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Intelligent Chatbot Model to Enhance the Emotion Detection in social media using Bi-directional Recurrent Neural Network

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Abstract— A Chatbot is like a digital assistant, can be pretrained or have self learning capability. It can be trained to understand the user queries and respond in natural language of the user during a conversation. Chatbot can actively help human to involve in a digital conversation since it can make use of the natural language processing. The existing Chatbot enhances the communication but it does not improvise the information when it is needed. And sometimes they go beyond the topic during conversation which is a major drawback. The proposed bot could identify the emotional status of the users and can provide suggestions using Bi-directional Recurrent Neural Network and tensor flow library functions. The popularity of the chat bots lets our system to be used for much variety of applications. These chat bots be used to automate the various fields like e-learning, e-government and web based models.

Keywords—Chatbot, self learning, B-RNN (Bi-directional Recurrent Neural Network), Tensor flow.

1. INTRODUCTION

Machine learning is one of the well developing technologies that offer solution to limited man power capacity with better results at reduced costs. The one tool that enhances customer interaction is chat bot which is becoming a part of our daily life. Chat bots are machine learned programs that interacts and improves the user experience. There are two types of chat bots first AI based chat bots, which is intelligent, has dynamic learning capability and it can update them constantly. The Second is a fixed chat bot which has programs with fixed information cannot be able to handle all the queries. It offers only limited interaction.

Some chat bots are programmed only for certain responses that they cannot respond more than not being what they have been programmed. These chat bots cannot detect the emotions, tone of voice or any other human expressions that are put forward in a message and this can sometimes confuse them into what they think the user wants, for example if a user is being contemptuous it can be easily misread. Chat bots called intelligent system and are installed with the intension to increase the speed of responses and to improve customer interaction. However, due to limited time and data-availability for self-updating or improving, this process appears to be more time-taking and costly.

There are two main types of chatbot depending upon the domain. Open domain chat bots can answer questions about a great variety of topics, whereas closed domain chatbots only function inside a specific domain in which they have knowledge. A Chabot used to react on Twitter statuses would be seen as open domain and a Chabot used to order pizza would be seen as closed domain, but a chatbot to answer all types of financial questions would be somewhere in between (although more closed domain than open domain).

Chabot's can be either retrieval-based or generative-based. Retrieval-based means that answer are retrieved from an underlying dataset. The retrieval process can be simple using rule-based sentence matching, or advanced using an ensemble of machine learning techniques. These systems will always return an existing answer from a set of pre-defined responses. Generative-based chat bots do not give predefined responses; these systems generate the response themselves. Fig.1 represents that there are roughly four types of chat bot framework.



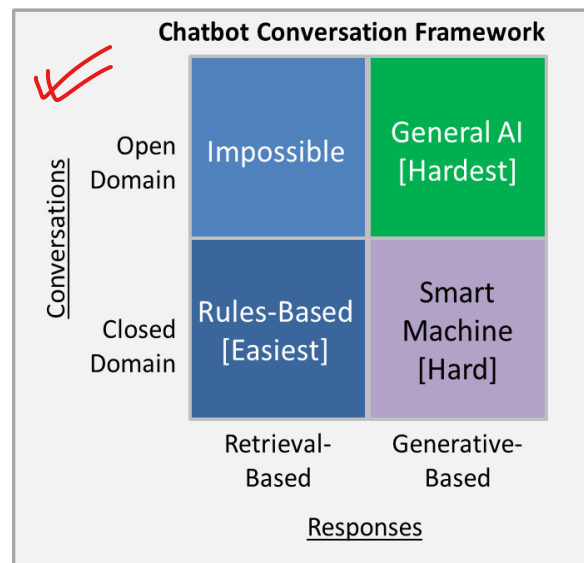


Fig.1: Chat bot framework types.

Open domain with retrieval-based responses

Retrieval-based responses are responses from a fixed set, in an open domain. This fixed set can be any possible question that anyone can think of. But this cannot be done and therefore this type of chatbot is impossible to create.

Open domain with generative-based responses

In this type chatbot can be able to answer any possible question and the user gets an appropriate response. To solve this problem generative-based type is used called Artificial General Intelligence (AGI). This means that the chatbot is a smart machine that can successfully perform the same intellectual tasks as humans can. This area is being researched intensively.

