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Chatbot Therapy: Enhancing Student Wellbeing in College

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Abstract: Chatbots are special agents that respond with the user in natural language just as a human would reply. Specifically, social chatbots are the ones which establish a strong emotional relationship with the user. The main concept behind this chatbot was to provide mental relief to students who undergo different levels of stress and which can be the onset of an inimical depression. In this paper, we proposed an intelligent social therapeutic chatbot which distributes the text into emotion labels namely, Happy, Joy, Shame, Anger, Disgust, Sadness, Guilt, and Fear. Further, based on the emotion label, it identify the users' mental state such as stressed or depressed using users' chat data. For emotion detection, we deployed three popular deep learning classifiers namely, Convolutional Neural Network (CNN), Recurrent Neural Network (CNN), and Hierarchical Attention Network (HAN). In particular, the proposed methodology of the chatbot is domain specific where through the users' interaction, the chatbot will try to prevent the pessimistic actions and rebuild more constructive thoughts.

Keywords: Artificial Intelligence, Depression, Natural Lan- Guage Processing, Students, Therapeutic Chatbot.

1. INTRODUCTION

A computer program which conducts a conversation with humans either in voice or textual method is commonly called, a chatbot [1]. So, when programs convincingly imitate human as a conversational partner, it is said to pass the famous Turing Test. Many such chatbots namely, ELIZA [2], PARRY [3], and ALICE [4], were earlier designed to pass the Turing Test [5]. Chatbots are devised in dialogue functionality and are broadly classified into two types. First one is based on a fixed set of hand-crafted rules where the chatbot would reply according to previously mentioned regulations and the second one is an intelligent bot. Apple Siri, Google Allo, Microsoft Cortana are some currently available chatbots and they use Natural Language Processing (NLP) which provides the machine with the ability to allow communication between machine-to-user and user-to-machine using human natural language. Stress and mental depression which are often terms asso- ciated with proletariat or working class is seldom associated with university students not accepted as a normal disease over the world. According to Association for Medical Education in the Eastern Mediterranean Region (AMEEMR) [6], 33.92% nursing students observed moderate to high-level stress, post-graduate students (i.e. residential, master degree students) have shown symptoms of stress up to 45.8%, orthopedic trainees have experienced stress 27.6%, etc. Apart from daily exercises and yoga, the most efficient way of curbing depression in the youth is by encouraging them to have a disclosure of their feelings and emotions to trustworthy parties. With increasing paranoia amongst people, it is, however, difficult for people to find someone who can ensure the confidentiality of their information. Thus, contemporary youth prefers talking to a machine rather than a human being. This led to the evolution of the idea of therapeutic chatbots [7].

In this paper, we proposed an intelligent therapeutic chatbot to reduce the mental illness (such as stress, depression) of youth. To overcome from the mental illness, one need to chat with the proposed chatbot for a while. In this process, bot will ask few questions to the user to understand the problem. Based on the chat data, bot will identify emotions of the user to calculate the percentage of negativity in chat. Further, with the help of negative content in the chat, bot will classify the level of mental status as normal, stressed or depressed. To extract the emotion from the user chat data, we deployed three well known deep learning algorithms namely, Convolutional Neural Network (CNN) [8], [9], Recurrent Neural Network (CNN) [10], and Hierarchical Attention Network (HAN) [11].

The rest of the paper is structured as follows: Section II describes related work. The proposed system is discussed in Section III. Results are shown in Section IV and conclusion of the paper is given in Section V.

