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An Improved CNN and BLSTM Based Method to Perceive Mood of Patients in Online Social Networks

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Key words: Sentimental analysis, recommendation system, deep learning, CNN, BLSTM, social networks

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Abstract: In today's world social network play a vital role and provides relevant information on user opinion. This study presents emotional health monitoring system to detect stress and the user mood. While it has often been difficult for those outside a network of family and friends to identify persons who may be at risk of suicide, we can turn to Web2.0 and the blogs hosted on social networking sites to give a helping hand. Blogs such as those on my space have been the focus of many high-profile youth suicide cases in recent years, where suicidal youth have posted messages prior to taking their own lives. This problem is traditionally solved by using machine learning approaches. For instance, sentences can be classified according to their readability, using pre-built features and classification algorithms like SVM, Random Forest and others. Depending on results the system will send happy, calm, relaxing or motivational messages to users with psychological disturbance. It also sends warning messages to authorized persons incase a depression disturbance is detected by monitoring system. This detection of sentence is performed through convolution neural network (CNN) and bi-directional long term memory (BLSTM). This method reaches accuracy of 0.80 to detect depressed and stress users and also system consumes low memory, process and energy. We can do the future work of this project by also including the sarcastic sentences in the dataset. We can also predict the sarcastic data with the proposed algorithm.

INTRODUCTION

Now days, the number of active social network users has grown drastically. This high number of users on social networks is mainly due to the increase of the number of mobile devices, such as smart phones and tablets[1]. Currently OSN has became universal means of opinion, expression, feelings and they reflect the bad habits or well ness practices of each user. In recent years, the messages posted on social networks have been used by many applications in the industry of healthcare information. Sentiment analysis refers to the management of sentiments, opinions and subjective text.

Sentiment analysis provides the comprehension information related to public views, as it analyze different tweets and reviews. It is a verified tool for the prediction of many significant events such as box office performance of movies and general elections[2]. Sentiments contain a variety of featured values like tri-grams and bi-grams by means of polarities and combinations. So sentiments are being assessed both as negative and positive aspects through the numerous support vector machines, by using training algorithms[3-4]. The sentiment analysis is multi disciplinary field, because it includes numerous fields such as computational linguistics, information retrieval, semantics, natural language processing, artificial intelligence and machine learning .Existing research has produced numerous techniques for various tasks of sentiment analysis, which include both supervised and unsupervised methods. In the supervised setting, early papers used all types of supervised machine learning methods (such as Support Vector Machines (SVM), Maximum Entropy, Naïve Bayes, etc.) and feature combinations.

Unsupervised methods include various methods that exploit sentiment lexicons, grammatical analysis, and syntactic patterns[5]. Several survey books and papers have been published, which cover those early methods and applications extensively. Since about a decade ago, deep learning has emerged as a powerful machine learning technique and produced state-of-the-art results in many application domains, ranging from computer vision and speech recognition to NLP[6].

MATERIAL AND METHODS

The use of social media for communication: R. Glavan, A. Mirica and B. Firtescu,[7]. Social media takes on many different forms including magazines, Internet forums, we blogs, social blogs, micro ging, wacks, pod casts, photographs or pictures, video, rating and social book marking. With the world in the midst of a social media revolution, it is more than obvious that social media like face book, twitter, my space, skype etc., are used extensively for the purpose of communication[8].

Music recommendation system based user's sentiments extracted from social networks: R. L. Rosa, D. Z. Rodriguez and G. Bressan[9].This paper presents a music recommendation system based on a sentiment intensity metric, named enhanced Sentiment Metric (eSM) that is the association of a lexicon-based sentiment metric with a correction factor based on the user's profile. This correction factor is discovered by means of subjective tests, conducted in a laboratory environment[10].

Detecting stress based on social interactions in social networks: 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 ata set from real-world social platforms to systematically study the correlation of user's stress states and social interactions[11-12]. 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 Convolution Neural Network to leverage tweet content and social interaction information for stress detection[13].

