Smart model for Depression detection Using Deep Learning

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Abstract— In this research paper to classifying Depression detection People datasets using a deep neural network model, namely, Smart model for Depression detection (SMDD) is proposed. The suggested SMDD model keeps the forward and reverse sequential data and assigns a normal or depressed rating to them. We checked their public data set findings using a variety of machines and profound learning models. There are certain disadvantages as well, such as the use of a limited dataset and the use of just Twitter. Furthermore, we did not use the pre-trained Video data sets model on the data collection, as well as unbalanced class labels, resulting in lower system performance. we evaluated work by utilizing deep learning approaches to evaluate the method's performance. The use of balanced classes in training data would increase the accuracy of the proposed approach and, as a result, the reliability of function representation schemes.

Keywords— *Smart model for Depression detection , Depression detection , convolutional neural network , artificial intelligence.*

I. Introduction

Depression, a widespread mental condition, affects nearly 300 million people worldwide. Sadness, a reduction of participation in athletics, an improvement in appetite and sleep patterns, energy deprivation, strong thought problems, and an increased risk of suicidal ideation are some of the symptoms[1]. People are often unable to pursue clinical counsellors or therapy for help with their mental health issues. According to the (WHO), less than half of those suffering from depression receive treatment (in certain nations, less than 10 percent). The WHO also noticed that depression is on the rise, with a net spike of over 90 percent in cases of depression between 2015 and 2018. Although promising treatments for depression have been developed, the WHO states that one of the major barriers to effective treatment is the inaccuracy of diagnosis. It is also critical to incorporate a simple and efficient approach for valid and effective pre-screening of depressive symptoms. As the WHO called on its Participants at the 2018 Seventy-First World Health Assembly [2], such an answer could not only rely on a self-assessment questionnaire, but also on a health approach that utilizes new technologies. According to a recent WHO recommendation, such an inexpensive system will reduce the risk of erroneous assessment and lower social stigma. Stress has been related to human behaviour in studies. A lack of muscle coordination (also known as laryngeal control) is one of the signs of depression, which is induced by a disruption in the brain's basal ganglia. Voice sound contains information on a person's medical illness, according to Quatieri and Malyska[3].. Other researchers looked at how depression and the usage of this information in classification and prediction systems affect common paralinguistic speech characteristics. The quantification of predictive depression evaluation (ADD) algorithms could be aided by these comparisons. The Computer Machinery Association organised the 2017 AVEC "Real-life Depression and Efect Recognition Workshop and Challenge," which centred on basic studies on depression[5]. The results of the other reviews were satisfactory. They used video, in their systems, and they were able to predict PHQ-8 values from video, data stronger than the baseline. The use of profound convolutional neural networks in this paper provides a novel method for automated video-based depression screening.

II. RELATED WORK

(France B. Kulkarni et al.,2018) Fisher vector encoding left Bow's demerits (terms). And LTrP has improved the Local binary pattern's demerits and performance. The outcome of this strategy is either 'depressed' or 'not depressed.' (A. Mulay et al., 2020) The analysed symptoms of the person are classified into one of the following depression categories: Minimum, Mild, Medium, and Serious are all options. The two key elements of the depression diagnosis process are video input and the Beck Depression Inventory. (S. R. Kamite et al., 2020) build an algorithm that effectively predicts depression to indicate the answer to frames the mathematical model that effectively finds and also predicts depression such that the old method of identification can be implemented and expanded S. Mantri et al. (2015) By recognising gestures, this intelligent device developed by us aids in the diagnosis of depressive symptoms. Depending on the degree and level of depression of the patient, an assessment is done and the appropriate steps are enforced. (N.S.Alghamdi et al., 2019) analysed different classifications for machine learning, and the SVM selected generated the best outcomes, with a text analytical system score of 79.81 percent. (M. El Barachi et al. 2019) study offers fascinating insights into the ability to utilise sensory technologies and data processing to improve epileptic treatment for patients, as well as the possibility to handle customised healthcare.

