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Twitter Sentiment Analysis Using Deep Learning

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Abstract. It is well established that the tweet sentiment analysis is still focused on conventional messages, such as film reviews and product reviews, while significant improvement has been made as deep learning becomes widespread, and comprehensive data sets are accessible for training (far from just emoticons and hashtags). Nevertheless, prior opinion analysis experiments typically performed on tweets, i.e. only two forms of global polarities (i.e. optimistic and negative) occur with their work/validation/test data sets. What is more, systems' judgments are not actively aligned with the specified appraisal objects. In this paper, we have discussed some deep learning approaches for twitter sentiment analysis. We also trained our model using CNN and RNN to get some good accuracy results.

1. Introduction

Sentiment analysis is the automated mechanism for interpreting a written or spoken thought about a certain topic. Sentiment analysis has been a crucial method for interpreting this data in an environment where daily we produce 2, 5-quintillion bytes of data. It helps businesses to obtain crucial knowledge and optimize operations of all sorts [1]. Sentiment Analysis is often referred to as Opinion Mining. This builds structures to classify and collect views inside the statements collected and it is related to the research field of natural language processing (NLP) [1]. Such structures typically derive properties of the phrase, for instance, subject, popularity, and opinion holder. The subject mainly deals with the item or the topic that the users are discussing, the popularity deals with the identification of a favorable or unfavorable scenario from the perspective of the speaker, and the opinion holder is the person or the organization that presents the opinion.Sentiment analyses are a matter of significant concern because they have a range of functional applications. Because the amount of texts that convey views is continuously growing on the Internet, which is publicly and privately accessible, are published on journaling pages, forums, blogs, and social networking [1]. Sentiment Analysis is an automated method of reading and organizing text data into positive, negative, or neutral emotions. Making a Twitter Sentiment Analysis using machine learning can make companies understand how users know about their products. [2]. Twitter is allowing brands to reach the broader market and connect with customers without any intermediaries and with more than 321 million daily users sending 500 million tweets daily. In the event of a limitation, advertisers may accept negative news more quickly and if it goes viral, they can end up facing an unnecessary publicity issue. This is one of the reasons that social media analytics – analysis of social network posts or feedback – has become a vital tool for encouraging social networking. [2]. Monitoring Twitter requires firms to know their customers, keep updated on what is being said about their products and their opponents, and uncover new trends in the market. Are clients asking about a product positively or negatively? Yes, that's exactly what the study of sentiments indicates. [2].

Twitter monitoring helps businesses to consider their customers, keep current with their products and competition, and identify emerging market developments. Are consumers concerned about a commodity as good or negative? Yeah, that's what the study of emotions decides [2]. Doing a Twitter Sentiment Study using machine learning will help companies realize how customers think about their products Doing a Twitter Sentiment Study using machine learning will help companies realize how customers think about their products Doing a Twitter Sentiment Study using machine learning will help companies realize how customers think about their products Doing a Twitter Sentiment Study using machine learning will help companies realize how customers think about their products Doing a Twitter Sentiment Study using machine learning will help companies realize how customers think about their products Doing a Twitter Sentiment Study using machine learning will help companies realize how customers think about their products Doing a Twitter Sentiment Study using machine learning will help companies realize how customers think about their products Doing a Twitter Sentiment Study using machine learning will help companies realize how customers think about their products.

About 80% of digital data nowadays is unstructured which is no exception to data obtained by social network networks. As the knowledge is not pre-defined, sorting and evaluating are hard. Thanks to Machine Learning and NLP, we are fortunate that models can now be developed, learning from examples and used for processing and organizing text data [2].Sentiment analytical systems from Twitter can be used to arrange broad tweets and automatically determine the polarity of each message. And, the best thing, is to save precious hours for staff quick and easy and to concentrate on activities that will have a larger impact. The major advantages of sentiment analysis can be identified as follows:

- *Scalability:* Let's say you've got to review a hundred company tweets. Although you can do this manually, manual execution can take hours and hours and finish incoherently and not observable. You can simplify this function and provide cost-effective outcomes within a very limited amount of time by doing Twitter sentiment analysis [1].
- *Real-Time Analysis:*Sentiment analyses in Twitter are important to see abrupt improvements in consumer moods, to track the rise in detractors and concerns, and to take steps until the issue escalates. You can view the products in real-time to get suggestions that can help you make improvements or modifications if necessary [2].
- *Consistent Criteria:*Sensitivity is a subjective activity to interpret a text. Once manually done, two members of the same team will interpret the same tweet differently and the findings are incomplete. You can set the parameters to examine all the data and achieve more accurate and reliable outcomes by training a deep learning algorithm to perform a Twitter sentiment analysis [2].

The document is framed in terms of the proposed framework into various sections. Section - 1 includes the introduction to the analysis of twitter sentiments, section - 2 includes the literature review in which the popular works related to the deep learning methodologies in association with twitter sentiment analysis, section - 3 discusses various deep learning methodologies, section - 4 discusses the various steps involved in the analysis of twitter sentiments, section-5 discusses the outcomes of the expected results from the proposed framework and section - 6 includes the conclusion obtained from the proposed the framework.

2. Literature Review

Santos et al. [6] proposed a framework that utilizes the deep conventional neural network for the identification of sentiment that exists in the sentence level to character level. The data utilizes for the framework are movie reviews and twitter messages obtained from the Standford sentiment treebank

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and twitter corpus. It was based on binary classification with categories of positive and negative sentiments. The accuracy was obtained for the classification of the sentiment analysis utilizing the twitter corpus of 86.4 percent. Kalchbrenner et al. [7] proposed the neural design of a neural network with several convolution layers representing word vectors (initialized in random values) latent, thick, and inferior to data. They are using a dynamic neural network to classify film reviews and Twitter with sentiments. Experiments reveal that neural networks focused on unigram and bigram are stronger than the hierarchical convolution model. This proposed framework was tested in four different scenarios of prediction of sentiments in cases such as the binary classes, the six-way classes, multi-classes, and supervision distance.

Socher et al. [8] proposed the recursive tensor-based network is used for sentiment analysis, describing a term through a word vector and a parse tree, and then using the tensor-based composition approach for computing vectors for a higher tree node. The proposed work was implemented on the huge number of phrases is 215154 of 11855 sentences. The binary classification of positive and negative sentiment classification was improved and obtained from the presented work is 85.4%. Johnson et al. [9] utilized the convolutional neural network deployed to a high-dimensional text classification achieved better in comparison with the classical methods on a variety of benchmark categorization data sets, while models are more challenging and costly to train. The work also utilized was extended to mix the various convolutional layers for improving accuracy. Li et al. [10] tried to understand the scenarios in which the recursive networks can present a better performance when compared to the classical methods. Benchmarking recursive neural network models against the sequential RNN process for NLP activities, including sentence and phrase-level emotion classification. This study was able to understand the restrictions of the classical methodologies and guidelines for the enhancement of the recurrent models.

Barbosa et al. [11] suggested a methodology for the automatic detection and classification of sentiments from the tweet corpus in two-phases. Tweets were classified as factual and subjective tweets were then described as good or poor in the second process. Following features such as prior term polarity and POS, spatial features include re-tweets, hashtags, relation marks, punctuations, and exclamation. The process of the suggested methodology was leveraged noisy data labels were utilized for the training scenario. The limitations identified for this methodology is that the collected corpus containing antagonistic sentimental statements. Po-Wei Liang et al. [12] used API for the processing of Twitter information. Training data are split into three groups (camera, video, mobile). The data is described as positive, bad, and unintentional. Comments on the opinion are filtered. The Naive Bayes Unigram model was used to simplify the presumption of freedom. The Shared Knowledge and the Chi-Square Extraction Process even removed useless features. In the end, the direction of the tweet is predicted. Positive or negative, for example, Kamps et al. [13] to assess the emotional meaning of a word in different ways, utilizing the WordNet lexical database. On WordNet, they established an adjective gap metric and defined semantic polarity.