Hunting suicide notes in web2.0 - preliminary findings: This paper will explore the techniques used by other researchers in the process of identifying emotional content in unstructured data and will make use of existing technologies to attempt to identify at-risk bloggers [14] . Using a selection of real blog entries harvested from My Space .com, supplemented with artificial entries from our research, we test the accuracy of a simple algorithm for scoring the presence of certain key words and phrases in blog entries[15-16]. Despite the simplistic approach taken, the preliminary results of this study were very promising. While some social networking sites allow users to tag a blog post with a particular mood or emotion, to make an informed prediction on a blogger's state of mind it may also be valuable to analyze the content of their postings. The automation of this process is made possible through two main approaches, linguistic analysis and text categorization[17]. Due to the complexity and diversity of linguistic features, it can often be difficult to accurately match linguistic representations with a blogger's conscious or subconscious intention.

Deep learning based document modeling for personality detection from text: N. Maunder, S. Peoria, A. Gelbukh and E. Cambria[18] the authors train a separate binary classifier with identical architecture, based on a novel document modeling technique[19]. Namely, the classifier is implemented as a specially designed deep convolution neural network with injection of the document level Marissa features, extracted directly from the text, into an inner layer[20]. The first layers of the network treat each sentence of the text separately; then the sentences are aggregated into the document vector[21]. Filtering out emotionally neutral input sentences improved the performance[22]. This method out performed the state of the art for all five traits and the implementation is freely available for research purposes. Deep Learning was firstly proposed by G. E. Hinton in 2006 and is the part of machine learning process which refers to Deep Neural Network[23]. Neural network is influenced by human brain and it contains several neurons that make an impressive network. Deep learning networks are capable for providing training to both supervised and unsupervised categories[24]. Deep learning includes many networks such as CNN (Convolutional Neural Networks), RNN (Recurrent Neural Networks), Recursive Neural Networks, DBN (Deep Belief Networks) and many more. Neural networks are very beneficial in text generation, vector representation, word representation estimation, sentence classification, sentence modeling and feature presentation[25].

RESULTS AND DISCUSSION

Existing system: Machine Learning is that field of study that provides computers the aptitude to find out while not being expressly programmed. Millilitre is one of the foremost exciting technologies that one would have ever come upon[26-27]. Because it is clear from the name, it provides the pc that creates it additional the same as humans the power to find out. Machine learning is actively being employed these days, maybe in more places than one would expect[28].

Types of machine learning: Machine learning implementations are classified into 3 major classes, betting on the character of the training “signal” or “response” on the market to a learning system[29-30].

1. Supervised learning
2. Unsupervised learning
3. Reinforcement learning
4. Semi-Supervised learning

Supervised learning: When associate degree algorithmic rule learns from example knowledge and associated target responses which will carry with it numeric values or string labels, like categories or tags, so as to later predict the proper response once displayed with new examples comes beneath the class of supervised learning[31-32].

Unsupervised learning: Whereas once associate degree algorithmic rule learns from plain examples with none associated response, going away to the algorithmic rule to work out the info patterns on its own[33]. This sort of algorithmic rule tends to reconstitute the info into one thing else, like new options that will represent a category or a brand-new series of un-correlated values[34].

Reinforcement learning: When you give the rule with examples that lack labels, as in unsupervised learning[35-36]. However, you may accompany associate example with positive or feedback per the solution the rule proposes comes beneath the category of Reinforcement learning, that's connected to applications that the rule ought to produce picks (so the merchandise is prescriptive)[37].

Semi supervised learning: Where associate degree incomplete coaching signal is given: a coaching set with some (often many) of the target outputs missing[38-39]. There's a special case of this principle called Transduction wherever the complete set of downside instances is understood as learning time, except that a part of the target area unit is missing[40].

