Depression recognition over fusion of visual and vocal expression using artificial intelligence

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ABSTRACT
Depression is a mental illness that usually goes untreated in people and can have catastrophic consequences, including suicidal thoughts. Counselling services are widely available, but because depression is a stigmatized illness, many people who are depressed decide not to seek help. Therefore, it is essential to develop an automated system that can recognize depression in individuals before it worsens. In this study, a novel approach is proposed for identifying depression using a combination of visual and vocal emotions. Long short-term memory (LSTM) is used to assess verbal expressions and convolutional neural networks (CNN) to analyze facial expressions. The proposed system is trained using features of depression from the distress analysis interview corpus (DAIC) dataset and tested on videos of college students with frontal faces. The proposed approach is effective in detecting depression in individuals, with high accuracy and reliability.

Keywords:
CNN
DAIC dataset
Depression scale recognition
LSTM
Visual expression
Vocal expression

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1. INTRODUCTION
Around 350 million people all over the world suffer from depression, and the frequency is rising every year, according to research on the condition by the World Health Organization (WHO). Epidemiological research found lifetime prevalence of depression to be around 6.9% [1]. Depression is a psychiatric condition that causes extreme sadness and makes it difficult for sufferers to function normally in social situations. More gravely, depression can cause behaviors like self-harm and suicide [2]. Additionally, it may have an impact on significant life events like marriage timing and school success. The majority of persons who receive treatment for depression, according to [3], do not recover from it. The coronavirus disease 2019 (COVID-19) pandemic resulted in extraordinary actions like social segregation, worldwide isolation, and a state of health emergency. This disrupted daily life and caused a significant increase in anxiety and depression symptoms. Over time, the prevalence of depression has more than doubled worldwide. The wellbeing of a person depends on accurate diagnosis and treatment. Traditional diagnostic techniques for depression rely on self-reporting, which can be arbitrary and unreliable, resulting in incorrect diagnoses and insufficient care. Using numerous data sets to create an accurate and dependable detection system could be a way to enhance depression diagnosis and therapy. Currently, the standard clinical approaches for diagnosing depression are primarily based on the clinical diagnoses made by psychiatrists and the patients themselves. The diagnostic and statistical manual of mental disorders (DSM-5), the hamilton depression scale (HAMD), the beck depression inventory (BDI), and the patient health questionnaire (PHQ-9)
are currently the most widely used clinical diagnostic tools. Although correct diagnosis is challenging, these methods have limitations because the diagnostic procedure does not involve objective measurements[4].

A self-administered survey called the beck depression inventory II (BDI-II) [5] is used to gauge how severe depression is in adults and teenagers. Speech and facial expressions are used as biomarkers to determine an individual’s level of depression, which can be determined by looking at their BDI-II score as depicted in Table 1. There are 21 multiple-choice questions in the survey, each of which focuses on a different depressive symptom, such as mood, guilt, hunger, or sleep. Based on the person’s answers to these questions, the BDI-II score is determined, with each question receiving a number between 0 and 3 that reflects the severity of the symptom. Higher scores on the BDI-II scale, which goes from 0 to 63, indicate more severe depressed symptoms. Mental health practitioners frequently use the BDI-II to diagnose depression, track therapeutic progress, and assess the efficacy of various treatments.

Numerous data sets, including face pictures, and electroencephalogram (EEG), human voice, behaviour, and text, have frequently been employed in research using artificial intelligence (AI) technology to identify depression. Recent background research on the identification of depression shows many techniques and traits used by researchers to identify depression, allowing for significant comparisons between them. Table 2 gives a thorough summary of the state of art literature video data is used as features in [6], [7], AVEC datasets are used by the researchers and have achieved around 70% accuracy.