III. Comparative Study

There are various types of deep learning models available for depression detection. Several researchers have been conducted and many methods have been introduced. A comparative analysis of all these methods is essential to determine the most suitable method for a particular set of data. Some of the most famous methods available for depression detection are,

Neural network technique

Machine learning have been developing into for the past few years. Various machine learning models have been used to detect the words and activities[8] of a person to indicate their mental illness. Depending upon the answers provided by a person the features are being extracted and the final result is being produced by processing them through neural networks. In this method the text is considered as the major data of the patient. The text or the answers produced by the patient is being extracted into various features and they are grouped into different categories depending upon their answers. The questions are being pre prepared on the based upon the answers the data is being classified into various categories and scored depending Lee. With the help of the network system the scores are being analysed and the final output is being produced[9] categorizing a person into a depressed or not depressed state. This technique is also called as the context of remodeling since no amount of constraints are being applied to the questionnaire. The text based neural network modelling system is found to produce more accurate results than the other models.

A. Depression detection using artificial intelligence

Several depression detection techniques have been researched and developing continuously by the researchers. A recent study on artificial intelligence to detect the depression and the rate of depression was being done. Several participants were being included for the study and a virtual agent was placed to ask the questions.

The final output in the first technique the rate of detecting depression was better. And in the second technique in case of preconditioned questions, the artificial intelligence system produced[10] better results compared to the previous method and finally in the sequence modelling experiment it was found that the result produced was advanced and accurate than the previous two models. These technologies are mostly used to assess the rate of depression in the patients with the help of the doctor.

B. Deep learning techniques

Along with the neural network techniques, there are various other techniques used to determine the depression rate of a person. A technique that has been used for several years is the deep learning technique. In case of deep learning technique[11], various features can be extracted from the text, audio, video, an image of a person to determine the rate of depression by using various training sets and deep learning model algorithms. Even though the neural networks are found to be more advanced the deep learning techniques especially the fusion ones have found to be produced accurate results.

Several researchers have been conducted to determine the various deep learning models and methods especially the hybrid fusion ones. In case of deep learning models which has been found out that the video-based and audio based deep learning models provide a more accurate result rather than the normal text based and image based deep learning models. Also compared to the uni modals the fusion models were found to perform better[12].

The fusion models provided more accurate results and they are being applied in various social media platforms to determine the mentality of the person depending upon the year text and various other post.

Various types of studies and models have been introduced in the deep learning model techniques along with various other model techniques like neural network model and machine-based learning model et cetera. In order to choose the better option a detailed comparative study is required. The following tabulation represents the various types of models that have produced better results and a detailed comparative analysis is being done among them.

Table 1: comparative analysis

Author name	**Approach**	**Advantage**	**Limitation**	**Research Gaps**
[13]	Artificial intelligence based neural network model	Machine based, the virtual model can be used several application	Absence of human presence	Only audio, text models were used for analysis.
[14]	Speech and spoken utterances are used to infer clinical depression. The following methods are used: motion history histogram (mhh), opensmile (open smile), harmonic model, deep learning model		Scarcity of text data.	Only audio, text models were used for analysis.
[15]	The features are extracted from a person's answers, and the final result is formed by processing the features using neural nets, which is dependent on the answers provided.	The model scored 71 percent and, on recall, scored 83 percent	More data needed to forecast depression.	Patterns The model detects undetected in scores of raw data. Not yet tested.

C. Extraction of video features using deep learning technique for depression detection

Several psychologists along with audio also sometimes record videos of the person to detect their depression with the help of the videos of obtained. In the case of a well-renowned psychologist with a lot of experience, they can easily determine the rate of depression in a patient easily by observing them. However, for certain psychologist and other kinds of doctors, it would be difficult[16] for them to analyse their rate of depression. Hence, in order to analyse the rate of depression many machine-based models are being researched for future application. One of the most common features that has been used in these researchers is extracting the facial expressions of the patient from the video recorded and determining the rate of depression.

