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Depression and Stress Monitoring System via Social Media Data using Deep Learning Framework

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Abstract: *Stress and Depression is one of the most broadly perceived and incapacitating mental issue that appropriately influences society. Automatic health monitoring systems could be pivotal and critical to improve sadness and stress recognition framework using social networking. Sentiment Analysis alludes to the utilization of natural language processing and content mining approaches planning to recognize feeling or opinion. Full of feeling Computing is the examination and advancement of frameworks and gadgets that can perceive, decipher, process, and mimic human effects. Sentiment Analysis and deep learning techniques could give powerful algorithms and frameworks to a target appraisal and observing of mental issue and, specifically of depression and stress. The application of sentiment analysis and deep learning methodologies to depression and stress detection and monitoring are discussed. In addition, a fundamental plan of an incorporated multimodal framework for stress and depression checking, that incorporates estimation investigation and full of feeling processing strategies, is studied. In particular, the paper traces the fundamental issues and moves comparative with the structure of such a framework.*

Keywords: Deep learning, Ehealth, stress and depression, sentiment analysis, social media

I. INTRODUCTION

Social media is arguably the richest source of human generated text input. Opinions, feedbacks and critiques provided by internet users reflect attitudes and sentiments towards certain topics. We presents a knowledge-based system, which includes an emotional health monitoring system to detect users with possible psychological disorders specially depression and stress [1] [4]. Symptoms Of these mental illness are usually observed passively. In this situation, author argue that online social behaviour extraction offersan opportunity to actively identify mental illness at an early stage [5].

Depression and stress is one of the most common and disabling mental disorders, and has a relevant impact on society [5]. Currently, methods for depression and stress detection and diagnosis rely on self-reporting coupled with the health care practitioners informed assessment. The provision of effective health monitoring systems and diagnostic aids could be crucial and important to improve health professional's work and lower healthcare costs. Sentiment and deep learning technology could help to tackle these objectives by providing effective tools and systems for objective assessment. Such tools and systems do not aim to replace the psychologist or psychiatrist but they could support their decisions.

Our approach, New and innovative for the practice of mental problem detection, it does so do not trust the self-disclosure of those psychological factors. Instead, a machine learning technique that is detection of mental problem in social networks which exploits the features extracted fromsocial network data for identify with precision possible cases of mental illness detection [5] [8].

II. LITERATURE SURVEY

Renata L. Rosa, Gisele M. Schwartz, Wilson V. Ruggiero, and Dem´ostenes Z. Rodr´ıguez - Online Social Sites (OSN) give important data on users feeling about varioustopics. Along these lines, applications, for example, checking and suggestion frameworks (RS) can gather and dissect this information. This paper exhibits a Knowledge-Based Recommendation System (KBRS), which incorporates an enthusiastic wellbeing observing framework to distinguish clients with potential mental unsettling influences, explicitly, depression and stress using CNN, BLSTM-RNN algorithms and the eSM2 opinion metric for disposition appraisal.

Guang Yang, Haibo He, Fellow, IEEE, and Qian Chen - Estimation investigation on microblog posts has been examined inside and out, sentiment analysis of posts is asyet testing a result of the restricted logical data that they ordinarily contain. In microblog situations, emojis are much of the time utilized and they have clear passionate implications. They are significant enthusiastic signs for microblog nostalgic analysis. They address this issue by developing an enthusiastic space as a component portrayal framework and anticipating emojis and words into the passionate space dependent on the semantic composition using enhanced convolutional neural network algorithm.

M. Al-Qurishi, M. S. Hossain, M. Alrubaian, S. M. M. Rahman, and A. Alamri - In this paper, author propose a coordinated web-based social networking content investigationstage that use three level of features, i.e., user produced content, social graph associations, and user profile exercises,to dissect and identify atypical behaviors that go amiss altogether from the standard in huge scale social networking sites. A few sorts of investigations have been directed fora superior comprehension of the distinctive user practices in the discovery of exceptionally versatile vindictive users. This system used PCA algorithm for feature extraction and Profile-Based Collection Technique, Time-Based and GradualEnhancement Technique for real time data collection.