Table 1. The BDI-II scores and corresponding depression degree

<table>
<thead>
<tr>
<th>BDI-II score</th>
<th>Depression degree</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-13</td>
<td>None</td>
</tr>
<tr>
<td>14-19</td>
<td>Mild</td>
</tr>
<tr>
<td>20-28</td>
<td>Moderate</td>
</tr>
</tbody>
</table>

Table 2. The comparison of the different traits and methods used to evaluate depression

<table>
<thead>
<tr>
<th>Authors</th>
<th>Features</th>
<th>Dataset</th>
<th>Algorithm</th>
<th>Result</th>
<th>Demerits</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shah et al. [7]</td>
<td>Video</td>
<td>AVEC2014</td>
<td>VGG16</td>
<td>Accuracy - 68.75%</td>
<td>Only utilized facial features.</td>
</tr>
<tr>
<td>Singh et al. [8]</td>
<td>Video audio</td>
<td>DAIC - WOZ</td>
<td>PCA, SVM</td>
<td>F1 - 0.82</td>
<td>It does not provide a comparative analysis of its results with other existing methods.</td>
</tr>
<tr>
<td>Pampouchidou et al. [9]</td>
<td>Video audio</td>
<td>Own datasets</td>
<td>LBP, HOG, LSTM, CNN</td>
<td>Accuracy - 70%</td>
<td>A small patient group was engaged in the dataset.</td>
</tr>
<tr>
<td>Zhou et al. [10]</td>
<td>Video audio</td>
<td>D-Vlog dataset</td>
<td>LSTM, CNN</td>
<td>F1 - 0.75</td>
<td>The dataset was gathered from a particular age group and demographic.</td>
</tr>
<tr>
<td>Niu et al. [2]</td>
<td>Audio text</td>
<td>DAIC - WOZ</td>
<td>BLSTM, TCNN</td>
<td>F1 - 0.9074</td>
<td>Potential technical complexities or resource requirements.</td>
</tr>
<tr>
<td>Rustagi et al. [12]</td>
<td>Facial expression and text data</td>
<td>Fer 2013</td>
<td>CNN, RNN</td>
<td>Accuracy - 85%</td>
<td>Only text and visual traits were considered.</td>
</tr>
<tr>
<td>Shekar and Kumar [13]</td>
<td>Face circumference audio</td>
<td>Facial expression dataset from Kaggle</td>
<td>CNN</td>
<td>Accuracy - 64%</td>
<td>Only utilized facial features, not considering head posture or eye movement.</td>
</tr>
<tr>
<td>Wang et al. [14]</td>
<td>Audio</td>
<td>DAIC - WOZ</td>
<td>CNN, GAN</td>
<td>MAE - 10.21, RMSE - 7.96</td>
<td>It only focuses on audio features and does not consider other potential sources of information.</td>
</tr>
</tbody>
</table>

Changes in speech patterns, facial expressions, body language, and general behavior are a few of the symptoms of depression. Researchers and computers can detect nonverbal signs and subtle behavioral markers that are frequently missed in conventional text-or survey-based assessments by including audio and video data to the dataset. Voice inflection, speech cadence, hesitations, facial expressions, and body language can all reveal important details about a person’s emotional state and aid in the detection of depressive symptoms. The incorporation of audio and video data not only improves the sensitivity and accuracy of algorithms for detecting depression, but also offers a more complete picture of a person’s wellbeing, aiding in the understanding of the illness and the development of more accurate diagnoses for clinicians and
researchers. Video and accompanied audio is used by researchers in paper [8]–[10]. Various algorithms including principal component analysis (PCA), support vector machine (SVM), long short-term memory (LSTM), and convolutional neural networks (CNN) are implemented to improve accuracy of recognition [2], [11] have implemented the algorithm based on audio and text analysis. Even though 90% accuracy is claimed the technical complexities are more in these algorithms. Facial expressions and text is used in [12], [13] to develop the system. Audio features are only criteria used in [14] to achieve the recognition. The datasets frequently used in the literature include:

- DAIC-WOZ
- AVEC 2013
- AVEC 2014
- SEMAIN
- D-Vlog

A set of psychiatric interviews called the distress analysis interview corpus-wizard of oz (DAIC) is used to evaluate people’s mental health. This corpus’s DAIC-WOZ subset was created using a robotic agent that can communicate with people and recognize verbal and nonverbal indicators of mental illness. 189 audio and video clips as well as in-depth survey responses are included in the collection. The corpus includes WOZ interviews that were used to record and analyze samples for different verbal and nonverbal traits. The data can be utilized to create automated systems for the early detection and prevention of mental health issues and is a useful resource for researchers studying depression and related disorders. A relatively new area of study involves the analysis of audio and video to determine how people are feeling and how they are feeling by observing video frames, audio, and text [15]–[18].

The AVEC 2013 dataset [19]–[23], commonly known as the “audio-visual depression corpus,” contains 150 movies of people recorded with a camera and microphone while they perform depression-oriented tasks in a human-computer interface. Each recording contains only one person, and multiple recordings have a total of 84 subjects. The material contains recordings of 18 test subjects on three, 31 on two and 34 on one, the duration varies from 50 to 20 minutes and the average is 25 minutes. It takes a total of about 240 hours to watch all the clips. The age of individuals in the data varied between 18 and 63 years, with an average age of 31.5 years and a standard deviation of 12.3 years.

Only two of the original 14 activities-which were chosen due to strong participant agreement—are included in the AVEC 2014 selection. 300 movies, ranging in length from 6 to 4 minutes and 8 seconds, were the product. The assessment of anxiety and sadness is the focus of the two activities, which are each independently recorded. Five pairs of previously unreleased clips were additionally included to replace the few videos that were deemed unfit for the competition. The AVEC 2014 source videos were the same as those used in the AVEC 2013. The two tasks in this category are “Free Form” and “The North Wind,” in which participants recite passages from the German novel “Die Sonne und der Wind” (the sun and the north wind), respectively. SEMAIN corpus detects anxiety using face recognition. The corpus consists of dialogues between individuals and a simulated agent and is designed to explore the natural social cues that appear when interacting with an artificial human or robot. Sensitive artificial heater (SAH) technology was used for data collection. The corpus contains a total of 95 session files with both audio and video, video only, and separate audio files that can be used for testing, interpretation, and case studies. The D-Vlog dataset [1], [24]–[27] is a collection of films made facial expressions. The length and calibre of the movies vary, and the creators come from various social and mental health backgrounds. These videos have been published on YouTube and are open to the general audience. The information, which consists of more than 500 movies, has been utilised for research to build automatic algorithms to identify depression and anxiety based on speech patterns.

The proposed work focuses on, employment of artificial intelligence to recognize depression scales from fusions of visual and vocal expression. A unique method that combines LSTM for audio analysis with CNN for visual analysis is developed which is a novel approach for identifying depression using a combination of visual and vocal emotions. Useful features and models are detected to increase the precision of depression evaluation and identification. The influence of poor data quality on model performance is also addressed. The remainder of the text is structured as follows: The proposed model is thoroughly covered in section 2. Section 3 of this article discusses the results. The conclusion of our work and future research directions are presented in section 4.

2. PROPOSED METHOD

Through physiological research, it has been demonstrated that people with depression behave differently from people in good health in terms of their speech and facial expression. In order to predict a person’s state of depression, our suggested method makes use of a multimodal representation framework that
can integrate both visual and audible expressions. As seen in Figure 1, the proposed method consists of different algorithms for audio- and video-based depression recognition. Input, preprocessing, feature extraction, training, and classification are all processes in the system’s conventional pipeline. The CNN algorithm is used to train and classify the audio-based depression identification system while the LSTM method is used to train and classify the video-based depression recognition system.