Each video[17] is made up of multiple numbers of trains on the initial steps to separate all these frames into individual ones and later they are subjected to analysis With the help of haar features this algorithm separates the total image into different types of pixels and each and every single feature available in every pixel is being extracted. With the help of the classifier, these features are being analysed and the unwanted features are being removed. With the help of the following method, the data features are being obtained, analyzed[18], the important features are being separated, and finally depending upon the future the data is classified as depressed or non-depressed. Level of degree is also been entered into the support vector machine classifier so that it would be easier for the classified produce the result high moderate low moderate and no. Both are happy and the discuss the features are being compared with the result is being produced by the classifier. It has been found that the result produced highly Effective[19] and they are way more accurate than the previous techniques that have been used. However, compared to the text method the accuracy level of this method is lower.

In order to detect the relationship between the severity of depression and vocal prosody, several participants and interviewers were used. In the case of depressed individuals, there was will have the areas fluctuations and slurring that is not found in normal individuals. According to Derby et al, most of the listeners can determine the change in a particular persons frequency pitch and loudness. But it would take an experienced person to determine that the symptoms are the result of psychological depression[20]. With the help of a support vector machine determined the change in the voice of a person to detect the depression. In order to form perfect deep learning models, it consists of two stages. It includes the training stage and the classification stage. In case of a training stage, the data collected and inserted into the model to build a perfect classification model. The various parameters that indicate the rate of depression[21] where been classified under preprocessed. The acoustics and frequency range were calculated for each and every single parameter and stored in the database. Along with this, an SVM model was also used to determine the difference between a depressed patient and a non-depressed patient. This model determines the final result of the analysis.

Table 2: Extraction of video features using deep learning technique for depression detection

Study	**Year**	**Data-set**	**Description**	**Deep Learning/ Machine Learning technique used**
Yalamanchili, B et al.	2020	DIAC-WOZ data-set	Audio-video based data-set	Logistic Regression, Support Vector Machine (SVM)
Gong, Y. et al.	2017	2017 Audio/Visual Emotion Challenge (AVEC)	Audio-video based data-set	Regression
Valstar, M. et al.	2013	the third Audio-Visual Emotion recognition Challenge (AVEC 2013)	Audio-video based data-set	Regression techniques
Wang, Q., et al.	2018	Shandong Mental Health Center dataset	Facial-expression based dataset	Support Vector Machine (SVM)

IV. SMART MODEL

Depression detection technique using CNN A variety of experiments of depression evaluation[22] include evidence set studies to predict psychotic behaviour and suicidal ideation in individuals. The aim of these strategies is to use data from UCI and other Video to forecast people's life and behaviours by examining. The algorithm sketch consisted of a CNN. The identification algorithm included a proper classification of data set systems. The conclusions are based on the comments, but those people have no impact since they do not publicly express their feelings on public web sites. When forecasting whether or not a person is stressed, the data set prediction must be accurate. The Differentiation Algorithm[23] examines psychological data collected from a large variety of individuals in order to accurately determine whether or not people are anxious. The model aims to improve[24] the algorithm's grouping of data through various feelings, as well as the methods of facial and verbal analysis. For greater optimization[25], a variety of models have adopted the two-stage overview feature. The average detection rate for this process was 82.2 percent for males and 70.5 percent for females. Time perceptron study has provided an estimation of the amount of time spending on social networking platforms, and has been related to a rise in anxiety[26]. The model associates the function of depressive symptoms caused by social networking networks video posting as a significant source of mental stress[27]., the more anxious they get. Using deep convolutional neural networks, this paper proposed a method for diagnosing depression in voice. We evaluated five network architectures and choose[28] the best results for ResNet-34 and ResNet-50. The results point to a possible new method for the preliminary screening of suicidal individuals that makes use of short recordings of their video through audio spectrogram[29] Ming. It has been shown that spectrograms can produce SMDD algorithm based on CNN learning characteristics. the algorithm reached 80 and 87 percent precision. Given the demanding image on video, this was a sign of depression. Based on the video's local movement information, what is the most time-dependent CNN[30] connectivity pattern? How much can adding motion information to a CNN's predictions enhance overall performance? To account for temporal video dependencies, we modified a Convolutional network[31]. A frame stack is supplied into the CNN. This is a matrix CNN (height x width x colour channels). So an input tensor of (224, 244) The input for these tests is 224 x 224 x 6. To test this, Karpathy et al. used three alternative frame input models.