EfthymiosKouloumpis et al. [14] reviewed the usefulness of linguistic attributes to detect the sentiment that exists in Twitter messages. This document able to determine the value of current lexical technologies as well as attributes that record the knowledge used in social media on a casual and innovative level. And also tried to address the issue based on a supervised methodology, yet use current hashtags that exist in Twitter data for the training aspect. AliakseiSeveryn and Alessandro Moschitti [15] explains a deep tweet sentiment analysis learning framework. A new framework to initialize the component weights of a neural convolutional network, essential in training a precise framework while preventing the need for adding additional functionality, is the key contribution of the study. It utilized a neural language framework without surveillance to train the first-word encoding that is further tailored to a remote, supervised corpus by the proposed profound learning framework. The pre-trained network components are utilized to initialize the framework at the final step. The above-mentioned framework trains the latter in the quickly added accessible supervised training resource from the official device appraisal campaign coordinated by Semeval 2015 for Twitter Sentiment Analyses.A distinction between the outcomes of the solution proposed and the frameworks used in the competition in the authorized test datasets indicates that the model proposed should be ranked on both the sentence-level subtask in the first two places. Anastasia Giachanou and Fabio Crestani [16] Provided an understanding of the subject by analyzing and discussing briefly the methodologies proposed on sentimental analysis based on Twitter research. The discussed research is classified as per its methodology. The report also offers a structured way to sentiment analysis on Twitter involving Twitter retrieval of thoughts, monitoring feelings over time, detection of irony, measurement of emotions, and tweeting of feelings. Tools utilized in the literature of the Twitter platform on sentiment analysis are also submitted briefly. The key contributors to the study are to address the proposed methodology for sentiment analysis in Twitter, the categorization of these methods according to the utilization of technologies, and the review of current research developments on the subject and its associated areas.

The literature review can be summarised as the identification of the effectiveness of deep learning in the sentiment analysis based on the twitter corpus in a general scenario. Particularly, the convolution neural network playing a vital role in the extraction of features from the twitter corpus and thus able to classify among various sentiments more effectively when compared to the classical methodologies.

3. Methodologies

Deep learning focused on layers of ANN (artificial neural networks). Deep learning networks do not involve human involvement, since multilevel layers in neural networks place data in a hierarchy of concepts that ultimately learn from their own mistakes. However, even if the accuracy of the data is not good enough, it may be inaccurate. [3]. Data decides all this. It is the consistency of the data that essentially determines the validity of the results. We will use the methods below to define the twitter data and build our model.

3.1. Convolutional Neural Network

Surprisingly, CNN, which is most widely utilized in computer vision applications, provides an extremely effective paradigm for emotion analysis tasks. The hope is that the model should then execute such convolutions on picture pixels in a sentence inside the embedded space of the terms. The model may take negations or n-grammars, containing new sentiment details, as convolutions occur in adjacent terms [4].

3.1.1. Algorithm: The algorithm includes the four major steps such as the convolution operation in certain layers and those will be referred to as convolutional layers, maximum pooling operation in certain layers and those will be referred to as pooling layers, the complete data will be obtained in a single-dimensional format such an operation will be made with certain layers and those referred to as flattening layers, and finally, fully connected or dense layers are utilized for the classification purpose and those layers are referred to as fully connected layers and all these operations are mentioned as follows:

- *Convolution:*This is an operation completely adopted from mathematical functions scenario which would help to transform the data from the existing dimension to the modified dimension. It is a very crucial step in the case of deep learning.

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau)g(t-\tau)d\tau = \int_{-\infty}^{\infty} f(t-\tau)g(\tau)d\tau (1)$$

- *Max's Pooling:*The pooling layer works separately on each attribute of the data. Maximum pooling is the most common method used in pooling. For this pooling operation to conduct a filter will be utilized. The data in the region of that filter will be analyzed and the maximum value will be retrieved and placed in the middle position of the filter and that corresponding value in the data also modifies that implies the data would be reduced due to these pooling layers.