Huijie Lin, Jia Jia, Jiezhon Qiu, Yongfeng Zhang, LexingXie, Jie Tang, Ling Feng, and Tat-Seng Chua - In this paper, author find that users stress state is firmly identified with that of his friends in web-based social networking, and utilize a huge scale dataset from certifiable social stages to efficiently think about the connection of user's pressure states and social associations. author initially characterize a lot of stress related text, visual, and social traits from different perspectives, and afterward propose a novel half breed model - a factor diagram model joined with Convolutional Neural Network to use tweet substance and social collaboration data for stress discovery.

Budhaditya Saha, Thin Nguyen, Dinh Phung, Svetha Venkatesh - Psychological instability deeply affects people, families, and by expansion, society all in all. Informal communities enable people with mental issue to speak with others sufferers by means of online networks, giving a precious asset to thinks about on textual indications of mental medical issues. This paper discover quiet with a stress issue may likewise depression using Sequential minimal optimization (SMO) algorithm.

Chun-Hao Chang, Elvis Saravia, Yi-Shin Chen - In this paper, target building prescient models that influence language and standards of conduct, utilized especially in online life, to decide if a user is experiencing two instances of mental issue. These prescient models are made conceivable by utilizing a novel information assortment process, authored as Subconscious Crowdsourcing, which gathers a quicker and progressively solid dataset of patients. Our tests recommend that extricating explicit language examples and social connection highlights from solid patient datasets can enormously add to advance examination and identification of mental issue. This paper used Linguistic Inquiry and Word Count (LIWC) and Latent Dirichlet Allocation (LDA) algorithms.

Andrey Bogomolov, Bruno Lepri, Michela Ferron, Fabio Pianesi, Alex (Sandy) Pentland- In this paper, propose an alternative approach providing evidence that daily stress can be reliably recognized based on behavioral metrics, derived from the user's mobile phone activity and from additional indicators, such as the weather conditions (data pertaining to transitory properties of the environment) and the personality traits (data concerning permanent dispositions of individuals). Our multifactorial statistical model, which is person-independent, obtains the accuracy score of 72.28% for a 2-class daily stress recognition problem. Moreover, author identify and discuss the indicators which have strong predictive power. This paper used TFIDF and LIWC algorithms for feature Extraction and Random forest for classification.

Bimal Viswanath† Alan Mislove Meeyoung Cha Krishna P. Gummadi –In this paper, study the development of action between users in the Facebook social network to catch this idea. Likewise find that connections in the action organizewill in general travel every which way quickly after sometime, and the quality of ties displays a general diminishing pattern of movement as the informal community interfaceages. For instance, just 30% of Facebook user sets connect reliably starting with one month then onto the next. Curiously, and locate that despite the fact that the connections of the movement organize change quickly after some time, many chart theoretic properties of the action arrange stay unaltered.

I.-R. Glavan, A. Mirica, and B. Firtescu - Social media tools devices are wide spread in web correspondence and are picking up prominence in the correspondence procedure between open organizations and residents. This investigation directs an examination on how online networking is utilized by Official Statistical Institutes to cooperate with residentsand scatter data. A straight relapse method is performed to inspect which web based life stages (Twitter or Facebook) is a progressively viable apparatus in the correspondence procedure in the official insights territory. This examination proposes that Twitter is a more amazing asset than Facebook in upgrading the connection between legitimate insights and residents, conforming to a few different investigations. Next, played out an investigation on Twitter organize qualities talking about ”authentic measurements” utilizing NodeXL that uncovered the unexploited capability of this system by legitimate factual offices.

A. E. U. Berbano, H. N. V. Pengson, C. G. V. Razon, K. C. G. Tungcul, and S. V. Prado - The paper presents further research on neural engineering that focuses on the classification of emotional, mental, physical and no stress through the use of Electroencephalography (EEG) signal analysis. Stress is one of the leading causes of several health-related problems and diseases. Therefore, it becomes necessary for people to monitor their stress. The human body acquires and responds to stress in different ways resulting to two classifications of stress namely, mental and emotional stress. Traditional methods in classifying stress such as through questionnaires and self-assessment tests are said tobe subjective since they rely on personal judgment. Thus, in this study, stress is classified through an objective measure which is EEG signal analysis. The features of the EEG recordings are then pre-processed, extracted, and selected using Discrete Wavelet Transform (DWT). These features are then used as inputs to classify stress using Artificial Neural Network (ANN) and validated using K-fold Cross Validation Method. Lastly, the results from the software assisted method is compared to the results of the traditional method.