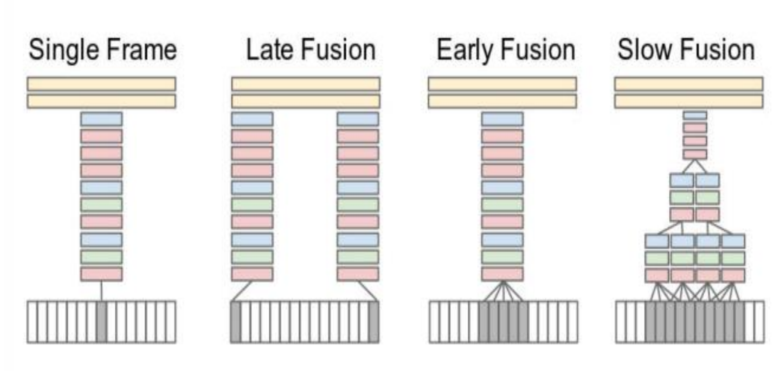

Figure 1: , comparing each with a simple classification frame model.

The single frame model is a simple example of video categorization that involves adding predictions through single frames or images. Late Fusion combines the opening and last frames of a clip. The Early Fusion model uses early fusion to retrieve a larger adjacent component from the clip. Finally, the Slow Fusion model uses a much more complicated method, combining four convolutional layer segments that partially overlap. together. Individual efficiency was enhanced by the Slow Fusion method, but not by a significant amount compared to the Single Frame model. It was determined that integrating the results of both models yielded the most significant overall findings. (Single + Early + Late + Slow) is a combination of the words single, early, late, and slow.

A. Multiresolution CNNs

A convincing approach for Video processing is another quite important issue explored in this research work. The CNN multi-resolution functions as follows: two different inputs are supplied to separate convolutionary layers.

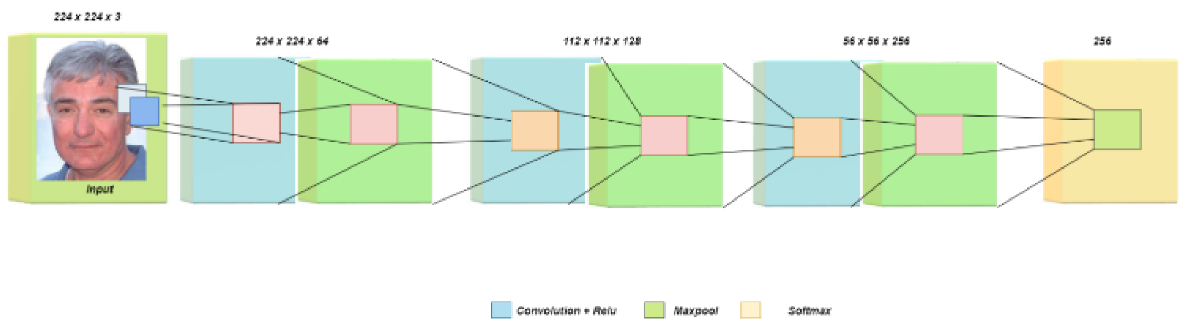

Figure 2: classification frame model.

This approach saves Convolutional layers a lot of time. This reduced dimensionality regime increases rpm by 2–4x. It is quoted at 5 clips per second for a single frame network and 20 clips per second for multiple resolution networks. Instead of parallelizing 10–50 model replicas across their processing cluster, they suggest employing a high-end GPU. There is also a little improvement over a single-frame model that comprises all 178 frames.

