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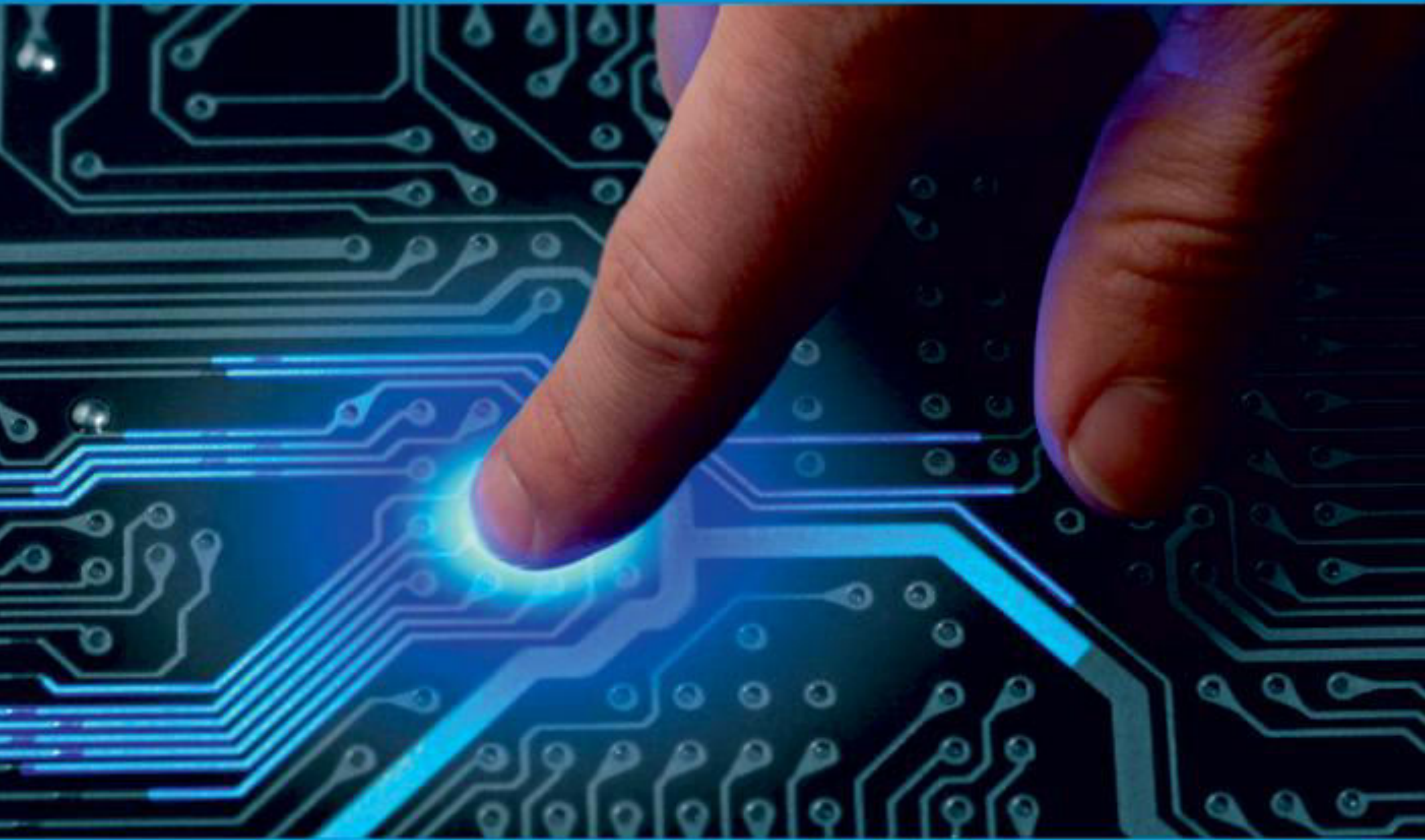

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Emotion Recognition System Using Chatbot

Priyanka More, Snehal Sargar, Ashwini Shinde, Rutuja Mane, Asst Prof. S.Patil

Department of Computer Science and Engineering, ADCET, Ashta, Maharashtra, India

ABSTRACT: A chatbot is similar to a digital assistant that can be pre-learned, or have the ability to self-learn. What could possibly fill the request submitted by the user, and the answer, naturally, in the user's language during a conversation. A chatbot can help a person to engage in a digital conversation, because it can be used for natural language processing. The Chat-bot interface to improve communication, but it's never to improvise, even when it is needed. And sometimes, they go off topic during a conversation, it is not a serious flaw. The proposed bot is able to determine the emotional state of the users and of the recommendations, with the help of the functions in the long-term memory, and a library with tensor flow. The popularity of the chat, the y will allow us to operate our system with a number of different applications. These chatbots can be used for automation in various areas such as e-education, e-governance, and the internet model.

