Virtual Assistant with Sentiment Analysis

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***Abstract*—Today technological development is growing day by day. Earlier simplest there has been a pc machine wherein we are able to do simplest few tasks. But now system learning, synthetic intelligence, deep learning, and a few greater technologies have made pc structures so enhanced that we are able to carry out any form of assignment. In such a generation of development if humans are nonetheless suffering to have interaction with the usage of diverse enter gadgets, then it's now no longer really well worth it. For this reason, we evolved a voice assistant with the usage of python which permits the consumer to run any form of command in linux without interplay with the keyboard. The foremost assignment of voice assistants is to reduce the usage of entering gadgets like keyboard, mouse etc. It may even lessen the hardware area and cost.**

I. INTRODUCTION

Virtual Assistant

In this era of technology, everything that human beings can do is being replaced by machines. One of the main reasons is change in performance. In today's world, we train our machines to think like humans and do their tasks by themselves. Therefore, there came a concept of the virtual assistant.

A virtual assistant is a digital assistant that uses voice recognition features and language processing algorithms to recognize the voice commands of the user and perform relevant tasks as requested by the user. Based on specific commands given by the user a virtual assistant is capable of filtering out the ambient noise and returning relevant information.

Virtual Assistants are completely software-based but nowadays they are integrated into different devices and also some of the assistants are designed specifically for single devices like Alexa.

Due to the drastic evolution of technology, the time has come to train our machines using machine learning, deep learning, and neural networks. Today we can talk to our car with the help of a Voice Assistant. Today, all large companies use Voice

Assistant so that their users can receive machine help through their voice. So with the voice assistant, we move to the next level of advancement where we can talk to our machine.

These kinds of digital assistants are very beneficial for antique age, blind & bodily challenged people, children, etc. through ensuring that the interplay with the system isn't an assignment anymore for people. Even blind individuals who couldn't see the system can have interaction with it through the use of their voice only.

Here are some of the basic tasks that can be done with the help of a voice assistant: -

- Reading Newspaper
- Getting updates of mail
- Search on web
- Play music or video
- Setting a reminder and alarm
- Run any program or application
- Getting weather updates

These are some of the examples, we can do many more things according to our requirements.

The Voice Assistant that we have developed is for Windows users. The voice assistant we have developed is a desktop-based built using python modules and libraries. This assistant is just a basic version that could perform all the basic tasks which have been mentioned above but current technology is although good in it is still to be merged with Machine Learning and Internet of Things (IoT) for better enhancements. So, with the help of a virtual assistant, we will be able to control many things around us single-handedly on one platform.

Sentiment Analysis

The observation of public opinion can offer us with precious information. The evaluation of sentiment on social networks, which include Twitter or Facebook, has turned out to be an effective approach of studying approximately the users' critiques and has an extensive variety of applications. However, the performance and accuracy of sentiment evaluation is being hindered through the demanding situations encountered in herbal language processing (NLP). In recent years, it's been verified that deep studying fashions are a promising technique to the demanding situations of NLP. This paper evaluates today's research which has hired deep studying to remedy sentiment evaluation problems, which include sentiment polarity. Models the usage of time period frequency-inverse record frequency (TF-IDF) and phrase embedding were implemented to a sequence of datasets. Finally, a comparative observation has been carried out at the experimental consequences received for the exclusive fashions and enter features.

II. LITERATURE REVIEW

Deep Learning:

Deep mastering adapts a multilayer method to the hidden layers of the neural network. In conventional gadget mastering approaches, functions are described and extracted both manually or through utilising characteristic choice methods. However, in deep mastering fashions, functions are discovered and extracted automatically, reaching higher accuracy and performance. In general, the hyper parameters of classifier fashions also are measured automatically. Figure 1 suggests the variations in sentiment polarity class among the 2 approaches: conventional gadget mastering (Support Vector Machine (SVM), Bayesian networks, or selection trees) and deep mastering. Artificial neural networks and deep mastering presently offer the pleasant answers to many issues withinside the fields of picture and speech recognition, in addition to in herbal language processing. Several varieties of deep mastering strategies are mentioned in this section.