B. Transfer Learning in Video Classification

Transfer Learning has been extensively explored in the realm of video detection, and it is a straightforward concept to understand[32].

The following transformation processes were investigated: finer tuning of the top layer, finer tuning of the top three layers, and fine tuning of all layers. Example: When the top layer is polished, the remaining network weights are 'frozen' by testing, resulting in the weights only being involved in the network's forward passage after that.

As a result of reading this research[33], the findings in the areas of time fusion and multi-resolution techniques have marginally improved. Transfer Learning, on the other hand, produces results that are extremely open-minded. When it comes to moving learning, if the Slow Fusion technique had been more effective, the results from the Single Frame network could have been critical.

- Process with Specific Goals Neurons with learning weights and prejudice are incorporated in the goal-functioning[34] network of neurons. Each neuron takes a number of different inputs, calculates a weighted sum, sends the result through an activation function, and then responds by producing an output. Because the output is disseminated to the softmax layer, the network as a whole has a negative loss function. Softmax is a completely connected layer that is also responsible for performing the output sampling procedure, as previously stated.
- A convolutional neural network's embedding layer is the first layer that maps[35] word indexes to low-dimensional vectors, and it is the first layer to perform this mapping. For the most part, it is a lookup table from which we can benefit from the results. The total sentence length (Vwr) is used to determine the amount of vocabulary a student has. Using its own embedding in a phrase of N W terms, each term is read in its own way. After all of the words have been converted to vectors, they are sent into the convolution sheet for processing.
- As depicted in the Figure 2 the construction is separated into distinct levels. One is the embedding layer, which transforms each video frame into its associated built-in vectors, and the other is the transforming layer, which is responsible for the majority of the build processing and encoding[36]. In this step, predefined filters iterate across the matrix, narrowing it down to the smallest possible matrix. The third layer is a down layer known as softmax, which reduces the sentence matrix and measures the loss function of the sentence matrix. The embedded search tool can be used to acquire the word embedding for a sentence. The embedding layer generates a matrix that is padded to ensure that each video frame is properly represented. Existing filters reduce the size of the matrix and yield convolved functions, respectively. These aggregate properties have been significantly weakened. The output of the modified characteristics is disseminated over the entire pooling layer in order to increase the amount of sampling of the transformed characteristics. Descriptions are presented in a variety of sizes and formats in various filters. The suggested approach makes use of a class of filters known as. There are a total of 33 filters in use at this time. When the filter is applied to a sentence, it iterates through the sentence's original matrix until it reaches a minimum matrix. Rather than training our own embedding, we make advantage of Tensorflow's embedding lookup function to find an appropriate embedding. The padding in embedded video frames is used to ensure that all phrase matrices are the same size and form as one another.
- Neurons with learning weights and bias are incorporated in the goal-functioning network of neurons. Each neuron takes a number of different inputs, calculates a weighted sum, sends the result through an activation function, and then responds by producing an output. Because the output is disseminated to the softmax layer, the network as a whole has a negative loss function. In addition to performing the output sampling procedure, Softmax is a fully connected layer in the architecture. The embedding layer of a convolutional neural network is the first layer in the network that translates word indexes to low-dimensional vectors, and it is the most important layer. For the most part, it is a lookup table from which we can benefit from the results. The total number of frames in a video. Each phrase is interpreted in the context of its own embedding in a frame of reference.

Analysis of Previous Works The AVEC2013 and AVEC2014 databases are utilised to estimate depression levels on the test sets. This lets us compare our method to previous work. Based on them, we may conclude that our method accurately detects depressed persons. This STA network combines spatiotemporal information from the speech spectrum with frames associated with depression detection, resulting in good performance. The works only provide geographic and temporal information. EEP also explains the contrasts between our strategy and other attempts on the AVEC2013 test set. "A" stands for audio and "V" for visual modalities. The phrase "A+V" stands for audio and video combined. The '/' signifies that the result was not supplied.