Closed domain with retrieval-based responses

These types of chatbots are trained on a dataset with text on a certain domain. Questions inside the domain will be answered with one of the responses in the training dataset. The chatbot does not have an answer to questions asked outside this domain, and to unforeseen questions inside the domain. The way most companies deal with this problem is that when there is a question the chatbot cannot answer the question is passed to a human.

Closed domain with generative-based responses

This type of chatbot uses smart machine technology to generate the answer to a question. Generated response makes the chatbot able to handle questions present in the underlying dataset but also new questions. This type of chatbot can also deal with interactions that are longer than one question and one answer and they tend to give more human-like answers and can have their own personality. Disadvantages of these types are that generative responses increase the complexity of the problem by a lot, generated answers are usually full of grammatical errors and these chat bots require huge amounts of training data.

As open domain retrieval-based systems are impossible and open domain generative based systems have not even been successfully built. Closed domain chat bots more specifically used more often in financial domain. Both retrieval-based and generative-based closed domain systems are already applied in practice today. The main focus of a chatbot is giving reliable and grammatically correct answers. This is the reason, the closed domain retrieval-based chatbot is most appropriate. In the future, when generative-based techniques have improved and a larger dataset of domain questions and answers is available it might be possible to create a generative-based chatbot for the same case.

2. LITERATURE SURVEY

Eliza is the first NLP computer program created by Joseph Weizenbaum in 1964 [1]. Eliza is one of the first chat bot programs that are capable of attempting the Turing test. Eliza was originally designed to emulate a psychotherapist. Eliza mimicked the conversation by using pattern matching technique and substitution methodology that gave the users an illusion that ELIZA understood the conversation. The drawback of ELIZA is that it does not have a framework for contextualizing events. Eliza produces more complications like writing the script in Upper case and lower case which has a huge disadvantage of the bot Eliza. Figure 2 depicts a sample dialog of Eliza.

```

EEEEEE LL      IIII ZZZZZZ  AAAA
EE      LL      II      ZZ  AA  AA
EEEEEE LL      II      ZZ  AAAAAA
EE      LL      II      ZZ  AA  AA
EEEEEE LLLLLL IIII  ZZZZZZ  AA  AA

Eliza is a mock Rogerian psychotherapist.
The original program was described by Joseph Weizenbaum in 1966.
This implementation by Norbert Landsteiner 2005.

ELIZA: Is something troubling you ?
YOU:  Yes. I'm trying to describe you for a research paper I'm writing. What sh
ould I say?
ELIZA: You are sure.
YOU:  Yes, I'm sure.
ELIZA: I see.
YOU:  What can I tell them about you?
ELIZA: You seem to need to tell them about me.
YOU:  I absolutely need to. Please help.
ELIZA: That's quite interesting.
YOU:  I agree.
ELIZA: You say you agree ?
YOU:


```

Fig.2. A sample dialog with ELIZA

Chatbot named PARRY was the next developed in 1972 by Kenneth Colby [2]. PARRY had a conversational strategy, which was much more serious and advanced program than ELIZA. Hence, PARRY was always termed as “ELIZA with Attitude”. PARRY Chatbot was developed to simulate a paranoid individual with mental illness. PARRY was the first Chatbot that passed the Variation of the Turing test.

Jabberwacky is one of the chatterbot developed by Rollo Carpenter [3] on aiming on mimicking a natural human chat in humorous and entertaining manner. Jabberwacky was one of the early attempt of introducing artificial intelligence through human conversation. The main aim of this Chatbot is to migrate from text based to fully voice operated system. Jabberwacky program retains all the conversations and finds appropriate responses by matching patterns in their context.

Researchers continued to develop various models with natural language computing capabilities, but none were cleared by passing the Turing Test. AIML is used to declare pattern-matching rules that link user-submitted words and phrases with topic categories for specifying the heuristic conversation rules. It won the Loebner Prize however the program was unable to pass the Turing test. The ALICE system consists of two modules namely Alice bot engine and AIML KB [8]. It is eXtensible Markup Language (XML) based, and supports most chat bot platforms and services that are in use today. Figure.3. shows the ALICE chatbot conversation with the user.



Chat Bot – ALICE
(AI Foundation)

- Human: hi my name is Carla
ALICE: How are you doing, Carla.
Human: what is your name?
ALICE: My name is ALICE.
Human: what is your full name?
ALICE: ALICE = Artificial Linguistic Internet Computer Entity.
Human: when were you born?
ALICE: I was connected to the net on November 23, 1995.
- Human: Have you passed the Loebner Prize?
ALICE: The Loebner Prize is an annual Turing Test sponsored by New York philanthropist Hugh Loebner. Dr. Wallace and ALICE won in 2000. The ALICE program was ranked "most human computer" by the panel of judges.
- Human: who is Dr. Wallace?
ALICE: He is a famous computer scientist, the author of ALICE, and a graduate of Carnegie Mellon.
- Human: Where does Dr. Wallace work?
ALICE: he works from his home in San Francisco.

