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Deep Learning based Depression Estimation using Facial Expressions

Chhaya Nayak[1], Dr. Sachin Patel[2]

[1]*Research Scholar Department of Computer Science, SAGE University, Indore*
[2]*Associate Professor Department of Computer Science, SAGE University, Indore*

Email: chhaya2007@gmail.com , drsachinpatel.sage@gmail.com

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***Abstract** –The serious mental health condition of depression may greatly impact a person's daily life. Chronic sorrow, lack of interest in once-enjoyed activities, weariness, changes in food or sleeping patterns, difficulties focusing, feelings of hopelessness, and other symptoms are typical symptoms of depression. Effective treatments are readily available to help control symptoms and enhance the quality of life. Deep learning, a subset of machine learning, has been utilized to identify and analyze brain activity patterns that may indicate depression. Deep learning models use artificial neural networks to learn from and make predictions on large data sets. These models can accurately identify patterns and relationships within complex data sets, including brain activity data. Researchers have used deep learning models to analyze EEG (electroencephalogram) data from depressed patients and healthy controls. By comparing the brain activity patterns between these two groups, deep learning models have been able to identify unique features specific to depressed individuals. This analysis has also led to the development of predictive models that can accurately classify individuals as depressed or not based on their brain activity patterns.While deep learning is still in its early stages of development for mental health applications, the potential for improving depression diagnosis and treatment is promising. As research progresses, deep learning models could become a valuable tool in aiding mental health professionals in identifying and treating depression.*

***Keywords-** Deep Learning, CNN, PHQ, Multimodal, Depression*

I- INTRODUCTION

A serious mental health condition called depression can have an effect on a variety of aspects of your life. A complicated and varied illness, depression has an impact on a person's social, physical, and mental health. Depression may be genetic, environmental, or a combination of the two causes. In an effort to comprehend and examine the various components that contribute to depression, numerous research studies have been done globally. Depression is more than just a brief period of sadness or depression. It frequently entails ongoing depressive emotions, thoughts of hopelessness, or losing interest in past interests. Changes in eating, sleeping habits, energy levels, focus, and general well being might also result from it. The depression level of a person can be as mild, moderate, or severe depending on the number of symptoms and their intensity. There are a few therapy choices accessible; treatments and services range from therapies to counseling sessions. There are additional treatments using brain simulation [5]. According to a WHO assessment, there are over 280 million depressed persons in the globe, and there are close to 800,000 suicides attributed to depression each year [1][2]. The fourth most common disease in the world, depression has emerged as a major issue that affects individuals of all ages, including children, teenagers, adults, and the elderly. Due to a lack of early services and therapies for depressed patients, more than 80% of people do not receive the correct care [6, 7].

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Depression estimation models based solely on deep learning are not meant to replace a clinical diagnosis. They can serve as supportive tools for healthcare professionals and researchers, but a proper diagnosis should always be made by qualified mental health professionals based on comprehensive assessments.

Depression estimation using deep learning models with artificial neural networks is an area of ongoing research. Artificial neural networks, which are the foundation of deep learning, can be used to analyze various data types related to depression and mental health. Here's how it can be applied.

Depression estimation using deep learning typically involves the analysis of various data types, such as text, images, speech, or physiological signals which can be summarized as follows.

i. Text-based analysis: For processing sequential input, like text two types of networks mostly used Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNNs). These models can acquire patterns and linguistic cues related to depression by training on massive datasets of text from people with and without depression. They can analyze textual material from forums, social media, and electronic health data to determine the severity of depression.

ii. Image-based analysis: For image processing, convolutional neural networks (CNNs) are frequently utilized. They can be trained using datasets of body language, facial expressions, or other visual clues related to depression. These models are capable of identifying minute adjustments in body language or facial expressions that might be signs of depression.

iii. Speech-based analysis: Speech patterns can be analyze with the help of Recurrent Neural Networks or Convolutional Neural Networks. By processing audio data, these models can identify features in the voice that are associated with depression, such as changes in pitch, tone, or speech rate.

iv. Multimodal analysis: Some research combines multiple data types, such as text, images, and speech, into a single deep learning model. These multimodal models aim to leverage the complementary information from different sources to improve depression estimation accuracy.

It's important to remember that while these models might offer insightful information, they are not intended to replace professional mental health evaluations. Estimating depression solely through deep learning models is a complex challenge, and their reliability and generalizbility in real-world scenarios require further research and validation.