Limitations of existing work:

- The existing system shows accuracy of only 60%
- It uses only Random Forest Algorithm to process the data
- Its efficiency of processing the results is slow and so the results appear
- It user interface is not friendly
- It shows error in some results. It does not process all the data; it leaves some of the data

Algorithms Used:
Random forest may well be a machine learning formula that belongs to the supervised learning technique. It is typically used for every Classification and Regression problem in cubic centimetre, it's supported the conception of ensemble learning[41]. The idea here is that if you have a bunch of training examples, such as I’m so happy today!, Stay happy San Diego, Coffee makes my heart that the word “happy” is correlated with text having a positive sentiment and use this to predict on future unlabeled examples[44]. Logistic regression is a good model because it trains quickly even on large data sets and provides very robust results. Other good model choices

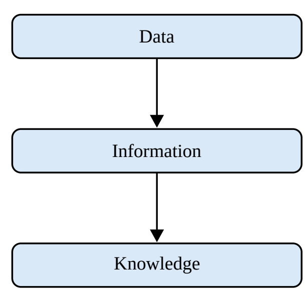

Fig.1: Flow diagram- ML working

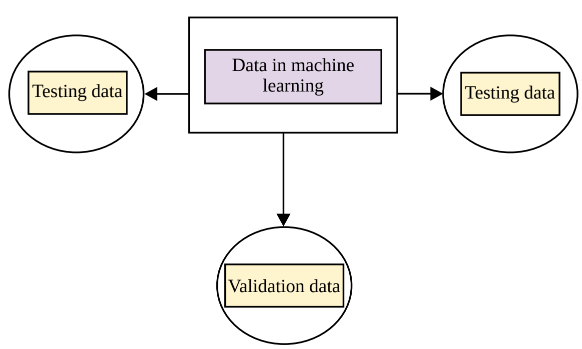

Fig. 2: Flow diagram for Data splitting

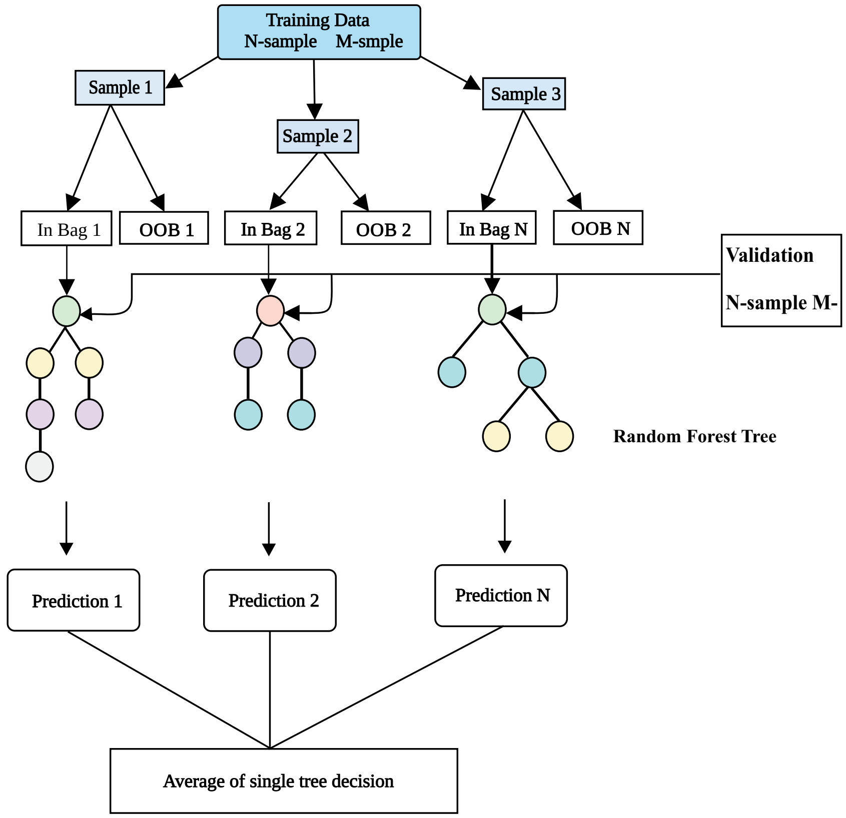

Fig. 3: Architecture diagram-random forest

Fig. 4: Uploading the dataset file which contains messages

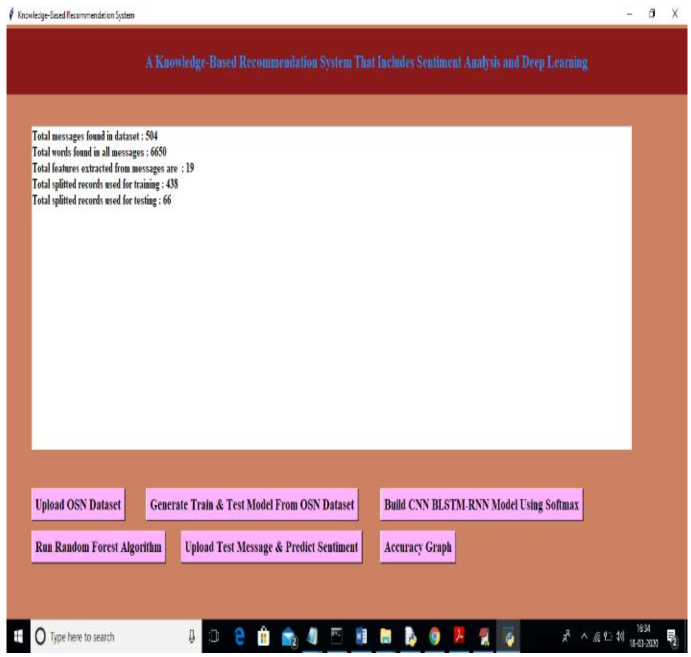

Fig .5: Records to test the prediction performance

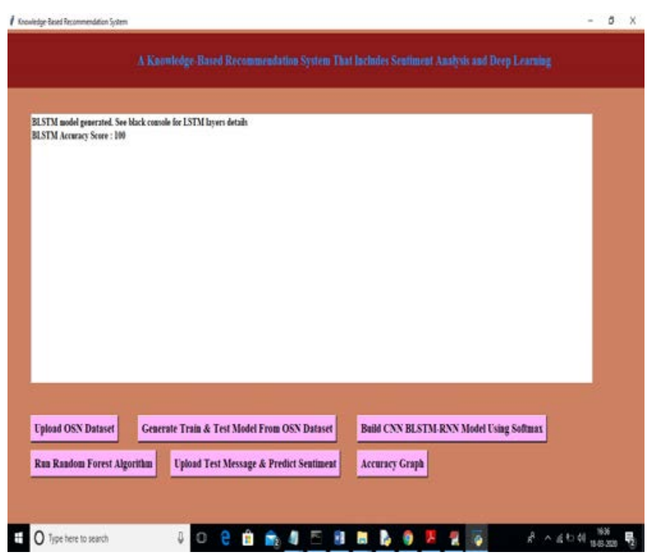

Fig. 6: Proposed BLSTM model generated and the accuracy is shown as 83.94%

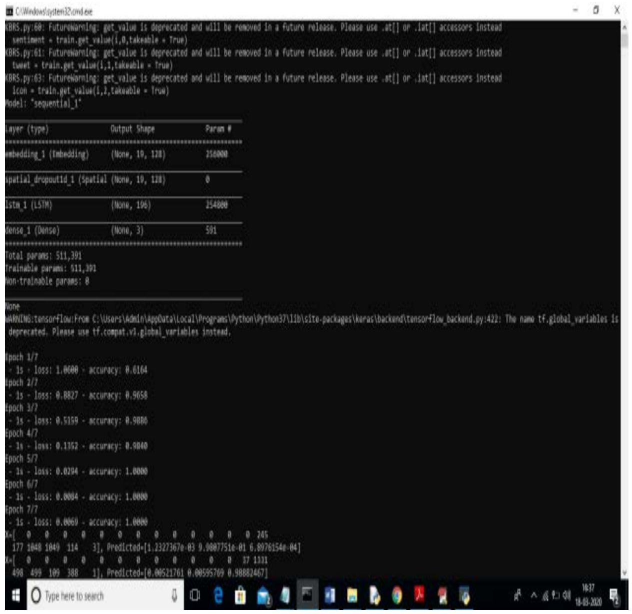

Fig. 7: In the above screen we can see the iterations to generate prediction layers