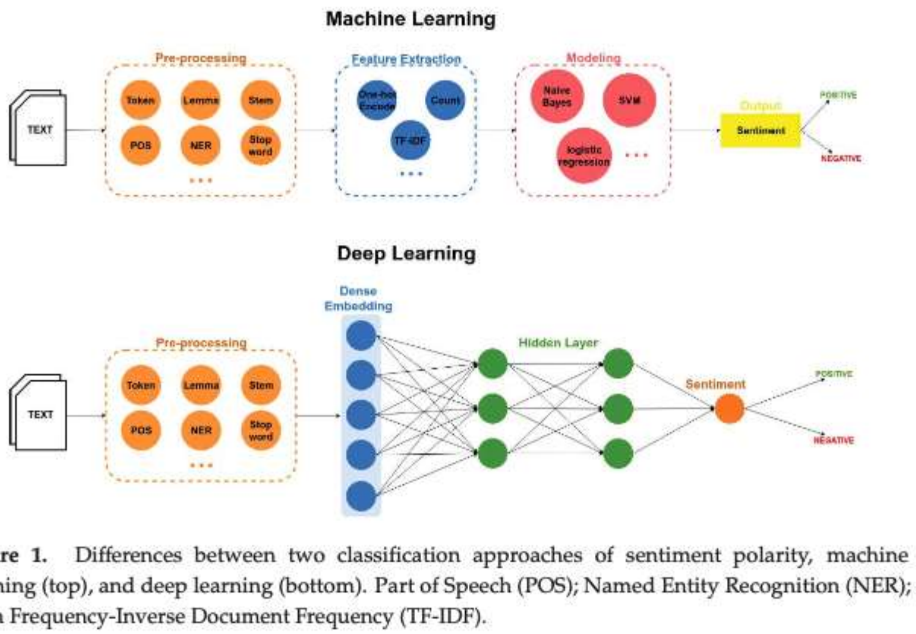


Figure 1. Differences between two classification approaches of sentiment polarity, machine learning (top), and deep learning (bottom). Part of Speech (POS); Named Entity Recognition (NER); Term Frequency-Inverse Document Frequency (TF-IDF).

Deep Neural Networks:

A deep neural community [21] is a neural community with greater than layers, a number of which are hidden layers (Figure 2). Deep neural networks use state-of-the-art mathematical modeling to system facts in lots of special ways. A neural community is an adjustable version of outputs as capabilities of inputs, which includes numerous layers: an enter layer, along with enter facts; hidden layers, along with processing nodes known as neurons; and an output layer, along with one or numerous neurons, whose outputs are the community outputs.

Convolutional Neural Networks:

A convolutional neural network is a completely unique sort of feed-in advance neural network at the start employed in areas which incorporates computer vision, recommender systems, and natural language processing. It is a deep neural network shape [22], usually composed of convolutional and pooling or subsampling layers to provide inputs to a totally-associated kind layer.

Convolution layers clean out their inputs to extract features; the outputs of a couple of filters can be combined. Pooling or subsampling layers reduce the choice of features that may increase the CNN's robustness to noise and distortion. Fully associated layers perform kind tasks.