KEYWORDS-Chatbot,tensor flow, Emotion recognition, natural language processing

I. INTRODUCTION

Feelings and emotions play an important role in human interaction. Emotion is a mental and physiological state, which is a subjective and private. We recognize a person's emotions through his words, the gesture, the face, the language of body and gestures in action. It is an emotional expression, it should be the general Happiness, Sadness, Anger, Disgust, Surprise, and Fear. Because these days a lot of people are using the text-in devices that interface to extract the emotion of a text, which is of great importance. That is why it is hugely important to emotion, text, and phone calls are to be understood by machines, which in the end provides the user with an emotional response.

Machine Learning is one of the best of the best to develop technology, to offer a solution to the problem of limited human resources, with the best results at a low cost. It is the only tool which interacts with the customers, is not a chatbot, which will be an integral part of our day to day life. Chatbots are a machine learning applications, which work to enhance the user experience.

There are two types of chatbots: the first one is the chatbots based on artificial intelligence, intelligent features the dynamic movement, the ability to learn, and can update them. The second one is a robust chatbot is a program of solid information, which is not able to handle all the requests. This suggests that there is only limited interaction. Some chatbots are programmed using only some of the answers that they are not able to respond to anything any longer but to be the way they were programmed to be. These chatbots are not able to identify the emotion, sound, or any other human expression that is being presented by the music, which can sometimes be confusing to them, not what they think they would like the user to, for example, if a user is behaving in a different way, it can be easy to misinterpret. Chatbots or intelligent systems are installed in order to increase the response rate and improve customer interaction. However, due to the limited time and availability of the information for the update or improve this process, and probably a very time-consuming and expensive. There are two main types of chatbots, depending on the domain. Chatbots, in an open-domain, it is possible to answer questions about a variety of topics, while chatbots in a closed domain, the function only works in areas where there is knowledge for all. Shabo, which is used, in order to respond to the status of the Twitter, you will be accepted by an opendomain, and a Shabo, which is used to order a pizza, in a closed area, however, a chatbot to answer any financial questions, it will be somewhere in the middle, despite the fact that in a closed-domain, than in the open.

II. RELATED WORK

This paper focus chat assistant which can recognize and monitoring the human emotion and understand the natural language conversation, the most crucial technologies in the conversational psychiatric counselling service. A. Emotion Recognition There In previous work, there are several types recognition about user’s emotion: text, image and video and audio proposed an emotion recognition approach for mobile social network services. They found 10 features that indicates the emotional state of the user; those features were mostly determined by the behavioural user patterns and the

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contextual user pattern (e.g., each typing speed and location). Emotional classification showed 67.52% accuracy on average for the 7-emotional states that follows: happiness, surprise, anger, disgust, sadness, fear, and neutral. showed committee machines a framework that has structure of deep CNNs. It show robust face expression recognition. The paper demonstrated those model on the SFEW2.0 competition dataset that released for the EmotiW2015 challenge. The model structures are 3 levels of hierarchical committees. They achieved test accuracy of 61.6 %, which highly outperforms the baseline of 39.1 %. In , they align temporal the audio and visual streams by utilizing the soft attention mechanism. They added emotion embedding vectors in output layer of RNN. It locates and re-weight the perception attentions along the audio visual stream. There are limitations in performance for previous emotion recognition methods using a single feature only. Human can inference emotions of the others from integrated information. Also, human recognizes the degree of emotional state and responses from the circumstance condition. So, for the intelligent assistant, integrating multi-modal information is inevitable. The integration can be obtained by adjusting the strength of each model from the various information in multiple data source at the same time. Also, they are used just one directional dialogue analysis. They only focused on the emotional analysis itself. The root of the limitation is, until now, user emotions are inferenced by only one-time recognition from external factors. B. Chat Assistant for Mental Healthcare Chatbots broadly are used for the intelligent assistant applications. In common, they generate responses from the user's input. The chatbot need to have a capacity to analyse natural language dialogue. introduces a smart mobile healthcare assistant. They improve patient-doctor interactions, Argues that the chatbot can substitute professional counsellor by intervening alcohol drinking habits. Emotional intelligence is necessary as an essential function of digital companion. To do this, we need to develop a deep interaction model that recognizes complex and long term emotions in various conversations continuously. Just as human counsellor need to learn from many interaction and communication to react counselee properly, the emotional intelligent assistant should communicate and learn opinions and emotions with many people. Through this, it is necessary to develop a system that learns common elements firmly and improves oneself by continuously learning the characteristics and emotional state of the individual.

