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Automatic Assessment of Depression Level Prediction using Deep Learning

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ABSTRACT

Automatic depression assessment based on visual cues is a rapidly growing research domain. The present exhaustive review of existing approaches as reported in over sixty publications during the last ten years focuses on image processing and machine learning algorithms. Visual manifestations of depression, various procedures used for data collection, and existing datasets are summarized. The review outlines methods and algorithms for visual feature extraction, dimensionality reduction, decision methods for classification and regression approaches, as well as different fusion strategies. A quantitative meta-analysis of reported results, relying on performance metrics robust to chance, is included, identifying general trends and key unresolved issues to be considered in future studies of automatic depression assessment utilizing visual cues alone or in combination with visual cues. The proposed work also carried out to predict the depression level according to current input of face images using deep learning as well as Google API.

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I. INTRODUCTION

Automatic depression assessment based on visual cues is a rapidly growing research domain. The present exhaustive review of existing approaches as reported in over sixty publications during the last ten years focuses on image processing and machine learning algorithms. Visual manifestations of depression, various procedures used for data collection, and existing datasets are summarized. The review outlines methods and algorithms for visual feature extraction, dimensionality reduction, decision methods for classification and regression approaches, as well as different fusion strategies. A quantitative meta-analysis of reported results, relying on performance metrics robust to chance, is included, identifying general trends and key unresolved issues to be considered in future studies of automatic depression assessment utilizing visual cues alone or in combination with visual cues. The proposed work also carried out to predict the depression level according to current input of face images using deep learning as well as Google API.

Motivation:

Recent classification schemes run the risk of confusing normal sadness with depression, raising the likelihood of false positive diagnoses. Depression assessment is a complex process and diagnosis is associated with a significant degree of uncertainty, given the lack of objective boundaries, and the need to evaluate symptoms within the person's current psychosocial context and past history.

The current work is mainly undertaken to find out the presence of depression in college students by studying their facial features. This system mainly uses different image processing techniques for face detection, feature extraction and classification of these features as depressed or non-depressed. The system will be trained with features of depression.

II. PROBLEM DEFINITION

Automatic detection of depression has attracted increasing attention from researchers in psychology, computer science, linguistics, and related disciplines. As a result, promising depression detection systems have been reported. In this proposed work these efforts by presenting the first cross-modal review of depression detection systems and discuss best practices and most promising approaches to this task.

III. EXISTING SYSTEM

As with any technology or tool there is always risk of misuse and therefore it is important to discuss general ethical considerations with pursuing this line of research. It is especially important to define and outline appropriate use of these systems. Mental health professionals should view language technology for depression detection as a mechanism to complement current diagnoses by giving them access to a novel and rich non-intrusive data source.

IV. LITERATURE SURVEY

Many studies have been conduced to identify the precise facial expressions that are related to depression. A study has been conducted for finding out Action Units (AU) related to different emotions exhibited by depressed patients [1].

The presence of AU12 which is associated with emotion smile was low in highly depressed patients. The presence of AU14 related to emotion contempt and AU10 related to emotion disgust was also present along with AU12. The video data for this study was collected through clinical interviews of depressed patients as well as nondepressed patients. The results showed that AU14 related to emotion contempt proved most accurate for depression detection Features related to eye movement to understand the eye activity of the depressed and features related to head pose movement to understand the head movement behavior of the depressed has been done in [2].

The classification of the features related to eye activity showed higher significance in detecting severe depression. Detection of depression from facial features can be done by measuring 'Multi-Scale Entropy' (MSE) on the patient interview video. [4] MSE helps to find out the variations that occur across a single pixel in the video. The entropy levels of highly expressive, non-depressed patients were high. The entropy level was low for depressed patients who were less expressive of their emotions. Another study presented a technique which uses analysis of facial geometry along with analysis of speech for depression detection [3].
This work says that the expressions associated with depression are found to be in lower frequencies in smaller duration videos. Therefore longer time videos need to be captured for effective depression detection. Datasets are also created by capturing videos of patients while answering clinical interviews. Interviews recorded were for both for depressed patients as well as non-depressed patients. Videos are also recorded from the diagnosis of depression till the patient has improved. [1][4]. Studies showed that there is a significant relation between facial features and vocal behavior of the depressed [5].