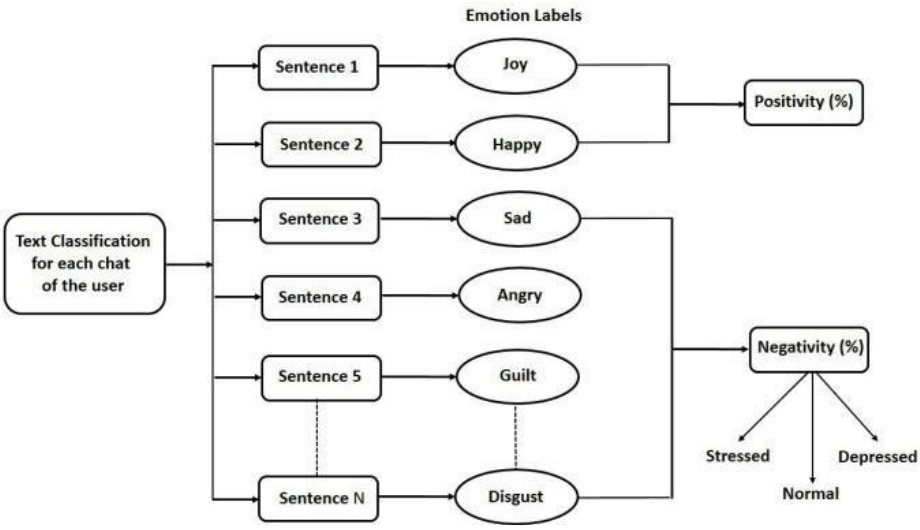

Fig. 1: System model for mental state identification using chat data.

2. RELATED WORK

In recent times, research related to chatbot has been in- crease significantly to facilitate in several applications [7], [12], [13], [14], [15]. In the paper, we briefly reviewed the conversational system methodologies which would analyze the emotional quotient of the user and try to become their virtual psychiatrist once they began to chat with the bot. A considerable amount of work has been done in the field of emotional analysis on the text written by a user in a chatbot [12], [13]. One of the successful chatbots that have been in the market so far is Woebot [16]. Wysa [17], another chatbot similar to Woebot, seems to be scripted sometimes which might annoy the user. According to Paul [18], Youper [19], the world‘s first ever emotional health assistant has a moodtracker and helps keeping track of the improvement in one‘s emotional and subsequently, mental health. According to Marianne [20], Headspace helps managing stress and anxiety of its users by motivating them for meditation and regular exercises.

3. PROPOSED SYSTEM

In this work, we have proposed an intelligent chatbot which takes users‘chat as the input and after processing, it will give the users‘ mental state such as normal, stressed, or depressed. The proposed chatbot is trained in such a way that when any user‘s chat fed into the chatbot then it classify the text into several emotions such as Happy, Joy, Shame, Anger, Disgust, Sadness, Guilt, and Fear. Further, based on the emotions, it calculate the positivity and negativity percentage of each chat text. Finally, an algorithm proposed to classify the mental state of the user using negativity percentage. The proposed model of the chatbot is shown in Fig. 1.

A. Dataset Description

In this work, we have used ISEAR dataset [21] for emotion detection in text. The dataset consists of 7652 phrases and 1542 emotional words. It is categorized into several broad categories of emotions such as Happy, Joy, Shame, Anger, Disgust, Sadness, Guilt, and Fear.

B. Training and Testing

To identify the emotion from text, three deep learning algorithms namely CNN, RNN and HAN are deployed for training and testing. A pipelined process for training and testing is shown in fig. 2.

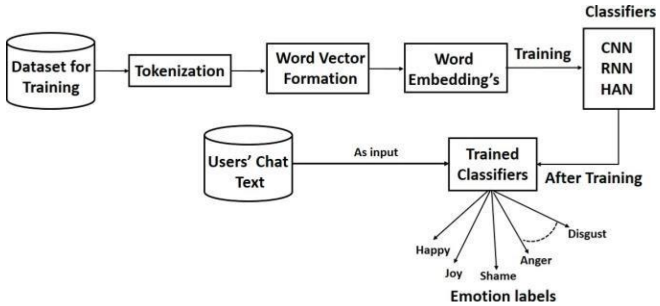

Fig. 2: Pipelined process for training and testing to identify emotion label from users' chat.

1) **Tokenization:** This process divides a entire text into a list of sentences by using an unsupervised algorithm to build a model for abbreviations, words, collocations, and words that start sentences. It must be trained on a large collection of plaintext in the target language before it can be used. The tool used for performing tokenization is Punkt Sentence Tokenizer [22].