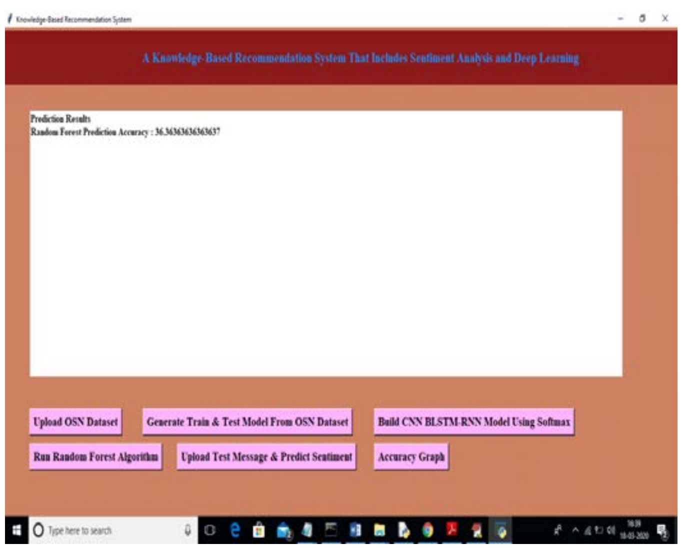

Fig. 8: The random forest prediction accuracy is 36% which is lower than proposed BLSTM accuracy

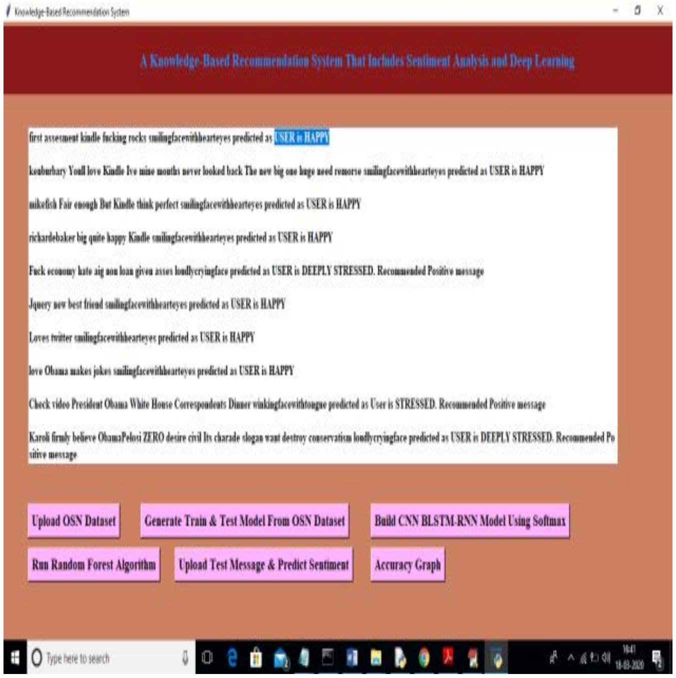

Fig. 9: In the above screen we can see each message application detected and mark with stress or non-stress status