In certain studies, patients were given wearable devises to monitor their physical health, emotional behavior and social interaction for identifying depression [6]. Some researchers have collected datasets by showing individuals film-strips to capture the facial expressions of subjects watching them. Data is also collected by giving a task of recognizing negative and positive emotions from different facial images [7].

Rather than analyzing a video for depression detection frame by frame, better results have been got for detection of depression when the video is considered as a whole. [8] For this the patient's face region is first initialized manually. Then KLT (KanadeTomasiLucas) tracker is used to track the face throughout the video. The KLT tracker extracts curvature information from an image, i.e. for a sad expression the corners of the mouth would be angled down. Video based approach showed more accuracy as it generalizes the face region more accurately and so the minute movements within the face region are also considered for depression detection. The students suffering from depression would show less attentiveness in classrooms. If the students' emotions are mapped to the activities done in classroom, their emotional state can be found out whether they are depressed or not, and based on this the teacher can help the student by paying more attention to that particular student. [11] If different faces in the same scene show the same positive or negative sentiment, it would help to understand the whole situation of the scene, whether subjects in the scene are happy or whether something wrong is happening in the scene [12].

V. PROPOSED SYSTEM

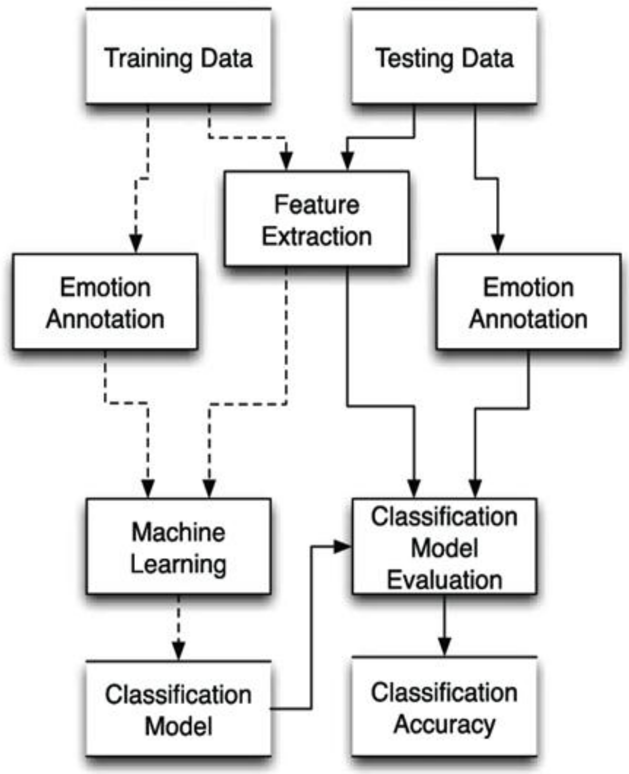

Fig 1. System architecture

Steps:

- Feature Extraction
- Normalization
- Classification
- Feature Selection
- Prediction

CNN Algorithm:

1. Classify dataset under labeled folders such as images
2. Read dataset
3. Read features of all images and label (here name of dataset folder) of it
4. Store it in model file
5. Get input image
6. Read features of input image
7. Compare features of stored features
8. Show label as prediction of nearly matched features.

VI. CONCLUSION

In conclusion, we presented a novel approach to optimize word-embedding for classification tasks. We performed a comparative evaluation on some of the widely used deep learning models for depression detection from tweets on the user level. We performed our experiments on publicly available datasets. Our experiments showed that our CNN-based models perform better than RNN-based models. Models with optimized embedding's managed to maintain performance with the generalization ability.
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