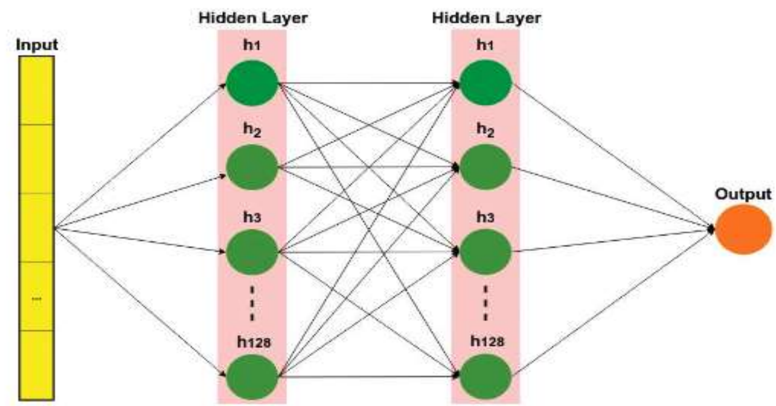


Figure 2. Deep neural network (DNN).

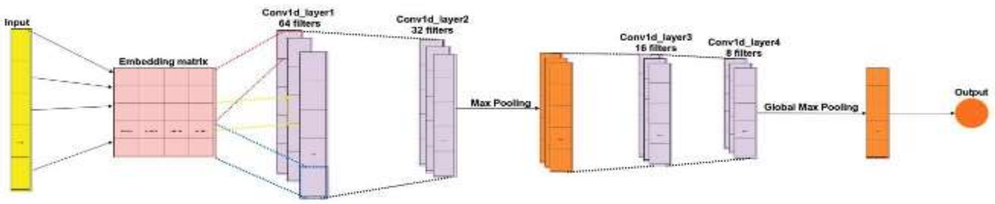


Figure 3. A convolutional neural network.

An example of a CNN shape can be seen in Figure three. The input facts have become preprocessed to reshape it for the embedding matrix. The determination suggests an input embedding matrix processed through the manner of four convolution layers and max pooling layers.

The first convolution layers have sixty 4 and 32 filters, which may be used to train certainly considered one among a type features; the ones are observed through the manner of a max pooling layer, this is used to reduce the complexity of the output and to prevent the overfitting of the facts. The 1/three and fourth convolution layers have 16 and 8 filters, respectively, which may be moreover observed through the manner of a max pooling layer. The final layer is a totally associated layer to reduce the vector of height 8 to an output vector of one, for the motive that there are classes to be predicted (Positive, Negative).

Recurrent Neural Networks:

Recurrent neural networks [23] are a category of neural networks whose connections among neurons shape a directed cycle, which creates comment loops in the RNN. The important feature of RNN is the processing of sequential facts on the idea of the inner reminiscence captured through the directed cycles.

Unlike conventional neural networks, RNN can not forget the preceding computation of facts and might reuse it through making use of it to the following detail withinside the series of inputs. A unique kind of RNN is lengthy short-time period reminiscence (LSTM), that's able to the usage of lengthy reminiscence because the enter of activation features withinside the hidden layer. This was delivered through Hochreiter and Schmidhuber (1997) [24]. Figure four illustrates an instance of the LSTM architecture. The entered information is preprocessed to reshape information for the embedding matrix (the system is much like the only defined for the CNN).

The subsequent layer is the LSTM, which incorporates 2 hundred cells. The very last layer is a completely related layer, which incorporates 128 cells for textual content classification. The final layer makes use of the sigmoid activation feature to lessen the vector of top 128 to an output vector of one, for the reason that there is training to be predicted (positive, negative).