III. PROPOSED ALGORITHM

A. *Pretreatment :*

It is the first step, as shown in Figure 1, which is derived from the first to the processing of this data. The punctuation marks are not included in the analysis, and the words that are translated to lowercase letters have been left out. Punctuation marks, such as [! # $ % &" (*) +,-/\: "< = >< @\^ ' { } ~)] also, to be taken from the original programmed. Each and every word in an expression to represent a whole number that is unique for each and every word. Instead, add a "0" (zero) in the very beginning, so that in every sense of the word, have the same length. Once this step is completed, the it is the numerical data, enter the data for the neural network. At this stage, primary treatment, we have to calculate the number of words, information, education, and the maximum number of words in a sentence. On the other hand, to carry out the classification, the SVM reference method in order to get the desired function. For SVM, we use the TFIDF features.

B. *Emotion Classification:*

Fig. 2 Displays a LSTM simulation diagram using KERAS software. The following layers forms LSTM for emotion classification: Embedding layer, LSTM stratum and output layer. Some parameters are necessary for the embedding layer as its input. There is only one neuron to the embedding layer. The word transmitted into this neuron will be converted into a true valued vector (output dimension) of required lengths. Once the network has been equipped we will obtain the masses of the embed layer. It implies that there is a true value length vector for every term. The embed process is implemented as perword2vec embedding approachfor Example: Consider the below input sentence which is given. Here firstly each sentence is segmented into a word in which further processing of the sentence happens through LSTM with the help of SoftMax process and finally emotion recognition from the input sentence will be obtained. Input Given: I believe that I am more sensitive to other people feelings and tend to be more compassionate. The person's emotional recognition from any of his / her outputs, including text is a nonfixed behavior, so we can infer from the text that the text's predominant emotion is one of them. The key shortcoming of existing methods is considering the precise and defined parameters for emotions to identify emotions from the text. In other words, the existing methods only assign each text to one of the emotional categories. The aim of this paper is to recognize all existing emotions in the text, and to determine the predominant emotion of the sentence only with minimal feature technology. To achieve

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that goal, we are proposing a hybrid deep learning model to automatically learn features. Our proposed model uses phrase structural knowledge and deep learning models in a hierarchical manner to provide sentence level functionality.

Our proposed multilabeling approach has the following steps:

1.Segmentation of sentences done for identification of emotional recognition through thesentence.

2.Word representation through use of word embedding method

3.The primary determination of emotion by the sentence using a Long-Short-TermMemory(LSTM)network.

