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Determining the Impact of Social Media on Mental Health Using Convolution Neural Network

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Abstract

The Image-Processing field has drastically risen in the past few years which has led to origination of such an effectual system that can help capture the human emotion in an uncomplicated way. There is are quisite to develop a pre-programmed system that captures facial images of human beings and analyse them, for effective depression of depression. We present the development of a system using deep convolutional neural networks (CNNs) for analysing mental health of different age group of peoples who use social media. The system is trained using the facial features of emotions (either positive or negative emotion). Then facial features are extracted and classification is done with the help of convolutional neural networks. The depression level is distinguished by perceiving and figuring the measure of negative emotions present in the entire video. Finally, we evaluate the system in terms of classification accuracy and speed.

Keywords: *CNN, ROI, Emotions, AlexNet, MATLAB*

1. Introduction

In individuals, depression is a result of the social change because of unfurling of the web, cell phones and internet-based life. The majority of the people will in general disguise their mental issues because of the social marks of disgrace identified with discouragement and furthermore because of companion pressure. A few people remain absolutely uninformed of their mental issues and in this manner stay denied of any assistance that may demonstrate fundamental to their psychological wellness. It is an extremely troublesome undertaking for guide to monitor the critical changes that happen in people groups because of gloom in an enormous number of people groups. Along these lines, we need and robotized framework that catches pictures of individuals and break down them for successful sorrow location. Outward appearances are the most significant type of non-verbal interchanges to communicate a persons' emotional or mental state.

The present investigations demonstrate that there is a solid association between the expanded use of social media and crumbling of mental health. The most active social media users i.e. young adults have a very high probability of developing some mental health issues and that too at a very young age.

Countless investigations are at present experiencing on 'Facial feature analysis' for emotion acknowledgment from pictures which successfully help in predicting psychological wellness state of individuals. This examination proposes a robotized framework that distinguishes melancholy levels in people by dissecting frontal face pictures of individuals.

Already many treatments are in existence to reduce the such disorders and improve the mental health conditions. Current trends used to observe fear, facial expressions, video recordings, learning difficulty, public speaking etc to find the current state of mental health of a human. Few more activities include response to potential threat, the initial response to know threat and response modulation to fear.

Earlier treatments used to include the diagnosis of the human threat response phases which included behavioural coding, eye blink and also contraction of muscle. These types of treatment were not able to show

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the accurate results, there were also few more techniques like Fear Potentiated Startle (FPS) in which some data were not so useful because of human nervousness.

There is a need to raise concern about the mental health as it not only affects the individual rather it affects each and every person around that individual.

Figure 1: Example of the various types of emotions present on a human face i.e. (a) angry, (b) neutral, (c) sad, (d) happy, (e) surprise and (f) disgust

2. Literature Survey

S.NO	AUTHORS	PAPER	DESCRIPTION	DRAWBACKS
1.	Pampouchidou et al.	**Facial geometry and speech analysis for depression detection (2017)**	A system was proposed which had the capability of filling in as a decision support system, taking a shot at the premise of the novel features extricated from facial geometry and speech, by deciphering non-verbal signs of depression. The proposed framework was assessed by coordinating the parameters and classification schemes.	The influence of emotions on inter-personal conversations made it obligatory to take into account the emotional state of a human mind. Emotions were recognised on the foundation of the input text.
2.	S. Harati et al.	**Discriminating the clinical phases of recovery from major depressive disorder using the dynamics of facial expression (2016)**	The various measurements of inconstancy were utilized to take out a portion of the unsupervised learning from videos of patients before and after brain simulation treatment for Major Depressive Disorder (MDD). The objective was to evaluate the treatment impacts on facial expressivity. Multi-scale entropy (MSE) was utilized to catch the transient variability in pixel intensity level at different time scales.	So as to unequivocally clarify the recognized covariance over the high dimension, a dynamic latent variable model (DVLM) was used. The results were based on unsupervised learning which cannot detect depression much efficiently.