Carla P. Oomen
ISF0372

Fig.3. A sample of ALICE chat bot conversation.

Siri one of the latest intelligent bot uses Automatic speech recognition to translate human speech into text which includes short utterances, dictations or questions [4]. Using natural language processing (NLP) as a part of speech tagging, noun-phrase chunking, dependency and constituent parsing. SIRI translates transcribed text into "parsed text". SIRI uses the intent analysis and previous questions it analyzes by using third party web services to perform actions like search operations, and question answering. Speeches that are identified as a question by SIRI are not answered directly, but it is forwarded to more general question and answering third party services.

Alexa is a voice based service provider by the Amazon Echo device. Alexa also uses NLP algorithms for voice conversation. It uses these algorithms to interpret, recognize and reply to the voice commands of the user. It is capable of various functions like making to-do lists, setting alarms, playing audio books, providing weather and traffic updates, playing music and much other real time information. Alexa can be used to control smart devices by identifying itself as an automation hub [5].

The Octopus is a multi agent system that is implemented through the multi agent system development framework MaSMT. The octopus chatbot supports chatting facility through text. Octopus has an action facility that handles limited tasks like execution of some command, open or closes some application, search some result etc. Searching facility is also available to search some files or data inside local network or in the HDD. The Octopus consists of 8 sub-systems namely core system, learning system, GUI (Graphical User Interface) system, action system, NLP system, communication system, searching system and data access system which are all implemented using java.

A novel software architecture called Basilica for building conversational agents that can support collaborative learning in an efficient way. This chatbot involves two or more learners that can interact with one or more conversational agents. This method is called collaborative team working, happens through a learning task. Mitsuku chatbot won the Loebner prize in 2013. It was one the most human like chatbot that is publically available.

The first wave of AI technology development that happened is in the form of chat bots. Social media platforms like Facebook that allows developers to establish a Chabot for their brand or service so that consumers can continue some of their daily actions from within their texting platform. This development of AI technology excited everyone as the possibilities for the way we use to communicate with brands have exponentially expanded.

Chatbots are widely been under development and deployed frequently more often comparatively than the previous decades. These chatbots are built differently for various purposes. Currently these chatbots have limited language support.

Voice-activated conversational agents like Siri, Google Now, Cortana, Samsung S Voice are not considered as chat bots. Bots have evolved to serve multiple purposes, such as content editing and brokering complex transaction. Chat bots can be used to provide advantage to companies, who can use them to reduce the time-to-response and provide enhanced customer service to increase customer satisfaction, and engagement. Unfortunately, some chat bots are specifically designed to be harmful.

From the above literature survey it is clear that chat bots are growing in a more robust and advanced manner. However, these chatbots does not satisfy the user's needs in one way or the other. All the above discussed works are meant only to start a conversation. The main aim of this project is to develop multi agent communication system that can communicate both with the users and with the other chat agents to solve complex problems.

3. METHODOLOGY

The advancement of the technology in the recent times has developed the integration machine learning and deep learning which can be improved in various fields. This method can be implemented in the development of chat bots. The required datasets can be gathered accordingly which plays a vital role in the chat bot development. This section describes about the data set collection, preprocessing and database creation which are used to create the required chatbot or the conversational bot.

A. *Dataset*

The dataset is the main aspect for the development of the conversational bot. The dataset resources needed are collected. The datasets like Cornell movie dialogue corpus can be used but it is not the expected raw data that is required for training the conversational bot. Hence a part of the dataset around a month of conversation from Reddit was downloaded which has approximately a million of comments for the chatbot. The dataset from the Reddit is chosen because it have the required tree structure and not in linear format.

These datasets can be processed and can be used to build the bot required. The comment and reply can be paired together to make a successful conversational trainer for our conversational bot.

B. *Data Preprocessing*

The data collected from the data sources may not be directly fed for processing. Initially all the comment in the dataset is considered as the “parent”. The replies to the parent are stored under the parent in the database. There can be more than one replies for a parent comment which can be confusing while training. To rectify this, the method used is to pair the parent comment and the reply with higher up-votes.