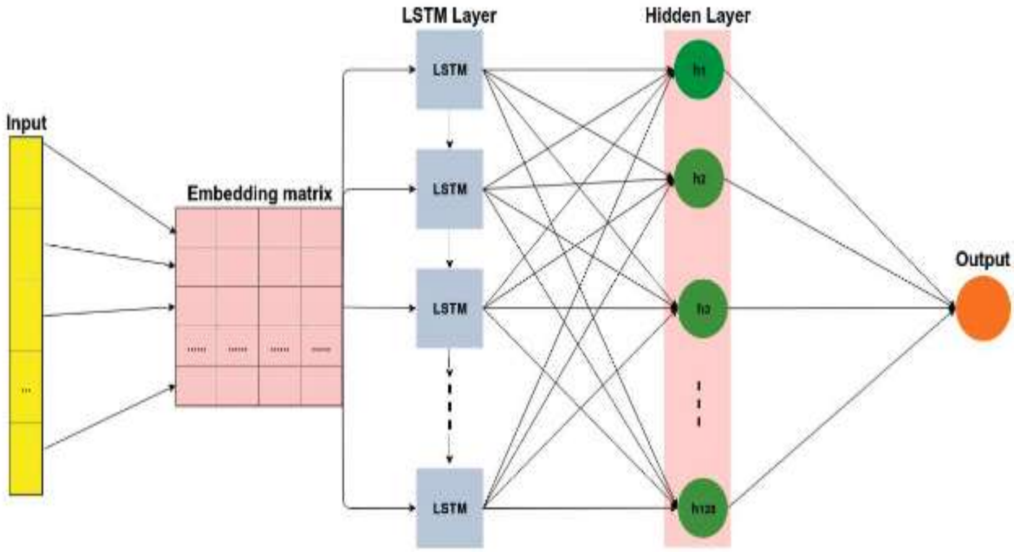


Figure 4. A long short-term memory network. LSTM, long short-term memory.

Sentiment Analysis:

Sentiment evaluation is a method of extracting data approximately from an entity and routinely figuring out any of the subjectivities of that entity. The goal is to decide whether or not textual content generated via the means of customers conveys their positive, negative, or impartial opinions. Sentiment class may be completed on 3 ranges of extraction: the issue or function level, the sentence level, and the record level. Currently, there are 3 procedures to deal with the trouble of sentiment evaluation [27]:

(1) lexicon-primarily based totally techniques

(2) machine-learning-primarily based totally techniques

(3) hybrid procedures

Lexicon-primarily based total strategies have been the primary for use for sentiment evaluation. They are divided into approaches: dictionary-primarily based totally and corpus-primarily based totally [6]. In the previous type, sentiment class is done through the use of a dictionary of terms, which include the ones observed in SentiWordNet and WordNet.

Nevertheless, corpus-primarily based totally sentiment evaluation does now no longer depend on a predefined dictionary however on statistical evaluation of the contents of a set of documents, the use of strategies primarily based totally on k-nearest neighbors (k-NN) [7], conditional random field (CRF) [8], and hidden Markov models (HMM) [9], amongst others.

Table 1. Summary of deep-learning-based sentiment analysis.

No.	Year	Study	Research Work	Method	Dataset	Target
1	2019	Alharbi el al. [19]	Twitter sentiment analysis	CNN	SemEval 2016 workshop	Feature extraction from user behavior information
2	2019	Kraus et al. [16]	Sentiment analysis based on rhetorical structure theory	Tree-LSTM and Discourse-LSTM	Movie Database (IMD), food reviews (Amazon)	Aim to improve accuracy
3	2019	Do et al. [53]	Comparative review of sentiment analysis based on deep learning	CNN, LSTM, GRU, and hybrid approaches	SemEval workshop and social network sites	Aspect extraction and sentiment classification
4	2019	Abid et al. [20]	Sentiment analysis through recent recurrent variants	CNN, RNN	Twitter	Domain-specific word embedding
5	2019	Yang et al. [52]	Aspect-based sentiment analysis	Coattention-LSTM, Coattention-MemNet, Coattention-LSTM + location	Twitter, SemEval 2014	Target-level and context-level feature extraction
6	2019	Wu et al. [60]	Sentiment analysis with variational autoencoder	LSTM, Bi-LSTM	Facebook, Chinese VA, Emobank	Encoding, sentiment prediction, and decoding
7	2018	Pham et al. [11]	Aspect-based sentiment analysis	LRNN-ASR, FULL-LRNN-ASR	Tripadvisor	Enriching knowledge of the input through layers
8	2018	Sohangir et al. [5]	Deep learning for financial sentiment analysis	LSTM, doc2vec, and CNN	StockTwits	Improving the performance of sentiment analysis for StockTwits
9	2018	Li et al. [17]	How textual quality of online reviews affect classification performance	SRN, LSTM, and CNN	Movie reviews from imdb.com	Impact of two influential textual features, namely the word count and review readability
10	2018	Zhang et al. [61]	Textual sentiment analysis via three different attention convolutional neural networks and cross-modality consistent regression	CNN	SemEval 2016, Sentiment Tree Bank	LSTM attention and attentive pooling is integrated with CNN model to extract sentence features based on sentiment embedding, lexicon embedding, and semantic embedding