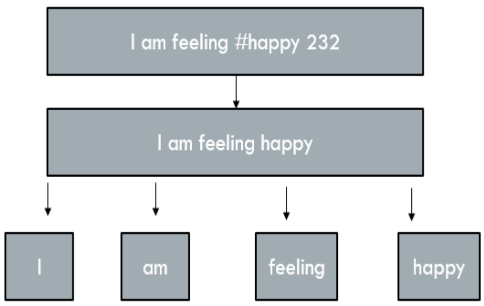

Fig1. Preprocessing of text

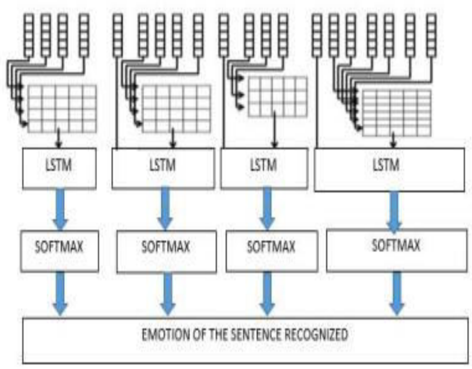

Fig2. Deep Model Structure

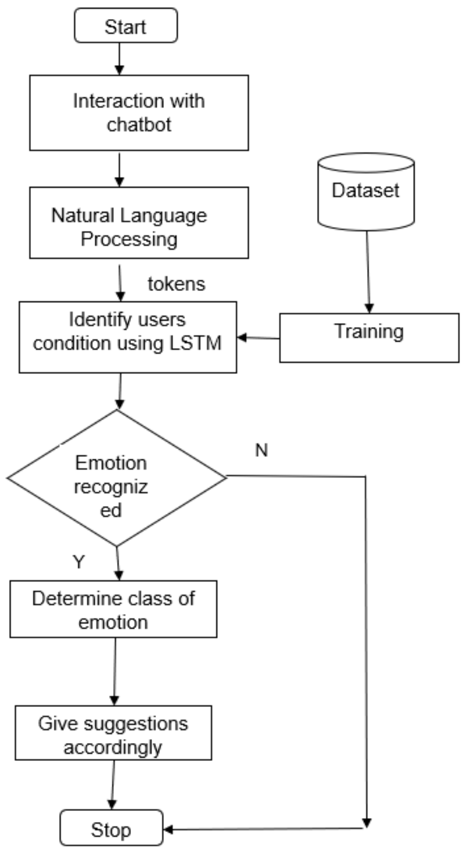

Fig3. Flowchart

Figure 3 illustrates following steps:

1. Interaction with chatbot User will interact with chatbot.
2. Natural Language Processing In natural language processing text analysis is done. As shown in Fig 2 it will provide preprocessing for the text. Text will be broken into tokens using tokenization. Punctuations are omitted in this analysis and words are translated into lowercase letters. The punctuation marks such as [! # $ % &" (*) +,-/\: "< = >< @\^ ' { } ~)] are also eliminated from the pre-training process.
3. Emotion recognition Word embedding method is used for word representation. As shown in Fig 3 LSTM with the help of SoftMax process will finally recognize the emotion from the input sentence.
4. Respond to user After classifying the emotion of the user the chatbot will reply to user.