2) **Forming Word Vector:** We used the unsupervised learn- ing algorithm used for obtaining vector representations for words is Global Vectors for Word Representation (GloVe) [?]. Training is performed on aggregated global word-word co- occurrence statistics from a corpus, and the resulting represen- tations showcase interesting linear substructures of the word vector space. The GloVe model is trained on the non-zero entries of a global word-word co-occurrence matrix, which tabulates how frequently words co-occur with one another in a given corpus. The tools provided in this package automate the collection and preparation of co-occurrence statistics for input into the model. The core training code is separated from these preprocessing steps and can be executed independently.

3) **Embedding's:** An embedding is a mapping of a discrete categorical variable to a vector of continuous numbers. In neural networks, embedding's term means low-dimensional, learned continuous vector representations of discrete variables. Neural network embedding's are useful because they can reduce the dimensionality of categorical variables and mean- ingfully represent categories in the transformed space which reduce the complexity. Neural network embedding's have three primary purposes:

1. Finding the nearest neighbor in space which leads to the formation of various cluster categories.
2. As an input to machine learning model for supervise learning.
3. For the relation between two categories i.e how much difference is there between two words on the basis of their hamming distance.

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C. Classifiers

In this work, Three popular classifiers of deep neural networks namely, CNN, RNN, and HAN are used for emotion classification from chat text.

1) **CNN:** It is a class of deep learning, feed-forward ar- tificial neural networks where connections between nodes do not form a cycle and use a variation of multilayer perceptrons designed to require minimal preprocessing [9]. When CNN on any text data is applied, a pattern is detected at every layer of convolution and the pattern could be N-gram word expression.
2) **RNN:** This allows to exhibit dynamic temporal behavior for a time sequence [10]. It is also a sequence of neural network blocks that are linked to each other's like a chain.
3) **HAN:** The overall architecture of the Hierarchical Atten- tion Network (HAN) consists of several parts: a word sequence encoder, a word-level attention layer, a sentence encoder, and

$$P(\%) = \frac{F(joy) + F(happy)}{Total\ no.\ of\ chat\ sentences(n)} \quad (1)$$

$$N(\%) = \frac{F(sad) + F(angry) + \ldots + F(disgust)}{Total\ no.\ of\ cha\ sentences(n)} \quad (2)$$

D. Mental State Identification

After the process of obtaining the emotion of each text of users' chat which is the process of assigning one of the emotion label to the text according to its content. For classification of the users chat into the category of different emotion classes are 'anger', 'disgust', 'fear', 'guilt', 'joy', 'sadness', 'shame', 'happy'. Based on the emotion, we proposed an algorithm as shown in Algorithm 1 to identify the one's mental state.

Algorithm 1 takes user chat data as the input to identify the users' mental state. After emotion classification of each text, it calculates positivity and negativity percentage using Equation 1 and Equation 2. Further, based on negativity percentage, al- gorithm will classify users' mental state in five classes namely, normal, slightly stressed, highly stressed, slightly depressed and highly depressed. According to the algorithm, if negativity percentage is below 20 then, it classify as normal. Next, if negativity percentage is in between 20-40 then, it classify as slightly stressed and if negativity percentage is in between 40- 60 then, it classify as highly stressed. Further, if negativity percentage is in between 60-75 then, it classify as slightly depressed and finally, if negativity percentage is above 75 then, it classify as highly depressed.