Machine-mastering-primarily based total techniques [10] proposed for sentiment evaluation issues may be divided into groups: (1) conventional fashions and (2) deep mastering fashions. Traditional fashions discuss classical device mastering techniques, which include the naïve Bayes classifier [25], most entropy classifier [12,13], or assist vector machines (SVM) [14].

The enter to the ones algorithms consists of lexical functions, sentiment lexicon-primarily based totally functions, elements of speech, or adjectives and adverbs. The accuracy of those structures relies upon which functions are chosen. Deep mastering fashions can offer higher effects than conventional fashions. Different varieties of deep mastering fashions may be used for sentiment evaluation, consisting of CNN, DNN, and RNN. Such procedures deal with type issues on the report level, sentence level, or thing level. These deep mastering techniques may be mentioned withinside the following section.

The hybrid approaches [15] combine lexicon- and machine-learning-based approaches. Sentiment lexicons commonly play a key role within a majority of these strategies.

Related Work:

The purpose of this study is to review different approaches and methods in sentiment analysis that can be taken as a reference in future empirical studies. We have focused on key aspects of research, such as technical challenges, datasets, the methods proposed in each study, and their application domains.

III. APPROACH

For sentiment analysis we will be using the US airlines reviews dataset from kaggle. We will filter out the columns that will be needed for our analysis which are 'text' and 'airline_sentiment'. As our analysis doesn't require a neutral expression so we will filter it out and store the remaining. We will be doing label encoding to classify positive reviews as 0 and negative as 1. After this we tokenize the reviews so that we can do encoding for model building. Now we will be building a deep learning model in which layers will be a dropout layer for regularization, LSTM which is a RNN model and is highly efficient for speech analysis tasks and a fully connected dense layer for outputs. After this we will compile and fit(train) our model on the processed data.

Recently, deep learning models (including DNN, CNN, and RNN) have been used to increase the efficiency of sentiment analysis tasks. In this section, state-of-the-art sentiment analysis approaches based on deep learning are reviewed.

Data Set Used: US airlines reviews dataset

The dataset contains tweets on US Airline of February 2015 classified in positive, negative and neutral tweets. The negative tweets are also classified on the basis of the negative reason.

This post is divided into two parts:

First part: Data analysis on the dataset to find the best and the worst airlines and understand what are the most common problems in case of bad flight

Second part: Training two Naive-Bayesian classifiers: first to classify the tweets into positive and negative And a second classifier to classify the negative tweets on the reason. In this way it is possible to upgrade the statistics of the first point, with new tweets.

This work can be useful for the airline company to understand what are the problems to work on.

Model Used: LSTM

Long short-term memory (LSTM) is an artificial recurrent neural network (RNN) architecture used in the field of deep learning. Unlike standard feedforward neural networks, LSTM has feedback connections. It can process not only single data points (such as images), but also entire sequences of data (such as speech or video). For example, LSTM is applicable to tasks such as unsegmented, connected handwriting recognition, speech recognition and anomaly detection in network traffic or IDSs (intrusion detection systems).

Also, we used fully connected dense layers for outputs because we do not have that prior information about data anymore, because we do not know what it learns in those deep layers. Thus, we use a Dense Layer, by giving all the inputs, we give the "full responsibility" to learn. Thus, by using fully connected dense layers, we are taking a step that we are not missing on accuracy anyhow.