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3.	Pampouchidou et al.	**Designing a frame-work for assisting depression severity assessment from facial image analysis(2015)**	An algorithm for breaking down facial expression utilizing fiery descriptors so as to detail a novel element choice just as a viable grouping process was proposed right now. The starting evaluation of the framework was introduced by applying local curvelet binary patterns.	The facial element utilized was the eye-pair. The descriptor was just geometry based which is deficient for productively characterizing the seriousness of the downturn. The most elevated arrangement exactness acquired was just 55.42%.
4.	Owayjan et al.	**FacedetectionwithexpressionrecognitionusingArtificialNeuralNetworks(ANN) (2016)**	This paper introduced a framework which recognized the emotions utilizing artificial neural systems. It was a mechanized vision framework structured and executed utilizing MATLAB. The counterfeit neural system utilized a Multi-layer Perceptron (MLP) with back propagation algorithm for highlight extraction and characterization.	The major drawback of the system proposed was the hardware dependency of the ANN. Also, when ANN produces an examining arrangement, it does not validate itself which reduced trust in the network. The network system structure was accomplished through experimentation.

3. Proposed System

The proposed system has the following steps. First the videos are collected from the public database or the videos can be recorded on our own. The database contains the videos of humans of different age groups who are using social media. The database also contains several videos of humans not using social media so as to compare the results at the end of the study. Second step is to perform the frame extraction from the testing videos. The cropping of the detected face region is proposed after this step. Third step is to use the deep learning model for detecting and classifying the facial emotions i.e. happy, sad, surprised, angry and disgust. Fourth and the final step is the determine the amount of positive and negative emotions on the human face. If the face consists of mostly negative emotions, we conclude that the person is suffering from severe case of depression. The depression level is divided into three categories- severe, mild and low.

The proposed system has a very high classification accuracy.

The current state of the mental health can be easily analysed with the help of facial expressions and emotions.

4. Implementation

The depression level identification based on the facial emotions can be done by the following modules. The videos are collected either from the public database or can be recorded on our own. There are two types of videos in the database i.e. people using social media and people not using social media. After the video acquisition, the process of frame extraction is performed. The face detection algorithm is implemented on each frame to detect the face in each frame. The computer vision face detection tool is utilised to take note of the facial region in each frame. The facial region extracted from each frame is then cropped for the next process. The new cropped region is called the Region of Interest (ROI).

After the above two process are implemented without any errors, the facial feature extraction is implemented using Convolution Neural Network (CNN). The proposed method shows how to use transfer learning to retrain AlexNet, a pretrained CNN to recognise the new set of images (Normalised biometrics). Transfer learning is typically utilised in applications which use deep learning. A system which is trained with deep learning is normally quicker and simpler to prepare than a system with haphazardly initialised loads without any preparation.

The network till now has learned rich component portrayal from a wide scope of pictures. From the outset, all the data is split into training data and validation data. The AlexNet has 25 layers. The system has an input size of 227x227. The classification layer and the fully connected layer are changed to perceive the facial emotions.

In the wake of characterizing the network structure, we specify the training options. A training cycle on the entire training dataset is known as an epoch. The maximum number of epochs range from 5 to 500. The system is trained with the initial learning rate of 0.01, using the architecture defined by layers, the data (training data) and the training options. Finally, the emotions are detected using the validation data with the help of the trained network.

The depression level is identified by figuring the contrast between positive emotions and negative

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emotions. If the human face has a very high number of negative emotions then he/she has a severe case of depression. If the face contains more negative than positive emotions then he/she is suffering from a case of mild depression otherwise the person isn't suffering from depression.

This study is executed with the assistance of MATLAB. It is a superior language for specialized processing. The framework has array as its essential component and doesn't require dimensioning.

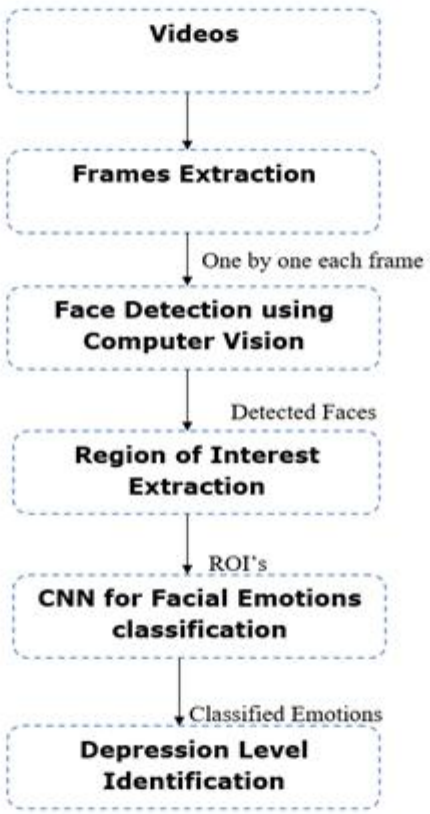

Figure 2: The architecture diagram of the flow of the implementation of the study conducted to determine the depression level with the help of frame extraction, face detection, ROI extraction, emotion classification and finally predicting the level of depression.