The depression state is decided after combining the output probabilities of the two modalities. The suggested strategy increases the accuracy and robustness of identifying depression by utilizing the advantages of both visual and auditory modalities. Standard performance measures including the confusion matrix, precision, recall, F-measure, and accuracy are used to assess how well our suggested techniques perform. Our results demonstrate that the fusion of visual and vocal expressions significantly improves the accuracy of depression detection compared to using only one modality. Proposed CNN technique for diagnosing depression includes the preprocessing, feature extraction, training, and classification phases. The video frames are preprocessed by being scaled to a uniform size and having their pixel values normalized to maintain consistency in the data. The features are extracted using the histogram of oriented gradients (HoG) approach. In the CNN model, which contains 4 convolutional layers, 4 max pooling layers, and 2 fully connected layers, rectified linear units (ReLU) acts as the activation function. The model is trained using backpropagation and a binary cross-entropy loss function. Overfitting is avoided by employing dropout regularization and early halting techniques.

Figure 1. Block diagram for the proposed system

The DAIC-WOZ database is used to diagnose psychological distress disorders such as anxiety, depression, and post-traumatic stress disorder. Before extracting features from the collected visual data for depression detection, pre-processing is necessary. In this step, the video frames are resized and normalized to ensure consistency in the data. Normalization involves adjusting the pixel values so that they have a mean of zero and a standard deviation of one, which helps to reduce any variation caused by differences in lighting or camera settings. These pre-processing steps help to ensure that the data is in a consistent format and ready for feature extraction. A variety of video attributes from the open face framework are retrieved and analyzed. These include,
- Facial landmarks: 68 spots on the face with estimated 2D and 3D coordinates from video
- HoG characteristics for both eyes’ gaze direction estimation on the aligned 112×112 region of the face
- Head pose: the 3D posture and orientation of the head Additionally, based on FACET software, assessments of emotion and facial action unit is done. We specifically present the following emotions: “anger,” “contempt,” “disgust,” “disgust,” “joy,” “fear,” “neutral,” “sadness,” “surprise,” “confusion,” and “frustration.”

Docker is used to expedite and simplify the feature extraction process. By encapsulating the feature extraction algorithms and their dependencies within a Docker container, the consistency and reproducibility of the process across various machines and environments is assured. This approach streamlines the deployment and management of feature extraction workflows, resulting in consistent and reliable outcomes. A training set and a testing set were created from the dataset. The pre-processed video frames are the CNN model’s input. The output of the CNN model is a binary classification indicating whether the individual is depressed or not. The CNN model is trained using 4 convolutional layers using ReLU as the activation function.
function. ReLU, which is applied per pixel and recreates all negative values in the feature map by zero, is an element-wise process. We utilized a flattening layer, two fully linked layers, and a convolutional layer after that. The fully connected layer’s purpose is to use these features to categorize the input image into different classes depending on the training dataset. The CNN model then applies a binary cross-entropy loss function and backpropagation. The goal of this loss function is to reduce discrepancy between the predicted and actual classifications, resulting in improved model accuracy. To prevent overfitting, the model is trained with early stopping and dropout regularization techniques. These approaches help improve the model’s generalization ability and enhance its performance in processing unseen data.

3. RESULTS AND DISCUSSION

The proposed algorithm was evaluated on a dataset of audio recordings from depressed and non-depressed individuals. It includes preprocessing, feature extraction, data preparation, LSTM network design, training, validation, testing, and post-processing techniques. The preprocessing step involves loading audio signals, removing noise, and normalizing them. The feature extraction step extracts mel-frequency cepstral coefficients (MFCC) features from preprocessed audio signals. MFCC is a widely used feature extraction technique in audio signal processing for various applications such as speech recognition, music classification, and speaker identification. The MFCC feature extraction process involves several steps. The first step is pre-processing, which includes removing any noise or artifacts that may affect the quality of the feature extraction. Common pre-processing techniques include filtering, normalization, and framing. The audio signal is then divided into small, overlapping frames typically 20-30 ms each. Each frame is then multiplied by a window function such as the Hamming or Hann window to reduce spectral leakage. Next, a Fourier transform (FT) is performed on each frame to obtain its frequency-domain representation. The frequency-domain representation of each frame is then passed through a mel filter bank, which is a set of overlapping triangular filters that mimic the non-linear frequency response of the human ear. The mel filter bank