- *Flattening:* Flattening transforms the data into a single-dimensionalformat at the next stage. The operation flattens the quality of the deep convolutional Layers to build a separate large feature vector and connect it to the final classification model.
- *Full Connection:* These layers are essential to predict the output in the planned framework. It mainly classifies the data obtained from the flattening layers.

3.2. Recurrent Neural Networks
RNNs are currently the most commonly developed and well-founded deep learning frameworks for NLPs. Since these networks are recurrent, they are beneficial for serial interface, including text jobs. We may be used for emotion analysis to predict the feeling frequently since each token is taken in a section of a text. The feel forecast is just the performance of the algorithm after all of the tokens have been identified in a sentence while the algorithm is completely educated [4].The introduction of an attention framework, which is a separately qualified component of the model, can also substantially increase RNNs. The model helps to determine increasing tokens add value to the text collection, helping the model to gain more information over time [4].

3.3. Recursive Neural Networks
Another successful solution in NLP was the multi-task learning method recently introduced. In this phase, a single model is performed together through a variety of activities to achieve the most precise accuracy in as many fields as possible. The theory is that the efficiency of the x-based model can be improved with its information and the corresponding y-and z-data tasks. The ability to cross conventional memory and a range of work weights provide modern, state-of-the-art accuracy. The Dynamic Memory Network and the Neural Semantic Encoder are two common MTL models that have achieved considerable success in sentiment analysis [4].

4. The Process of Twitter Sentiment Analysis
So far, various versions of the concept that can be part of twitter sentiment analysis have been discussed. It is essential to move on to the next phase of understanding the process of sentimental analysis evaluation on the twitter platform. It includes majorly four steps in this process as discussed as follows.

4.1. Steps involved in sentiment analysis of Twitter:
- *Step-1 - Data Gathering:*For any analysis, the data gathering phase is very crucial which is very similar in this aspect. At first, it is very essential to get register in the twitter developer API to extract the data. This API helps you to link in real-time to the Twitter data source and to receive messages. You will read all the tweets that suit a specific phrase, name, or hashtag and gather messages from other people as they are shared to Twitter. The API provides historical tweets that suit a predefined question (keyword, reference, hashtag, etc.) published up to 7 days ago. In this situation, you gather knowledge from the past, as opposed to real-time research.The Standard Search API is open but has a maximum of 7 days. Historical search APIs (such as Full-Archive Search and Historical Power Track) is being charged to provide links to the last 30 days of tweets or even tweets from the beginning of 2006. During a predefined time, the frame you can use this to search past tweets. It is helpful when monitoring in real-time keywords or hashtags.How to collect data from Twitter is one of the often asked queries. Some forms are free and others include the purchasing of info. There are various methods to do so. Moreover, some resources are developers-oriented, while others need no coding skills [2].
- *Step-2 – Data Preparation:* It is time to read the data after you have collected the tweets that you need to evaluate your sentiments. Social media was unstructured as we mentioned earlier. So, it's untreated, disruptive and must be cleaned up before we get to work on our platform for feeling research. This is an essential move as data quality tests are more accurate [2]. Before

uploading a Twitter file, you have to delete any kind of unnecessary material such as emojis, unique characters, and extra white spaces. It also involves changing the style, removing repeated tweets, or tweets fewer than three characters [2].

- *Step-3 - Creating A Sentiment Analysis Model:* After extracting the twitter data using many extraction tools, we train our model to create our model by using deep many learning approaches. Then we feed the data to our model and test the data. Then we get our results.