Modalities	Methods	Root Mean Square Error (RMSE)	Mean absolute error (MAE)
Audio	SMDD	7.23	6.13
	CNN	8.43	6.88
	Fuzzy logic	9.43	7.44
Video	SMDD	7.42	8.21
	CNN	8.88	6.78
	Fuzzy logic	8.54	6.43
Audio+ Video	SMDD	8.32	6.54
	CNN	11.43	9.24
	Fuzzy logic	10.91	8.43

It is more efficient than other pooling algorithms for each dimension of segment-level characteristics. Because statistical variables (mean, median, etc.). The FV encoding described in does not take feature order into account while constructing a dictionary. The research aims to improve detection accuracy in the AVEC2013 database. The approach captures hidden parameters in auto/cross-correlations of observed signals. They think the sorrow score is ordinal, therefore they partition it and look at the relationship between characteristics and partitions. Also, the AVEC2014 database provides the highest precision. This research shows the value of trying different tasks for diagnosing depression. By incorporating multiple occupations for the AVEC2014 database, our methodology beats most other methods in terms of video modality[40]. However, the effect of facial gestures on depression detection is neglected. The statistical histogram is used to create dynamic features in video, however it cannot capture the unequal distribution of attributes across time. The SMDD model overlooks the disparities between video frames. The strategies in this section use the attention mechanism to focus on key frames related to the desired task. Using the AVEC2013 and AVEC2014 databases, we duplicate their work to forecast depression levels.

On the AVEC2014 test set, we compared our method to previous works. "A" stands for audio and "V" for visual modalities. The phrase "A+V" stands for audio and video combined. "Ours with Con" refers to combining features from two jobs of "Northwind" and "FreeForm" into a single feature set utilising our method. The '/' signifies that the result was not supplied. Visual behaviours (e.g., FAU, landmark, Head Pose, and Gaze) cannot extract facial detail texture. The division of multiple face regions also improves the performance of the works of art. In this method, face motions are evaluated over the entire film without having to separate video segments. Our method provides the best prediction performance for multimodal fusion, especially when combining tasks from the AVEC2014 database. The choice linear combination approach is used because the concatenation of audio and video features used in it is weak in collecting complementary information between modalities. Unlike previous approaches, the SMDD model strategy uses the attention mechanism to extract complementary information between modalities. We also construct a scatter plot to show the difference between the ground truth and the predicted value.

The outcomes of the Fuzzy logic model, which used CNN and a combination of CNN and fuzzy logic algorithms, are detailed in length in this section. The question paper has many questions that focus on the learning processes that occur using AI-based technologies and simple ways. Table 2 presents the results of the aforesaid algorithms' parameter analysis. The SMDD model has the best accuracy (94.3%) and F1-score (0.931). The CNN technique for youngsters achieves the maximum accuracy of 85.3 percent, with an F1-score of 0.740. Table 2 shows that AI-based solutions outperform other methods.

Table 2: Comparison of results based on different machine learning algorithms

S.No.	**Machine Learning Algorithm**	CNN with multilayers	CNN with single layer
1.	SMDD	Accuracy: 97.3% F1-score: 0.822	Accuracy: 74.3% F1 Score: 0.692
2.	CNN	Accuracy: 89.2% F1-score: 0.743	Accuracy: 69.32% F1 Score: 0.680
3.	Fuzzy logic	Accuracy: 81.33% F1-score: 0.491	Accuracy: 79.44% F1 Score:0.698

V. CONCLUSION

Depression can be readily cured with the help of competent treatment and a quiet environment, but it takes time and effort. However, if depression is not effectively managed, it can sometimes result in self-harm or death. Various techniques were being employed to identify depression, and each methodology had its own advantages and disadvantages. Patients' video and picture recordings were used to conduct an analysis of their condition. Each and every one of these strategies was used to extract a characteristic of the person, and the characteristics were examined using a variety of classification models, including a deep learning depression model, which may be used to determine the rate of depression in a patient.

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