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# Depression Detection Using Convolutional Neural Network

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***Abstract: Clinical depression is a type of soft biometric trait that can be used to characterize a person. Because of its importance in a variety of legal situations, this mood illness can be included in forensic psychological evaluations. In recent years, research into the automatic detection of depression based on medical data has yielded a variety of algorithmic approaches and auditory indicators. Machine learning algorithms have recently been used successfully in a variety of applications. Automatic depression recognition - the recognition of expressions linked with sad behavior is one of the most important applications. Modern algorithms for detecting depression usually look at both geographical and temporal data separately. This research introduces a novel machine learning strategy for accurately representing face information associated to depressive behaviors from real-world medical data. Our suggested architecture outperforms state- of-the-art algorithms in automatic depression recognition, according to results from two benchmark datasets.***
***Keywords: Depression recognition, deep learning, deep neural network.***

## I. INTRODUCTION

Early recognition and accurate diagnosis of depression Studies focusing on individual-level neuroimaging data analyses are necessary if this approach is to be clinically useful [6] but the inherent complexity of the data and its analyses continues to be an obstacle [1].Identifying people with established depression does not usually present as a clinical challenge with standard clinical instruments but the potential for ambiguity, bias and low reliability of a are essential criteria for optimizing treatment selection and improving outcomes, thus reducing the economic and psychosocial burdens resulting from hospitalization, lost work productivity and suicide [2–4].

Individual- position neuroimaging data analysis examinations are needed, still the essential complexity of the data and its analyses remains a hedge. Depression is a current psychiatric illness in the wider public, with a continuance frequency of 20. It's linked to a high frequency of impairment, poor psychosocial functioning, and low life satisfaction, all of which are essential factors in determining treatment options and issues, as well as lowering the fiscal and emotional costs of hospitalizations, lost productivity, and self-murder. Psychiatric ails, including depression, are diagnosed substantially through consequences drawn from tone- reported data and observed general gesture, guided by specific individual criteria. Ambiguity, bias, and low trust ability are each important rudiments in perfecting treatment choices and issues, lowering the fiscal and emotional costs of hospitalization, lost productivity, and suicidal studies. The process was guided by the DSM- 5 bracket criteria.

Our approach, New and innovative for the practice of psychological disorder detection, it does so do not trust the self-disclosure of those psychological factors through the questionnaires. Instead, propose a machine learning technique that is detection of psychological disorder in social networks which exploits the features extracted from social network data for identify with precision possible cases of disorder detection. We perform an analysis of the characteristics and we also apply machine learning in large-scale data sets and analyze features of the two types of psychological disorders.

## II. METHODOLOGY

We want to use medical data to identify and assess depressed people. Determining a person's level of depression is difficult, especially given the unstructured nature of medical data. The lack of a publicly available massive benchmark dataset is among the biggest hurdles to depression intensity analysis. It's challenging to classify users from many angles and maintain track of relationships in multiple ways. Although users' behavior patterns are broad and varied, just a few show signs of despair.

We will first upload text input into the system, then preprocess it before performing core operations such as feature extraction and classification using CNN.CNN is a type of neural network with a distinct convolutional layer than other neural networks. CNN examines every corner, vector, and dimension of the pixel matrix to achieve picture classification.

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CNN is more robust to data in matrix form when it performs with all of the features of a matrix. Text data can be seen as sequential data, identical to data in a time series, or as a one-dimensional matrix. A one-dimensional convolution layer will be used. The model's concept is nearly identical, but the data format and dimension of convolution layers have altered. A word embedding layer and a one-dimensional convolutional network are required to work with Text CNN.

## III. RELATED WORK

Renata L. Rosa, Gisele M. Schwartz, Wilson V. Ruggiero, and Dem´ostenes Z. Rodr´ıguez - Online social networks (OSN) provide relevant information on users' opinion about different themes. Thus, applications, such as monitoring and recommendation systems (RS) can collect and analyze this data. This paper presents a Knowledge-Based Recommendation System (KBRS), which includes an emotional health monitoring system to detect users with potential psychological disturbances, specifically, depression and stress.

Guang Yang, Haibo He, Fellow, IEEE, and Qian Chen - Sentiment analysis on microblog posts has been studied in depth, sentiment analysis of posts is still challenging because of the limited contextual information that they normally contain. In microblog environments, emoticons are frequently used and they have clear emotional meanings. They are important emotional signals for microblog sentimental analysis. They address this issue by constructing an emotional space as a feature representation matrix and projecting emoticons and words into the emotional space based on the semantic composition.

M. Al-Qurishi, M. S. Hossain, M. Alrubaian, S. M. M. Rahman, and A. Alamri - In this paper, author propose an integrated social media content analysis platform that leverages three levels of features, i.e., user-generated content, social graph connections, and user profile activities, to analyze and detect anomalous behaviors that deviate significantly from the norm in large-scale social networks. Several types of analyses have been conducted for a better understanding of the different user behaviors in the detection of highly adaptive malicious users.