III. PROPOSED METHODOLOGY

In the proposed systemic approach, we formulate the taskas a classification problem to detect four types of detection of psychological disorders in social networks using the sentimentanalysis and ssdeep learning framework:

- Stress
- Depression
- Positive comments
- Negative comments

An innovative solution to monitor and detect potential users with emotional disorders, according to the classification of sentences with depressed or stressed content.

Architecture

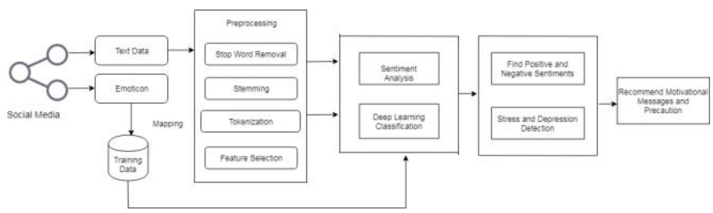

Fig. 1. Proposed System Architecture

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Algorithm

Naive Bayes Steps:

Given training dataset D which consists of documentsbelonging to different class say Class A and Class B

Calculate the prior probability of class A=number ofobjects of class A/total number of objects

Calculate the prior probability of class B=number ofobjects of class B/total number of objects

Find NI, the total no of frequency of each class Na=the total no of frequency of class A Nb=the total no of frequency of class B

Find conditional probability of keyword occurrence given a class:

P (value 1/Class A) =count/ni (A) P (value 1/Class B) =count/ni (B) P (value 2/Class A) =count/ni (A)

P (value 2/Class B) =count/ni (B)

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P (value n/Class B) =count/ni (B)

Avoid zero frequency problems by applying uniformdistribution

Classify Document C based on the probability p(C/W)

Find P (A/W) =P (A)*P (value 1/Class A)* P (value2/Class A). P(value n /Class A)

Find P (B/W) =P (B)*P (value 1/Class B)* P (value2/Class B). P(value n /Class B)

Assign document to class that has higher probability.

Recurrent Neural Network

ecurrent Neural Network(RNN) are a type of Neural Network where the output from previous step are fed as input to the current step. In traditional neural networks, all the inputs and outputs are independent of each other, but in cases like when itis required to predict the next word of a sentence, the previouswords are required and hence there is a need to remember the previous words. Thus RNN came into existence, which solvedthis issue with the help of a Hidden Layer. The main and mostimportant feature of RNN is Hidden state, which remembers some information about a sequence.

Steps:

Suppose there is a deeper network with one input layer, three hidden layers and one output layer. Then like other neural networks, each hidden layer will have its own set of weights and biases, let's say, for hidden layer 1 the weights and biases are (w1, b1), (w2, b2) for second hidden layer and (w3, b3)for third hidden layer. This means that each of these layersare independent of each other, i.e. they do not memorize the previous outputs.

A single time step of the input is provided to the network.

Then calculate its current state using set of current inputand the previous state.

The current ht becomes ht-1 for the next time step.

One can go as many time steps according to the problem and join the information from all the previous states.

Once all the time steps are completed the final current state is used to calculate the output.

The output is then compared to the actual output i.e the target output and the error is generated.

The error is then back-propagated to the network to update the weights and hence the network (RNN) is trained.

Mathematical Model

The mathematical model for Stress and DepressionMonitoring System is as-

$$S = \{I, F, O\}$$

Where,

I = Set of inputs

The input consists of set of Words/Emoticon/Microblog. Ituses Twitter and Facebook dataset.

