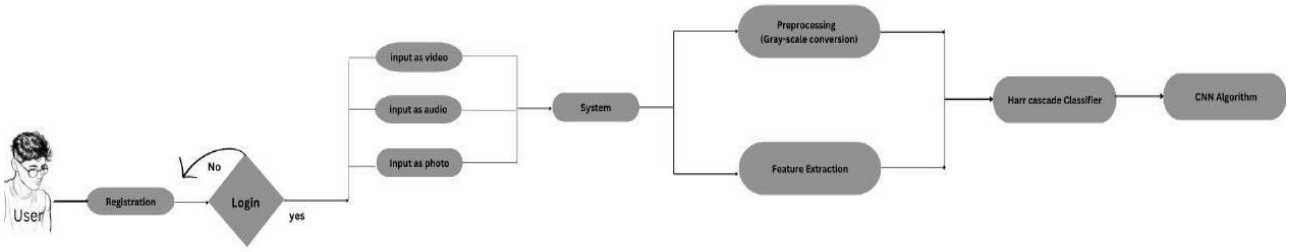

Prepossessing: The machine in this module will process the input. The prepossessing machine will train the dataset by eliminating the noise from the input before resizing it.
Feature Extraction: In this module, the user will input attributes for the machine, such as EMG, HR, ECG, andRESP Seconds.
Classification: Using the SVM algorithm, user testing value classification from train data (support vector Machine Algorithm). Machine learning will determine whether the individual receiving the input is depressed ornot. Here, we use machine learning with SVM to increase accuracy (support vector Machine Algorithm)

V.CONCLUSION:

In this research paper, we presented a comprehensive study on the development of a Depression Detection System using Artificial Intelligence (AI) and Machine Learning (ML) techniques, specifically focusing on audio and video inputs. Our objective was to design an innovative system that could effectively identify and detect symptoms of depression in individuals by analyzing their audio and video data.
Through our research, we successfully demonstrated the potential of using AI and ML algorithms for depression detection. We employed advanced techniques such as speech analysis, facial expression recognition, and sentiment analysis to extract relevant features from audio and video inputs. These features were then used to train and evaluate machine learning models, including deep neural networks and support vector machines.
However, it is important to acknowledge the limitations and challenges associated with this research. The availability and quality of audio and video data may vary, and there are ethical considerations regarding privacy and consent when dealing with sensitive personal information. Additionally, the generalizability of our findings across diverse populations and cultural contexts should be further investigated.
In conclusion, this research contributes to the growing field of mental health technology by demonstrating the potential of an AI-based Depression Detection System using audio and video inputs. The system has the potential to assist healthcare professionals in the early identification and monitoring of depression, facilitating timely intervention and support. Future work should focus on refining the system, conducting larger-scale studies, and addressing the practical implementation challenges to ensure its effectiveness and widespread adoption in real-world clinical settings. Ultimately, the development of such technologies holds promise in improving mental health care and enhancing the overall well-being of individuals.

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