People with depression disorders behave psychologically differently from average people. For instance, there are differences between the brain signal produced and the body's amount of feel-good neurotransmitters like serotonin and oxytocin [16]. Nuclear magnetic resonance (NMR), electroencephalography (EEG), and other auditory and visual signals all differ in depressed patients [17,18]. Psychologists are therefore unable to forecast depression's symptoms and severity with any degree of accuracy, which worsens the situations of depressed patients. Therefore, both patients and psychologists must use an accurate, automatic, and accessible method.

The paper is organized as follows: section II deals with the review of the existing techniques in the field of recommendation systems and teachers performance evaluation methods. The mathematical framework for the collaborative filtering used in the recommender system is given in section III. The proposed self-adaptive HMM based recommender system optimized with PSO is discussed in section IV. Section V discusses the effectiveness of the proposed strategy through the analysis of the performance parameters while section VI concludes the paper.

II- LITERATURE REVIEW

A study analyzed the relationship between depression and sleep disturbances. The study found that depression often leads to sleep disturbances, and individuals with sleep disturbances were more likely to develop depression [19].

Another research study which represent the relationship between depression and cognitive functions[20]. The results indicated that depression affects cognitive processes, such as attention, memory, and decision-making.

A study focusing on the relationship between depression and social support. The findings revealed that individuals with depression often lack social support, which can lead to further decline in mental health [21].

A comprehensive study on the use of social media platforms as a tool for evaluating and predicting depression was performed[19]. Their primary contribution is the use of user text posts for mental health surveillance using SVM classifiers and the suggestion of a depression index from social media posts. Crowd sourcing is used to collect the Twitter usernames of users who consent to having their previous posts indexed in order to extract user-centric content and interaction components. Despite not being real-time and being unimodal, their SVM with radial basis function predicts the onset of depression with 70% accuracy [10] [11].

In conclusion, depression is a complex and multifaceted disease that affects individuals' mental, physical, and social health. The interplay between different contributing factors, including sleep disturbance, cognitive functions, social support, and gut microbiota, has been widely studied.

However, some potential strategies for depression management that have emerged from these studies include:

1. Improving Sleep Quality: Sleep disturbance has been identified as a major contributor to depression. As a result, increasing the quality of your sleep through sleep hygiene practices (such as keeping a regular sleep-wake schedule and abstaining from coffee and electronic devices before bed) or cognitive-behavioral treatment for insomnia (CBT-I) may help lessen the symptoms of depression.

2. Enhancing Cognitive Functions: Deficits in cognitive functions, such as attention, memory, and problem-solving, are common in depression. Therefore, cognitive remediation therapy, which targets these cognitive deficits, may help improve depressive symptoms.

3. Increasing Social Support: Social support is a protective factor against depression. Therefore, interventions to enhance social support, such as group therapy or social skills training, may help alleviate depressive symptoms.

4. Modulating Gut Microbiota: There is growing evidence that depression may be influenced by the gut microbiome. Therefore, interventions aimed at modulating the gut microbiota, such as probiotic or prebiotic supplementation, may be a potential strategy for depression management.

In summary, understanding the interplay between different contributing factors of depression can help inform effective interventions for depression management. While more research is needed to develop and refine these strategies, early findings suggest that improving sleep quality, enhancing cognitive functions, increasing social support, and modulating gut microbiota may be promising avenues for depression management.

In addition, addressing underlying biological and psychological factors, such as inflammation, stress, and negative thought patterns, can also effectively reduce depressive symptoms.

Other potential interventions include exercise, mindfulness training, and psychotherapy, such as cognitive behavioral or interpersonal therapy.

It is essential to remember that depression is a complicated and diverse disorder, and that some people may respond better to some interventions than others. Therefore, for best results, a personalized approach to depression management is necessary.

In addition, medication and therapy are not mutually exclusive, and a combination of both may be the most effective form of treatment for some individuals. Additionally, it is essential for those who suffer from depression to have a solid support system and engage in self-care activities like getting enough sleep, eating well, and doing things they like. People who suffer from depression can lessen their symptoms and enhance their quality of life with the right care and assistance. A mental health expert, such as a therapist or psychiatrist, who can offer counseling and medication if necessary, should be consulted. It may also be beneficial to join support groups or ask friends and family for support. Engaging in self-care activities, such as exercise, relaxation techniques, and creative outlets, can also aid in managing symptoms and improving mood. It is essential to remember that recovery from depression is possible, and seeking help is the first step toward healing.