F = Set of functions

$$F = \{F1, F2, F3.....FN\}$$

F1: Data Collection

$$Dataset =< T, F >$$

Where,
T- Twitter F-Facebook
F2: Sentimeter
Sentimeter-Br2 is a word-dictionary with its respectivesentiment intensity (positive or negative words), considering n-grams, verbal tenses and adverbs. The sentiment intensity value of an S-sentence, using the Sentimeter-Br2
Where,
SU represents the sentiment score of an unigram,ST representsthe sentiment score of a trigram,SB is the sentiment score of a bigram,k is related to the sentence tense, k = 1, if the sentence has a verb in the past participle; and k = 0 if the sentence isin another tense or the sentence does not have a verb, p is the total number of unigrams in the F-sentence, with the exceptionof words with no sentimental intensity value (stopwords),q is the total number of bigrams, r is the total number of trigram.
F3: Enhanced Sentiment Metric

$$eSM(S) = Sentimeter_{Br2(s)} * C * exp(a_1 * A_1 *)$$

Where,
C represents a scale constant; a1...an represents binary factors related to age ranges, if one of them is equal to one, the others are zeros; A1...An are the weight factors of each age range, considering four ranges; g1 and g2 are binary factors related tothe gender; M and F are the weight factors of gender, man or woman, respectively; e1 e e2 represents binary factors related to educational level (higher education or not); G and nG are the weight factors of educational level, higher education ornot, respectively.
F3: Sentiment Analysis

$$Data =< w, N >$$

Where,
W – Words
N – Na¨ıve Bayes
F4: Classification

$$Data =< w, rnn >$$

Where,
W – Words
rnn – Recurrent Neural Network
O=Find Disorder (i.e. Positive comments, Negative comments,Stressed user, Depressed user)

IV. RESULTS AND DISCUSSION

Dataset

The dataset used to classify stress, depression, and nonstressand non-depression expressions, in the training phase, was built using sentences written by Users on an OSN. In total, 30,000 labeled Facebook messages were used.

Limitation of Traditional Machine Learning Algorithm

Machine Learning Algorithms Require Massive Stores of Training Data
Labeling Training Data is a hard Process
Machine learning algorithms are deployed, there will likely be more instances in which potential bias finds its way into algorithms and data sets.

Classification Accuracy

Experiments are done by a personal computer with a configuration: Intel (R) Core (TM) i5-2120 CPU @ 3.30GHz, 8GB memory, Windows 10, MySQL backend database andjdk 1.9. The application is dynamic web application for design code in Eclipse Oxygen IDE and execute on Tomcat server 9.5.
The overall accuracy of Na¨ıve bayes and Recurrent Neural Network classification technique . So this works gives better classification results.

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Calculation Formule:

TP: True positive (correctly predicted number of instance) FP: False positive (incorrectly predicted number of instance),TN: True negative (correctly predicted the number ofinstances as not required)

FN false negative (incorrectly predicted the number ofinstances as not required),

On the basis of this parameter, we can calculate fourmeasurements

Accuracy = TP+TN/TP+FP+TN+FNPrecision = TP /TP+FP

Recall= TP/TP+FN

F1-Measure = 2×Precision×Recall ÷Precision+ Recall

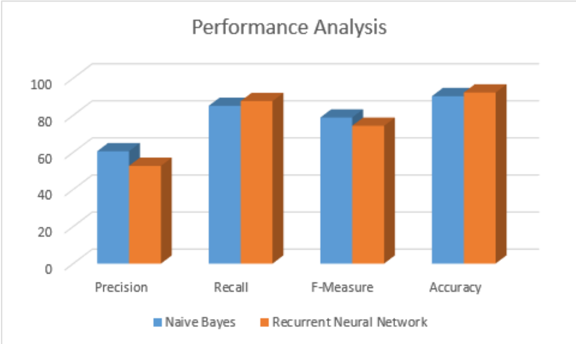

Fig. 2. Performance Analysis Graph

	Naive Bayes	Recurrent Neural Network
Precision	60.6	52.70
Recall	85.1	87.64
F-Measure	78.8	74.31
Accuracy	90.29	92.26

V. CONCLUSION

In this proposed system, automatically identifying potential online users with depression and stress is threatening people's health. Thus users suffering from depression can be identified and they might be helped before they take any drastic steps which might have a long lasting impact. Using the data ofthe social networks of the real world as a basis, study the correlation between the states of psychological disorder ofusers and their social interaction behaviour also recommend the user for health precautions to send by mail for user interaction.in this system not worked on social images.in future works, it tends to be applied in different services, such as customer complaint systems and user help frameworks to recognize unexpected changes of customers' feeling.

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