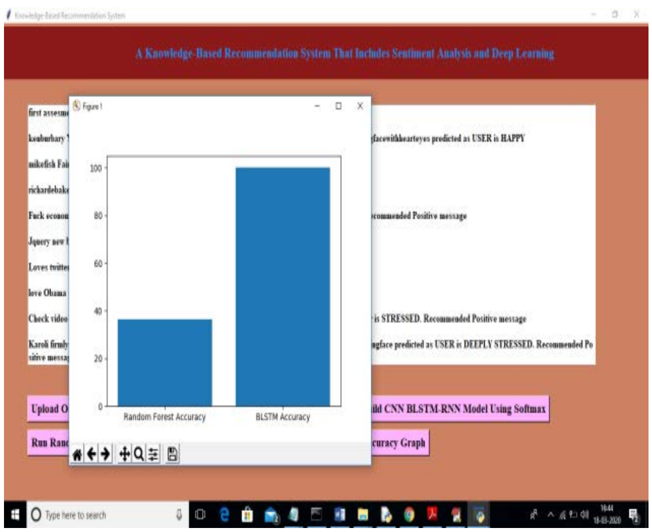

Fig. 10: Accuracy of BLSTM compared with Random forest

include SVMs and Naive Bayes[45]. These models can be further improved by training on not only individual tokens, but also bigrams or tri-grams. This allows the classifier to pick up on negations and short phrases, which might carry sentiment information that individual tokens do not[46-47]. Of course, the process of creating and training on n-grams increases the complexity of the model, so care must be taken to ensure that training time does not become prohibitive[48-49].

BLSTM algorithm: BLSTM is an associate degree extension of ancient LSTM. It will improve model performance on sequence classification issues[50]. In issues wherever all time steps of the input sequence area unit offered, BLSTM train two rather than one LSTM on the input sequence.

Convolutional NEURAL NETWORK (CNN): A convolution is the straightforward application of a filter to associate degree input that leads to activation. Indicating the locations associate degrees strength of a detected feature in an input, like a picture[51-52].

Upload OSN dataset: Using this module we will upload dataset to application. User profile and user data: database built from the data captured from OSNs. Messages: there is a database with 360 messages, 90 messages for each kind (relaxing, motivational, happy, or calm messages) to be suggested to the user by the recommendation engine[53-54]. The messages were written by 3 Specialists in psychology and validated by 3 other Specialists[55].

Generate train & test model from OSN dataset: Using this module we will read all messages from dataset and build a train and test model by extracting features from dataset[44]. Depression or stress detection by machine learning: the sentences are extracted from OSN and they are filtered by machine learning to detect depression or stress conditions. It is implemented in the emotional health monitoring system.

Build CNN BLSTM RNN model using SOFT MAX: Using this module we will build deep learning BLSTM model on dataset and then using test data we will calculate BLSTM prediction accuracy[56]. Hence they can successfully boil down a given image into a highly abstracted representation which is easy for predicting.

Upload test message predict sentiment & stress: Using this module we will upload test messages and then application will detect stress by applying BLSTM model on test data. In the proposed system, user's personal information and context information is used. However, users do not always post this related information. In case users do not post personal information, standard information is used, such as sleep routine of 8 hours, no unhealthy habits, no preferences about work or study. It is important to note that in our tests only 5% of the users do not post this information[57].

CONCLUSION

Various deep-learning techniques can be used for the prediction of Sentimental analysis and recommendation. The challenge is to develop accurate and computationally efficient medical data classifiers. In this paper the model contains the emotional health monitoring system, which uses the deep learning model and the sentiment metric named eSM2. The sentences are extracted from an OSN and then emotional health monitoring system identifies which sentences present a stress or depression content using machine learning algorithms and the emotion of the sentence content. This method reaches accuracy of 0.80 to detect depressed and stress users and also system consumes low memory, process and energy. Also, previous research into mood analysis can be utilized to assist with the categorization of blog posts, reducing the false positives caused by polls and surveys often posted on blogs . It can assist in confirming the risk of a blogger if their overall blogs carry a sad and desperate tone. At a more detailed level, sentiment analysis can be used to identify whether a keyword is relevant in a particular sentence, such that negated phrases such as "I don't want to kill myself" is not mistakenly flagged. We can do the future work of this project by also including the sarcastic sentences in the dataset. We can also predict the sarcastic data with the proposed algorithm for identifying drug addicts, gauging public opinion on political issues and optimizing viewer ship of advertising material. There are still a lot of other opportunities to expand on this research, for a cause which has such significant benefits for society.

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