In addition, leading a healthy lifestyle can be quite important in controlling depression. This involves avoiding drugs and alcohol, eating a balanced diet, getting enough rest, and engaging in regular exercise. Creating a regular schedule and establishing attainable goals can also add structure and help with symptom management.

It is essential to be patient with oneself and to remember that recovery is a journey that may involve setbacks and challenges. It may be helpful to keep a journal to track progress and reflect on experiences. Seeking professional help and practicing self-care can aid in managing depression and improving overall well-being.

Wang et al. [9] employed the Active Appearance Model (AAM) [10] to assess facial images and image sequences of depressed patients. The AAM offers a statistical model of tone variation and facial structure that is lifelike. The results of video analysis of depressed patients were contrasted with the predictions of the AAM model. The distinct areas of the face were given numerical values using FACS encoding[4]. In addition to the facial expression analysis, we also considered changes in the bilateral brow and corner of the mouth motions, blinking frequency, and eye pupil movement. Support vector machines (SVM), one of the best separation hyperplanes in the feature space, were used to categories the features. Radial Basis Function is used by the SVM classifier. They used facial features, such as the lateral canthus and glabellar regions, as well as markers like pupil movement and blink frequency, both of which are quite effective at detecting depression. The research of depression has become more complex by accounting for distinctive facial features including lip shape, eye color, and more.

III -PROPOSED MULTI-MODAL FRAME WORK

he general depression detection method is shown in Fig. 1, and it needs a suitable multimodal depression database to be trained and tested. The various visual depression datasets are briefly summarized in this publication.

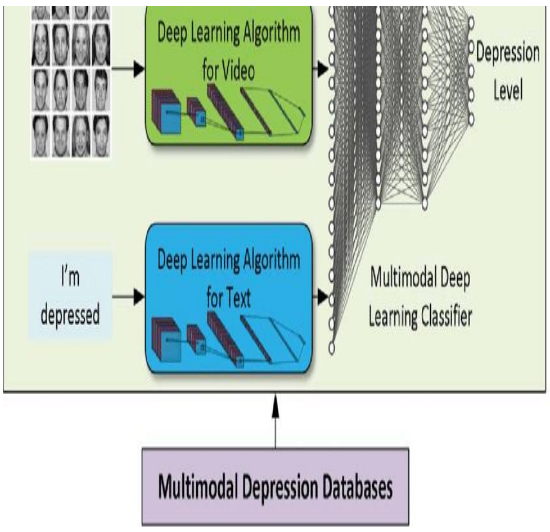

Fig. 1

IV-PROPOSED METHODOLOGY

The proposed model is based on two algorithms, CNN and LSTM, respectively. Convolution neural network, also known as CNN or ConvNet, is a deep learning algorithm that accepts input in the form of a picture, weights the input values, and then aids in classifying the output image [30]. In addition to image classification, Data analysis, pattern recognition, computer vision, and NLP activities all uses CNN [8]. CNN, sometimes referred to as Multilayer Perceptron, is a subclass of Artificial Neural Networks (ANN). CNN is an algorithm that draws inspiration from how neurons in the human brain are built [8]. The convolution operation is the basis of how CNN operates. As demonstrated in the example below and in Fig. 1, the convolution operation is carried out as follows. The CNN algorithm has the advantage that it requires significantly less processing time than other algorithms. Applications of the CNN algorithm include text recognition, speech recognition, image identification, pattern recognition, and issues with interpreting natural language. The architecture of the CNN algorithm includes the number of fully connected, max-pooling, and convolutional layers. ReLU is used in the proposed work as an activation function. A 0.25 dropout layer value is also used to address the overfitting problem. Flatten layers and convolutional layers are integrated [11, 3]. The output layer uses binary labels (0 and 1) to show whether a user is depressed or not. The structure of CNN Architecture is shown in Fig. 2.

The proposed work's methodology is as follows:

Datasets are derived from picture datasets[2][4][12] during the data collection process. These image databases include a variety of images. Of users, millions of whom suffer from depression. These pictures can be used to learn how to spot a depressed person.

Image Classification – Following data collection, images will be classified according to whether or not they show a person's face. Feature Extraction: Deep learning neural networks that are already in existence are utilized to extract features from images.

Designing Multimodel - To extract the characteristics of depression from an image, a multimodel architecture is created and trained using trained datasets that contain millions of photographs from various users.

Image Categorization: Supervised classifiers are built by learning the different kinds of images from the datasets already-existing images. The learnt classifier will be utilized to categorize people who are depressed.