Huijie Lin, Jia Jia, Jiezhon Qiu, Yongfeng Zhang, Lexing Xie, Jie Tang, Ling Feng, and Tat-Seng Chua - In this paper, we find that users stress state is closely related to that of his/her friends in social media, and we employ a large-scale dataset from real-world social platforms to systematically study the correlation of users' stress states and social interactions. We first define a set of stress-related textual, visual, and social attributes from various aspects, and then propose a novel hybrid model - a factor graph model combined with Convolutional Neural Network to leverage tweet content and social interaction information for stress detection.

## IV. PROPOSED SYSTEM

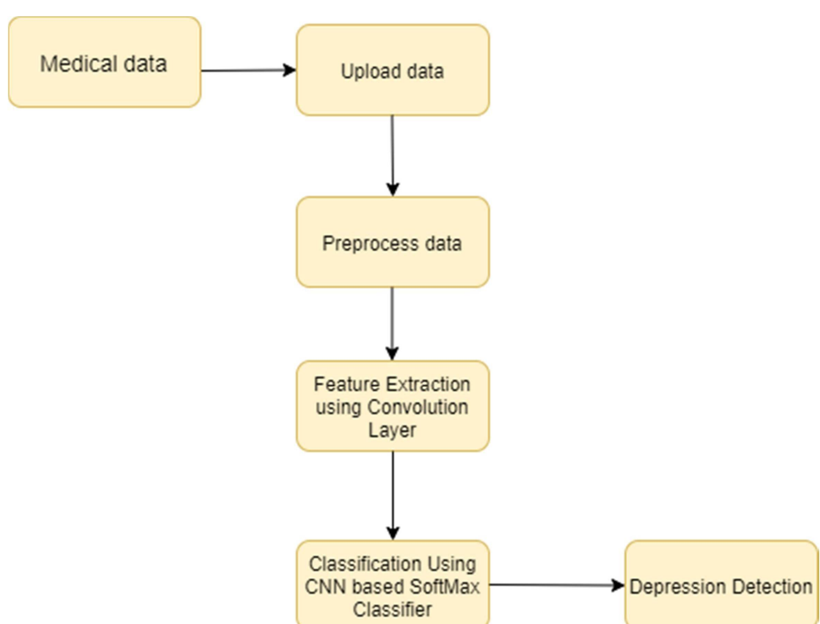


Figure 1. System Architecture

Algorithm: Convolution neural network

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### A. Convolution Layer

Layer of Convolution, the first layer to extract features from an input image is convolution (image). By learning visual attributes using small squares of input data, convolution preserves the link between pixels. Convolution of an image with different filters can perform operations such as edge detection, blur and sharpen by applying filters i.e., identity filter, edge detection, sharpen, box blur and Gaussian blur filter.

### B. Pooling Layer

Pooling layers would reduce the number of parameters when the images are too large. Spatial pooling also called subsampling or down sampling which reduces the dimensionality of each map but retains important information.

### C. Fully Connected Layer

In this layer Feature map matrix will be converted as vector (x1, x2, x3, …). With the fully connected layers, we combined these features together to create a model.

### D. SoftMax Classifier

Finally, we have an activation function such as SoftMax or sigmoid to classify the outputs.

## V. RESULTS AND DISCUSSION

The experimental result evaluation, we have notation as follows:
TP: True positive (correctly predicted number of instance)
FP: False positive (incorrectly predicted number of instance),
TN: True negative (correctly predicted the number of instances as not required)
FN false negative (incorrectly predicted the number of instances as not required),
On the basis of this parameter, we can calculate four measurements
Accuracy = TP+TN÷TP+FP+TN+FN
Precision = TP ÷TP+FP
Recall= TP÷TP+FN
F1-Measure = 2×Precision×Recall ÷Precision+ Recall.
The section shows overall accuracy of CNN classification technique

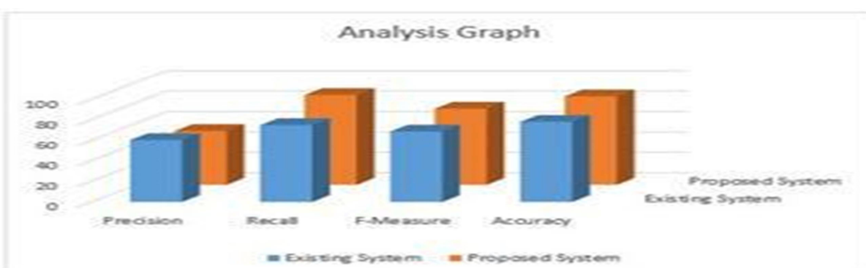


Fig. 2. CNN Classification Accuracy Graph

| | Existing System | Proposed System(CNN) |
|---|---|---|
| Precision | 60.6 | 52.70 |
| Recall | 75.1 | 87.64 |
| F-Measure | 68.8 | 74.31 |
| Accuracy | 78.29 | 86.26 |

Table No 1. Method Comparison

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## VI. FUTURE SCOPE

1) Will be able to spot depression and stress and address it.
2) Can provide a variety of treatment alternatives for those who are depressed, depending on their stage of sickness.
3) Assist users in achieving happiness.
4) Users will be able to improve their lives by receiving a personalized experience.