Also, as we have done that, to prevent our model from getting overfitted we used dropout layers for regularization. Dropout is a regularization technique for reducing overfitting in neural networks by preventing complex co-adaptations on training data. It is a very efficient way of performing model averaging with neural networks. The term "dropout" refers to dropping out units (both hidden and visible) in a neural network.

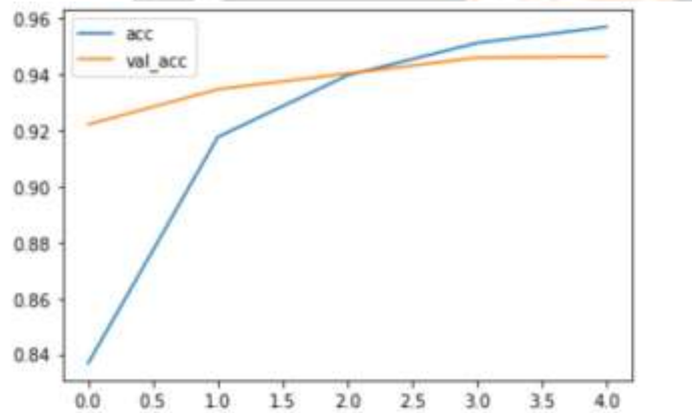
We trained the model with 5 epochs and thus at the end of the training we were almost able to get quite good accuracy scores.

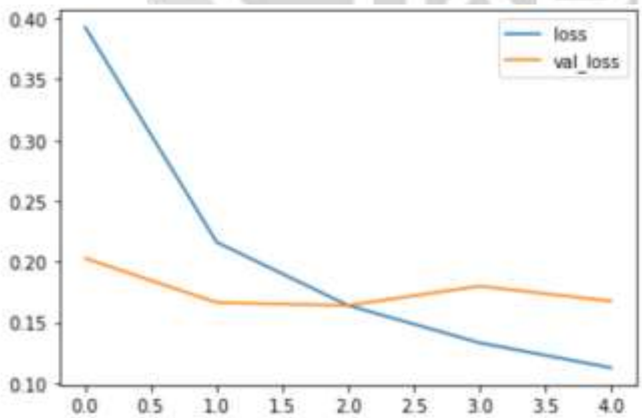
```
Epoch 1/5
289/289 [==============================] - 51s 172ms/step - loss: 0.3927 - accuracy: 0.8368 - val_loss: 0.2026 - val_accuracy:
0.9220
Epoch 2/5
289/289 [==============================] - 46s 158ms/step - loss: 0.2159 - accuracy: 0.9176 - val_loss: 0.1663 - val_accuracy:
0.9346
Epoch 3/5
289/289 [==============================] - 44s 154ms/step - loss: 0.1640 - accuracy: 0.9396 - val_loss: 0.1639 - val_accuracy:
0.9402
Epoch 4/5
289/289 [==============================] - 45s 157ms/step - loss: 0.1332 - accuracy: 0.9511 - val_loss: 0.1798 - val_accuracy:
0.9459
Epoch 5/5
289/289 [==============================] - 40s 138ms/step - loss: 0.1127 - accuracy: 0.9569 - val_loss: 0.1675 - val_accuracy:
0.9463
```

IV. RESULT

The results were as we expected. It was correctly rectifying the sentiments in the sentences based on the model and we were quite satisfied with it. In future, we will try to train the model with more datasets to increase its accuracy as well and to make it well diverse.

Also, we drew out the graphs between accuracy and val_accuracy & loss and acc_loss.





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In [14]: test_sentence1 = "Many people enoyjoyed the party."
         predict_sentiment_sa(test_sentence1)

         test_sentence2 = "This is the worst flight experience of my life!"
         predict_sentiment_sa(test_sentence2)

         Predicted label:  positive
         Predicted label:  negative
```

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