To store the data parameters like parent_id, comment_id, the parent comment, the reply comment and the score (up-votes) are used. Paired_rows are used to find the number of rows that are paired.

If the comment score is higher than the existing parent comment pair then the new comment will be replaced in the database.

C. *Database creation*

The database is the storage place for the preprocessed datasets. The dataset required for training the chatbot is stored after the cleaning process. The parent comments without replies are cleaned and then the dataset are stored.

The larger the dataset it takes more amount of time to store all the data. Hence the dataset is reduced in size by removing the unwanted comments, spaces and characters. The dataset thus stored has only the cleaned contents with parameters like parent, comment, parent_id, comment_id and the score.

D. *Role of Sentiment analysis*

The main role of sentiment analysis is to find the real time emotion of the user. Sentiment analysis is contextual mining of text which identifies and extracts subjective information from the source material.

With the ongoing advances in profound learning, the capacity of calculations to dissect content has improved impressively. Inventive utilization of cutting edge man-made brainpower systems can be a powerful device for doing top to bottom research.

Sentiment Analysis is one of the most common classifications tool for text that can analyze a statement and predict whether the sentiment is either positive, negative or in neutral form.

1) **Types of Sentiment Analysis**

There are many variations of sentiment analysis and sentiment analysis tools that varies from system to systems. These tools can focus on polarity (positive, negative, neutral) of a system that can find the emotions (angry, happy, sad, etc) or can detect the intentions (e.g. interested v. not interested) of the user.

Few system can also provide different variations of the polarity by detecting whether the positive or negative sentiment is affiliated with a particular feeling like happy, love, or excitement (i.e. positive feelings) or anger, sad, or distress (i.e. negative feelings).

a) *Emotion detection*

frustration, and many others. Many of the emotion detection system reside to lexicons which consist of lists of words and the emotions they convey.

b) Aspect-based Sentiment Analysis

When analyzing the emotions of products, the companies might be interested in what people are talking about the product whether the reviews are with a positive, negative or neutral polarity, but also about which particular aspect or features they are talking.

c) Intent analysis

Intent analysis basically identifies what the people need to do with the obtained data or text rather than what people need to say with that data or text.

d) Multilingual sentiment analysis

One of the difficult task for sentiment analysis is the multilingual sentiment analysis. It needs a lot of preprocessing work and that preprocessing work requires the use of a number of resources in which some of the resources are already available online like sentiment lexicons, but many others resources has to be created by the user.

There are various methods and algorithms that can be used to implement the sentiment analysis in the systems. They are classified as:

- **Automatic systems** depends upon the machine learning techniques and algorithms, which are used to learn from data.
- **Rule-based systems** which perform sentiment analysis based on a set of rules created by the user.
- **Hybrid systems** combines both rule based method and automatic approach.
The rule-based method defines a set of rules in the scripting language that can identify the subjectivity and polarity.

The rules may use a variety of inputs, such as the NLP techniques like stemming, tokenization, parts of speech, tagging and parsing can be used. Other resources, like lexicons (i.e. lists of words and expressions) are used.

For example in a rule-based implementation the following steps takes place.

1. It can define two lists of polarized words either negative words such as bad, worst, ugly, etc., or positive words such as good, best, beautiful, etc.,
2. For a given text, the number of positive words and the negative words that appear is counted.
3. If the number of positive word occurrence is greater than the number of negative words present, positive sentiment is given, vice versa. Otherwise, it returns neutral sentiment.

This system is very naïve since it doesn't take into account how words are combined in a sequence.

The Training and Prediction Processes

In the training process, the model learns to associate a particular text input to the corresponding output based on the datasets used for training. Then the feature extraction transfers the input text into a feature vector. These feature vectors are then fed into required the machine learning

In the prediction process, the feature extraction is used to convert the unseen text inputs into feature vectors. These feature vectors are then fed into the model, which generates predicted tags like positive, negative, or neutral.

Classification Algorithms

The classification usually involves algorithms like Naïve Bayes, Logistic Regression, Support Vector Machines, or Neural Networks.

- **Support Vector Machines** is a non-probabilistic model which uses text representation of examples and marks it as points in the multidimensional space.
- **Linear Regression** is one of the familiar algorithms in statistics which is used to predict the value of (Y) given a set of available features of (X).
- **Naïve Bayes** is a form of probabilistic algorithm that predicts the category of a text by using Bayes's Theorem.