V-EXPERIMENT ANALYSIS

The AVEC2013 [13] and AVEC2014 [9][14] depression datasets are used as our benchmarks in this section to assess how well the suggested multi-modal architecture performs. For determining the level of depression, the AVEC2013 and AVEC2014 datasets comprise the raw audio and raw face video data. The Audio/ Visual

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Emotion Challenge's 2013 and 2014 editions were the first to use these datasets. Using the audio-based spatio-temporal network on the raw audio data from the Extended Distress Analysis Interview Corpus (E-DAIC) dataset, we further investigated the impact of linguistic factors on the audio analysis [15]. We briefly outline the datasets, experimental design, and evaluation criteria first. Then we go into detail about a systematic ablation study for the parts of our framework. Finally, we contrast the proposed deep multimodal approach with state-of-the-art techniques.

Dataset

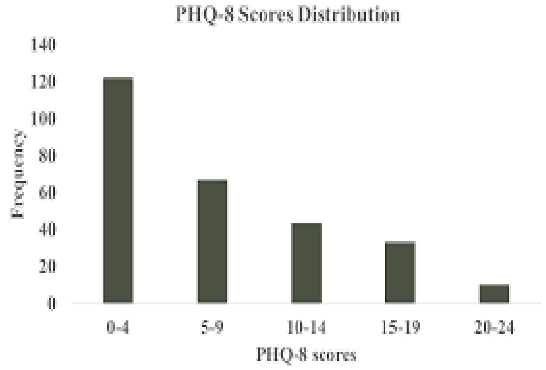
We used the AVEC2013 [13] and AVEC2014 depression datasets [14] to evaluate how well the proposed multi-modal framework performed in predicting the level of depression (i.e., BDI-II score). Later, a more detailed evaluation of the audio-based spatiotemporal network's performance is carried out using the E-DAIC dataset [15]. The depression dataset for the year 2013 contains 150 videos from 82 patients. The audio-visual depressive language corpus (AVidCorpus), a component of the AVEC2013 dataset, has 340 films from 292 people. Four sessions have five persons, while three sessions have 93, two have 66, and one has 128.

The AVEC2014 depression dataset, which is also a subset of AViD-Corpus, consists of 300 videos from 84 people. Participants in this dataset do two tasks: Northwind, in which they read aloud a passage from a story, and Freeform, in which they provide answers to prompts like "Discuss a sad childhood memory." There are 150 films in total, 150 for the Freeform task and 150 for the Northwind task.

The DAIC Wizard-of-Oz dataset (DAIC-WOZ dataset) is expanded by the E-DAIC [15] dataset. Unprocessed audio, text, and low-level visual features (Pose, Gaze, Facial Action Units, and Bag-of-Visual Words) are included in this dataset. Clinical interviews are part of the E-DAIC for conditions causing psychological discomfort, such as depression and posttraumatic stress disorder. The dataset includes 275 persons; 163 are used for training, 56 for development, and 56 for testing. Each interviewee could speak English, and they normally lasted five to twenty minutes. Along with the interview ID, each interview includes a PHQ8 score that goes from 0 to 24. The distribution of PHQ-8 scores in the E-DAIC dataset is shown in Fig. 2.

BDI-II score	Severity level
0–13	None or minimal
14–19	Mild
20–28	Moderate
29–63	Severe

Fig. 2



VI- CONCLUSION

Through this work we have presented a framework which evaluates a person's depression level using linguistic, audio visual features. As a result, it has been wrapped up in two sections. For Phase 1, a model that uses tagging from audio, video, and textual modalities to assess the likelihood that the person is depressed has been made public. A gating mechanism and sentence-level architecture are set up for the project. Models show that sentence-level looks perform better when compared to the other strategies. In the future, it might be possible to achieve a better level of feature retrieval. Several auditory metrics, including reaction time, the frequency of pauses, speech modulation, and quiet rate, may be examined in order to better understand the symptoms. The picture modality can be constructed for additional work. However, Future applications include the ability to record electrophysiological signals generated by the body. It can be mimicked, just like in an interview, when a person's body position can be seen, aiding in a more accurate diagnosis. Even when they only have mild depression, some people have a tendency to complain a lot, unlike the majority of genuinely depressed patients who prefer to speak less throughout the screening exam. As a result, it is still difficult to diagnose depression in its early stages. These tests can be useful in identifying depression, but a clinical diagnosis should always be made first.

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