## VII. CONCLUSION

From the consideration of all the above points we conclude that medical data may be a useful tool in discriminating between depressed and healthy individuals. Given the questionable reliability of diagnoses based on clinical symptoms, this quantitative methodology may be a useful adjunctive clinical decision support for identifying depression and it supports independent studies confirming the potential clinical utility of computer-aided diagnosis of depression using medical data.

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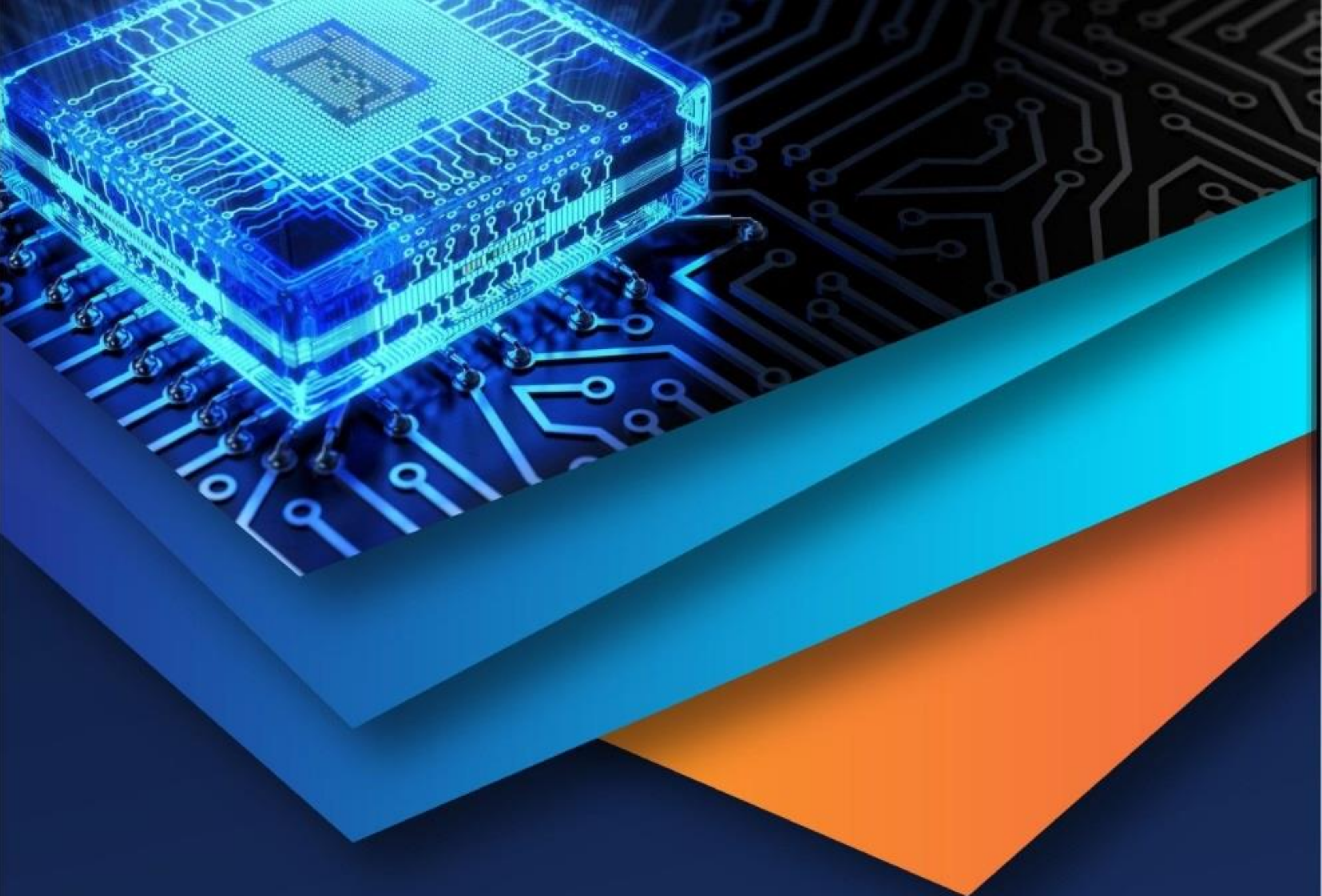


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