E. Role of Bi-directional recurrent Neural Network

To learn simple patterns and grammar sequence to sequence model is used. The context flow is determined by the bot using the sequence to sequence model. The BRNN algorithm is used to train the bot. The Bi-directional recurrent neural network has both the data used previously and the future. So it is easy to train the bot for a proper conversation. The Bi-directional recurrent neural network has the input sequence that goes forward and backwards whereas in recurrent neural network (RNN) only the input sequence goes to the hidden layer and to the final layer. The BRNN has two hidden layer for both the past input and the future input which makes it more suitable for our chatbot. The connection goes from input layer to the hidden layer and to the output layer in recurrent neural network. The connection in bi-directional neural network goes from input layer to the first hidden layer to the next hidden layer then to the output layer. As the inputs are carrying forwarded to hidden layer in RNN we get temporal characteristics. The flow of deep learning based chatbot model is shown below in Fig .4.

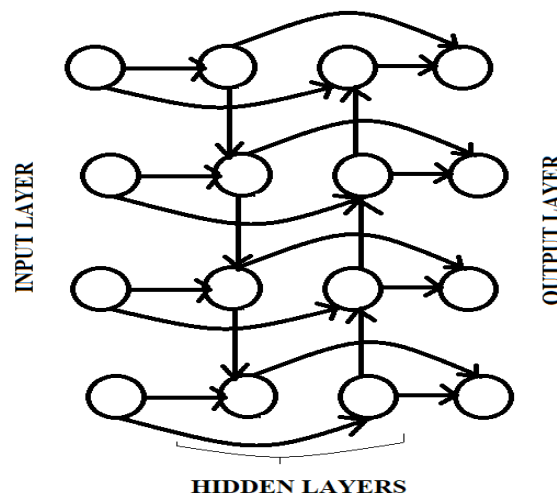


Fig. 4. Bi-directional recurrent Neural Network

4. MODEL IMPLEMENTATION

The model implementation describes about the working of chatbot. The sentiment analysis phase and the chatbot phase includes various phases like preprocessing the acquired data, training the data, testing the trained model to get the required model. Figure.5 describes the architecture of the proposed model.

The dataset are collected from the reddit conversation list to train. The data that are downloaded are in raw data format. It consists of various data's that are not useful for training like spaces, username, etc. , Therefore the needed to be cleaned before usage.

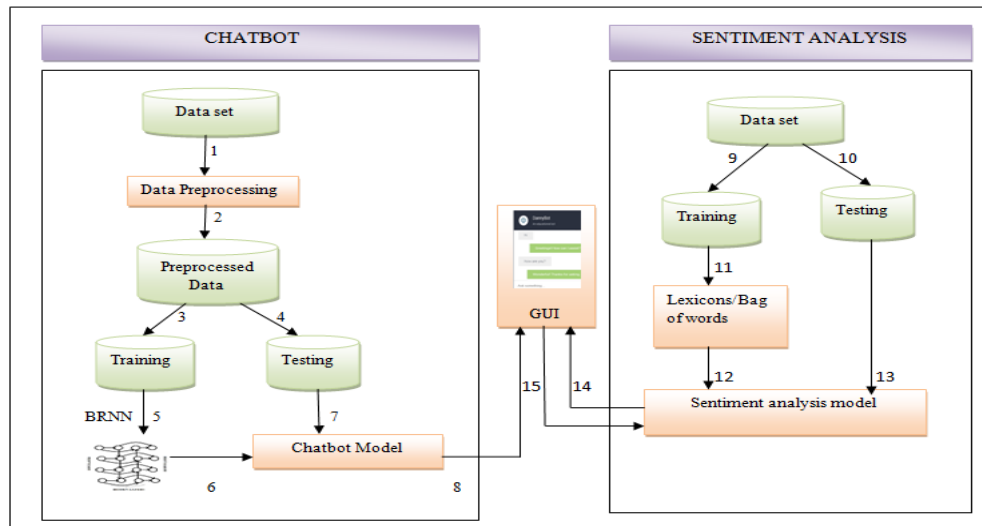


Fig.5. Architecture of the proposed model

The preprocessing includes removing unwanted contents in the dataset. The dataset once cleaned will have only the parameters that are needed to train the model. The preprocessed datasets also available online that can be utilized if needed.