Depression Level Identification

After the aforementioned modules are implemented successfully, the final step is to categorise the depression level. In this study we have categorised the depression levels as: No Depression, Mild Depression, Severe Depression.

Let the number of positive emotions be represented by P_e, the number of negative emotions be represented by N_e and the number of total emotions be represented by T_e. The percentage of negative emotions is used to determine the depression level and is represented by D_L.

$$D_L = (N_e / T_e) \times 100$$

Case 1: No Depression
This case is the simplest of all. If a person falls in this category, it means that there are a greater number of positive emotions than negative emotions.
Case 2: Mild Depression ($N_e > P_e$)
This case represents that the person might be suffering from a case of mild depression. This case constitutes that the negative emotions present lie in the range 55-75% and positive emotions lie in the range 25-45%.
Case 3: Severe Depression ($N_e >> P_e$)
This case represents that the person might be suffering from a case of severe depression. This case constitutes that the negative emotions present lie in the range of 76-95% and the positive emotions lie in the range 5-24%.

5. Result

In the earlier studies or researches, patients were approached to wear gadgets to watch their heart-rate.SometimestheirGPSlocationwastrackedinordertodetermineiftheywereskippingwork due to their current mental state. The traditional methods were not able to predict the facial emotions properly and achieved less accuracy. This study helped in predicting the severity of depression. This study was very useful in detecting the amount of positive emotions and negative emotions. The model is able to predict the outcome at the maximum accuracy.

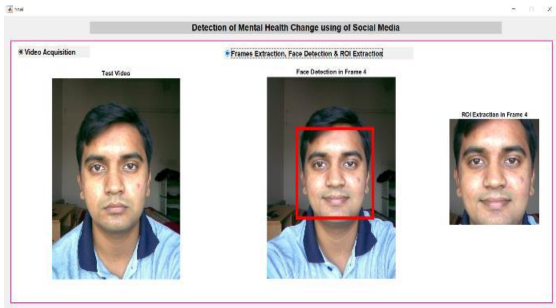

Figure 3: The figure shows the implementation of the frame extraction and face recognition module. The third picture shows the cropping of the frame and recognition of the Region of Interest (ROI).

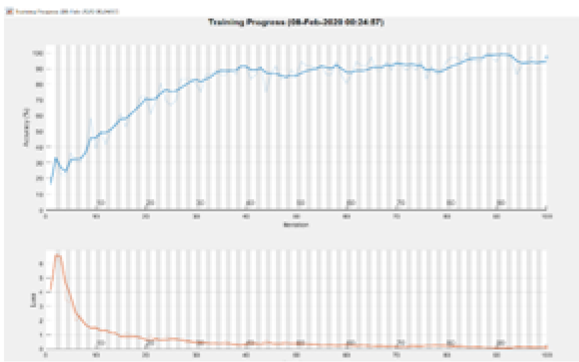

Figure 4: This figure demonstrates the accuracy % (represented in blue) and the loss % (represented in orange) during the training module

Figure 5: The figure shows all of the modules working together.

a) The frame extraction and ROI detection.
b) Facial emotion detection and classification
c) Depression level predicted

6. Conclusion

This study was attempted to discover the severity of depression for various age groups. The recordings in the dataset included recordings of individuals using social media and not using social media so as to compare the results. The presence of emotions like 'happy', 'neutral' (positive emotions) and 'angry', 'sad' and 'disgust' (negative emotions) was identified and were analysed. The dataset for training, validation and testing was gathered independently. The facial highlights were extricated and afterward arranged utilizing AlexNet CNN. The quantity of positive and negative emotions in every video was broken down and the results anticipated were 'serious depression', 'mild depression' and 'no depression' i.e. normal. The deep learning anticipated the result with the most extreme precision.

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