4. RESULTS

After performing tokenization on the dataset, we obtained the Number of Unique Tokens as 11577. Further, using to- kenization result, a total of 6118-word vectors, 9786-word vectors, and 48870-word vectors are obtained for CNN, RNN

Algorithm 1: Mental State Classification(MSC)

```
Input: A series of user chat (C)
Output: Classification of depressed or stressed
Notation : PE: positive emotion, NE: negative emotion, p p: positivity
  percentage, n p: negativity percentage.
Initialization: PE = 0, NE = 0
while (T in C) do
|      e = find emotion(T )
|    if ( e = joy || happy ) then
|     |      PE = PE + 1
|    end
|    else
|     |      NE = NE + 1
|    end
end
p p = find  positivity  percentage(PE) n p =
find negativity percentage(NE) if n p < 20
then
 |  Zero Depression.
end
else if n p > 20 & n p < 40 then
 |  Slightly Stressed



end
else if n p > 40 & n p < 60 then
 |  Highly Stressed,
end
else if n p > 60 & n p < 75 then
 |  Slightly Depressed.
end
else if n p > 75 then
 |  Highly Depressed.
end
```

(bidirectional Long Sort Term Memory (LSTM)) and HAN respectively using Glove 6B 100d.

For emotion classification in text, we deployed CNN, RNN (bidirectional Long Sort Term Memory (LSTM)) and HAN and the observations are as follow: CNN has achieved accuracy up to 75% with high consistency for 15 epochs. RNN and HAN have achieved up to 70% accuracy for 15 epochs as shown in TABLE I. However, they are not consistent enough throughout all the datasets. As RNN takes previous input into consideration, it takes huge time for the execution as compared to CNN and HAN. Hence, it is not preferable, for the huge dataset, in terms of time complexity. CNN model has outperformed the other two models (RNN and HAN) in terms of training time on the phrase dataset (ISEAR dataset [21]). However, HAN can perform better than CNN and RNN if we have a huge dataset [?].

Further, using the emotion label, Algorithm 1 will classify the mental state of user and advised to take the mental treatment as follows:

- Zero depression- No therapy requirement. The user is completely fine and requires no treatment.
- Slightly stressed- Relaxation required to shed stress. The user is mildly or occasionally stressed. She/he may need irregular breaks to cope up with stress.
- Highly stressed- Reduce stress in life. The user is mildly stressed and requires regular breaks between works to shed the accumulated stress.

Slightly depressed- Engage in recreational activities. The user is moderately stressed and on the borderline,

TABLE I: Emotion classification results using CNN, RNN and HAN.

Layer (type)	**Output Shape**	**Param #**
CNN)		
input 1 (InputLayer)	(None, 1000)	0
embedding 1 (Embedding)	(None, 1000, 100)	1157800
conv1d 1 (Conv1D)	(None, 996, 128)	64128
max pooling1d 1 (MaxPooling1)	(None, 199, 128)	0
conv1d 2 (Conv1D)	(None, 195, 128)	82048
max pooling1d 2 (MaxPooling2)	(None, 39, 128)	0
flatten 1 (Flatten)	(None, 128)	0
dense 1 (Dense)	(None, 128)	16512
RNN)		
input 1 (InputLayer)	(None, 1000)	0
embedding 1 (Embedding)	(None, 1000, 100)	1157800
bidirectional 1 (Bidirection)	(None, 200)	160800
dense 1 (Dense)	(None, 7)	1407
HAN)		
input 2 (InputLayer)	(None, 15, 100)	0
time distributed 1 (TimeDist)	(None, 15, 200)	1318600
bidirectional 2 (Bidirection)	(None, 200)	240800
dense 1 (Dense)	(None, 7)	1407

i.e., he/she may be on the getting highly stressed. Meditation, relaxation is the need of the hour.

- Highly depressed- Engage in recreational activities. The user is highly stressed. Meditation, relaxation is the need of the hours. Possible need to meet doctor.

4. CONCLUSION & FUTURE SCOPE

This paper highlighted the importance of a social thera- peutic chatbot especially for the students. In this work, we proposed an intelligent chatbot for mental state identification and their remedy. In order to identify emotion of user chat text, three deep learning algorithms namely, CNN, RNN and HAN were deployed. With the help of label of emotion, it also identify the mental state of the user such as stressed or depressed. In the future, we will increase accuracy for text classification methods. Currently, we have focused on minor details of the user as we believe that attending to their queries and alleviating them from the stress would be the need more information about the user would lead to an efficient and desired output.

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