After the required clean dataset is obtained it is used to train the model. The model is created and trained. Bi-directional neural network, a machine learning algorithm is used to train the model. Since it has two hidden layer that can go both forward and backwards the model could have both the data that is used in the past and the future data that are useful in prediction of the reply for the question asked in the chatbot. The chatbot needs to remember a series of words to form the long sentence reply. Hence the BRNN algorithm is used for such purpose.

Once the model is trained the chatbot can be used to perform the basic conversations with the user. The chatbot is named as Dannybot. The bot uses the trained model and the database created while training to reply to the questions asked by the user. PyQt is used to develop the user framework GUI. Hence the chatbot can have a user friendly look. The GUI is depicted in the figure.6 below.

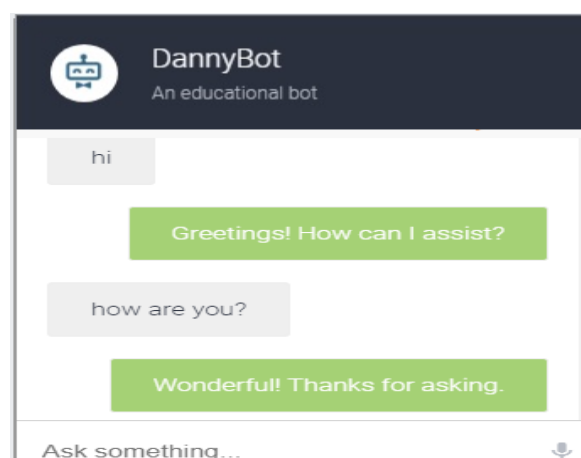


Fig.6. GUI for chatbot

The sentiment analysis part of the chatbot is done using the dataset that are downloaded online. The downloaded dataset is preprocessed, cleaned and are used to train the chatbot model.

Sentiment is analyzed by the following methods. The first step is the tokenization. Tokenization is a method of dividing the paragraph into different set of statements or dividing the statements into different set of words. The next step is to clean the differentiated data i.e. , removing the unwanted special characters or any other words that do not add any value to the analytics part of the statement. The unwanted words are called as the stop words. Stop words are filler words that does not add value to the statement like the, was, is, he, she, etc. ,

The next step of sentiment analysis is the classification step where the statement is classified as a positive or negative or a neutral one by giving them a sentiment score. Score is given as +1,-1 or 0 depending upon the classification. The model can be trained using the supervised learning method. Bag of words or Lexicons is used to train the model. Lexicons are a dictionary of pre-classified set of words. The calculation is done based on the sentiment score by combining the score of the words. In python the Textblob library is used which is used to find the sentiment of the statement given.

Once the emotion is found to be happy when the score is positive, sad when it is negative or neutral feeling when it is neutral. The Chatbot uses Parametric ReLU (PReLU) activation function of tensor flow to Play the song according to the emotion of the user which is shown in figure7.

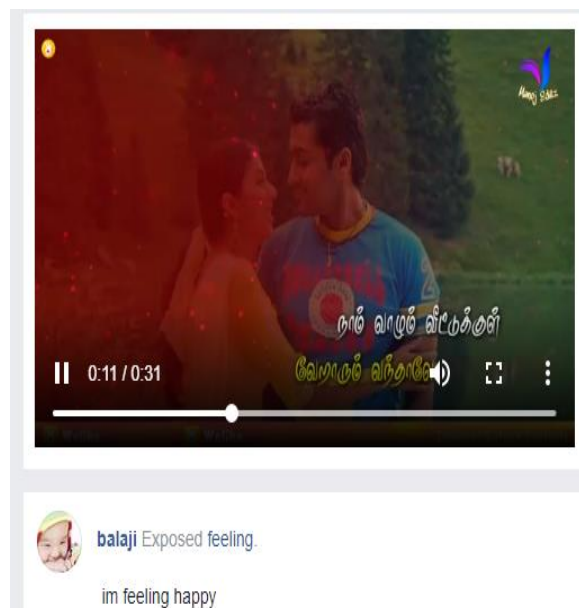


Fig.7. Playing songs depending on emotion of the user.

5. CONCLUSION

In future there is a need for attention for the people is required in all domains. Personally one cannot recruit a person for the purpose of attending the queries by the users. Hence the automation is required. Chatbot can be trained and implemented in our work system to do the job of the person. Chatbot can be implemented in various sectors that need to discuss with a user in a regular basis. Chatbot can be customized. The system can further be enhanced by suggesting solution for every problem that can occur to a user by completely training the chatbot for the purpose it is customized.

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