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IV. RESULTS AND DISCUSSION

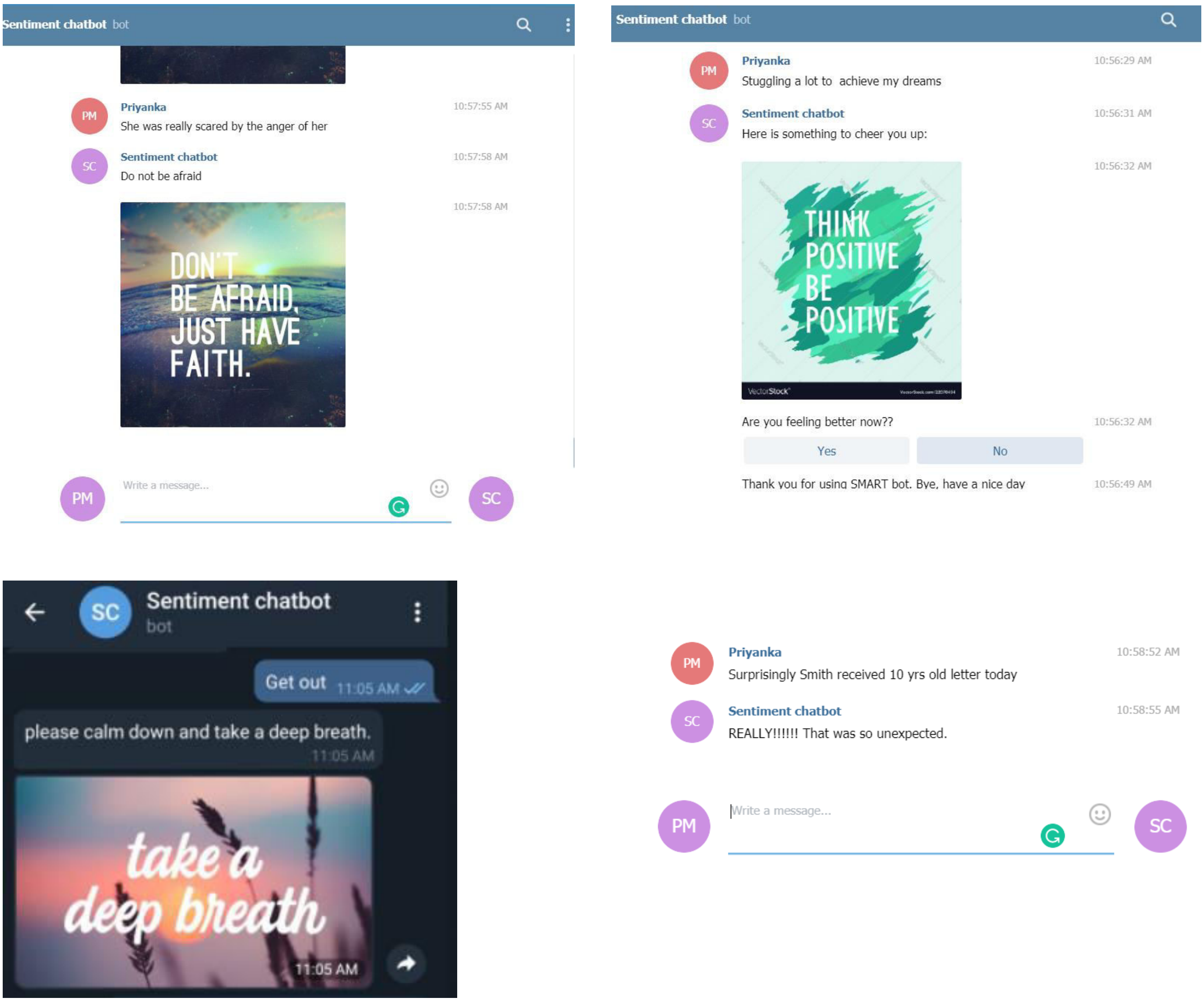

Fig.4 Output

The above Fig4 shows the working of LSTM model. We can see that emotion are classified into two categories that is positive and negative and according to that emotion chatbot gives response.

The performance evaluation of the model is also made in this section, along with a figure given below. On the comparison between the predictions that is correct prediction and wrong prediction the result of prediction is given over here. We can see that the result of correct prediction is high than wrong prediction .In the performance evaluation of LSTM model it gives 0.938 accuracy.

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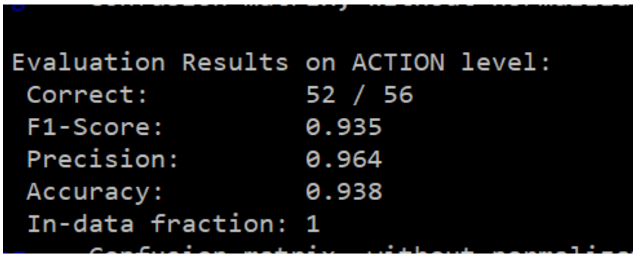

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Evaluation Results on ACTION level:
 Correct:            52 / 56
 F1-Score:           0.935
 Precision:          0.964
 Accuracy:           0.938
 In-data fraction: 1
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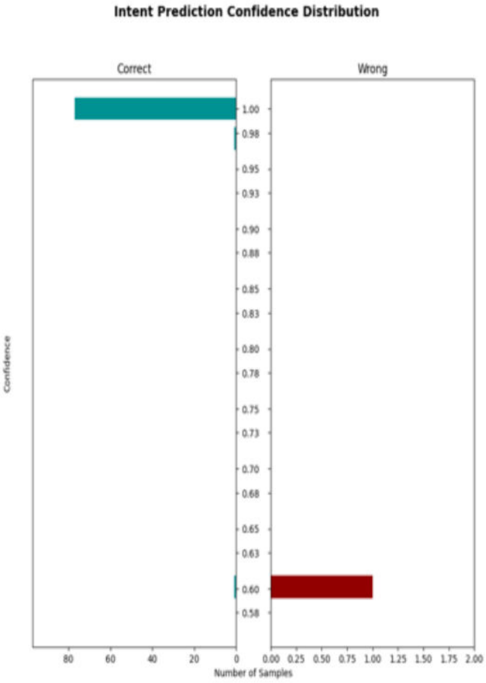

Fig5. Result Analysis

V. Conclusion and Future Work

Emotion recognition in conversation has been gaining popularity among NLP researchers. In this paper, we summarized the recent advances in this task and highlight several key research challenges associated with this research area. Further, we pointed out how current work has partly addressed these challenges, while also presenting some shortcomings. Overall, we summarised that an effective emotion-shift recognition model and context encoder can yield significant performance improvement over chit-chat dialogue, and even improve some aspects of task-oriented dialogue. Moreover, challenges like topic-level speaker-specific emotion recognition, ERC on multiparty conversations, and conversational sarcasm detection can form new research directions. Additionally, finegrained speaker-specific continuous emotion recognition may become of interest for the purpose of tracking emotions during long monologues. We believe that addressing each of the challenges outlined in this paper will not only enhance AI-enabled conversation understanding, but also improve the performance of dialogue systems by catering to affective information

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