3.1. Fusion

The fusion result of the CNN and LSTM models for depression detection is achieved by taking the average of the output from both models. This approach enables the strengths of both models to be combined, resulting in a more accurate and robust prediction. The final prediction is based on a threshold of 0.5, where if the output value is less than 0.5, the result is “not depressed,” and if the output value is greater than 0.5, the result is “depressed.” This approach provides a binary classification of depression detection that is easily interpretable and actionable for healthcare professionals. By combining the strengths of both models, we can achieve higher accuracy in detecting depression, ultimately improving the diagnosis and treatment of this prevalent mental health disorder.

3.2. Analysis of CNN algorithm

The performance of the proposed depression recognition is evaluated using different optimization algorithms. The CNN and LSTM models are used with each of these optimization algorithms and compared their performance using the test dataset. The results of the CNN algorithm are presented in Table 3.

From the comparative analysis of performance of the Adam and RMSprop optimizer for the training of video-based depression data, it is observed that Adam optimizer outperforms the RMSprop optimizer. The CNN algorithm with Adam optimizer achieved an accuracy of 93%. In the audio-based depression recognition system LSTM algorithm uses the classification of depression and non-depression. The results of audio-based depression recognition using LSTM algorithm with different optimizer are shown in Table 4.

From the comparative analysis of performance of the Adam, RMSprop, stochastic gradient descent (SGD), and Adagrad for the training of audio-based depression data, it is observed that RMSprop optimizer outperform than the other optimizer. The CNN algorithm with RMSprop optimizer achieved an accuracy of 83%. In the testing phase the final decision is given by considering audio as well as video probability of the classes. The average of both the probability is taken and class of maximum probability is considered as output of the depression recognition system. The performance of these models is analyzed using precision, recall, F1-score, and accuracy measures.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Optimizer</th>
<th>Precision</th>
<th>Recall</th>
<th>F1-score</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>CNN</td>
<td>RMSprop</td>
<td>0.96</td>
<td>0.76</td>
<td>0.81</td>
<td>0.83</td>
</tr>
<tr>
<td></td>
<td>Adam</td>
<td>0.93</td>
<td>0.93</td>
<td>0.92</td>
<td>0.93</td>
</tr>
</tbody>
</table>

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4. CONCLUSION

The proposed system is an innovative method for identifying depression that incorporates verbal and nonverbal clues. Using CNN for facial expression analysis and LSTM for speech expression processing, accurate classification of individuals as depressed or not depressed is achieved. The suggested approach is evaluated on videos of college students presenting frontal faces after being trained using depression features from the DIAC dataset. The outcomes reveal that proposed method is helpful in identifying depression with high accuracy and dependability. This automated technique is extremely valuable in identifying and treating depression at an early stage. It can lessen the effects of depression on people’s lives, such as disturbances to daily routines, academic performance, and social interactions, by offering prompt treatment. There are chances to improve feature extraction at a more sophisticated level in terms of future scope. Investigating additional audio aspects, such as reaction time, pause frequency, and quiet rate, may help us better comprehend the symptoms of depression.

REFERENCES

BIOGRAPHIES OF AUTHORS

Chandan Gautam is holding a B.Tech degree in Electronics and Communication Engineering from MIT WPU in 2023, Pune, is an accomplished Software Developer at Northern Trust. Awarded the first rank in her department and a gold medal, also served as the IEEE Chairperson, MITWPU in 2022. She demonstrates a compelling blend of leadership skills and academic prowess, contributing significantly to advancements in affective computing and multimodal emotion recognition, underscoring her dedication to the field. She can be contacted at email: chandangautam0607@gmail.com.

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