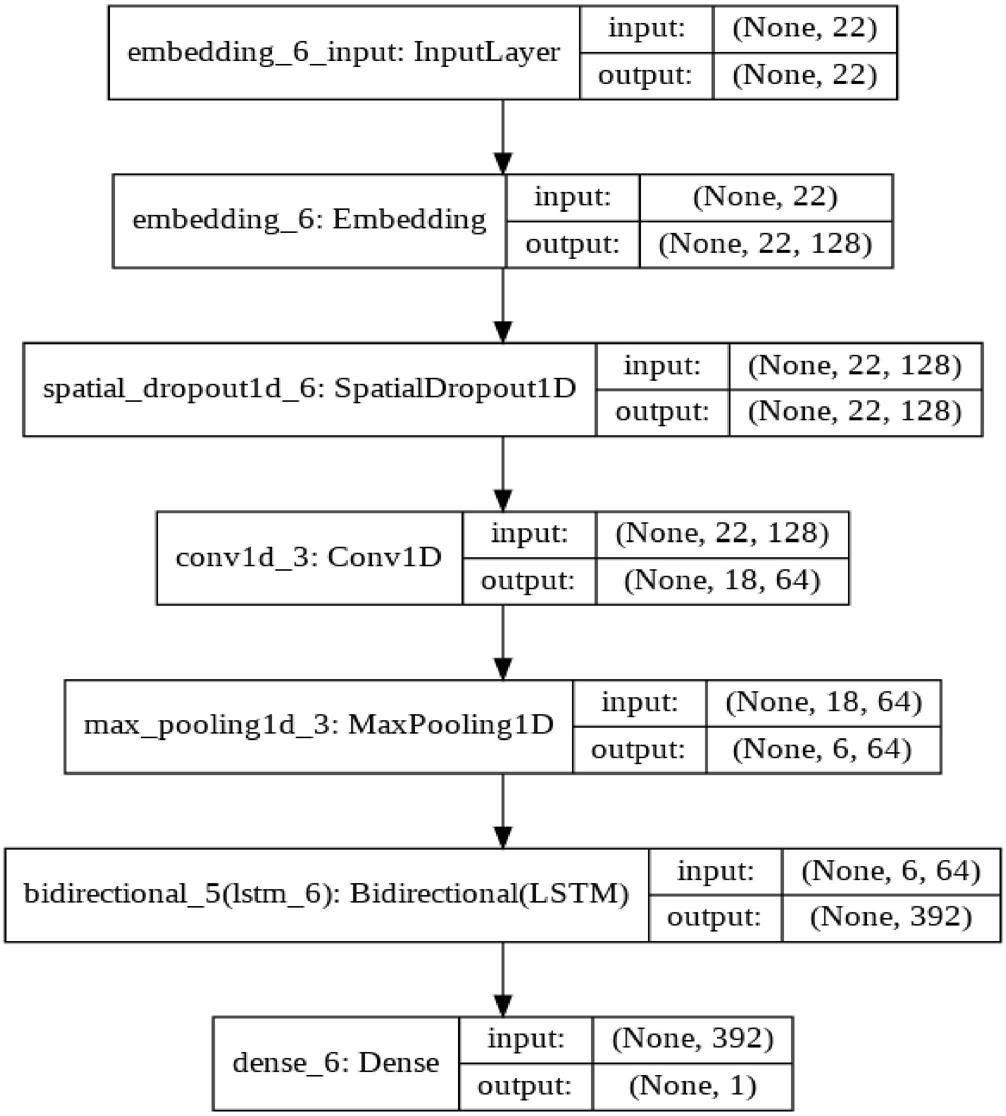

Figure 1. Flow Diagram of Data Training Process.

- *Step-4 - Visualization of the Results:*After getting the results, we visualize the results using graphs, plots, and tabular forms.

4.2. Various libraries and tools used for the analysis

For the aspect of sentimental analysis, various tools and libraries play a vital role without these tools and libraries unable to expect the efficient outcome of the sentiment analysis. It can be categorized these tools and libraries into three such as Developer Tools, Libraries, and Non-developer Tools.

- Developer Tools: Two popular tools which are very crucial in extracting the data are the Twitter API and the Standard Search API.

- Libraries: One who is working on a platform such as a python will be very beneficial as a lot of open-source libraries exist to perform various experimentation aspects. In this scenario, the Tweepy one such kind of library which is popularly used for sentimental analysis. This library is very user-friendly and allows you to quickly access messages from the Twitter API. Developers have been experimenting with this platform for more than 8 years; the community behind them is very successful.
- Non-developer Tools: Various non-developer tools are used such as Zapier, IFTT, and Tweet Download. Zapier is the tool for teams in different parts of the business (HR, customer service, marketing, product, etc.) to connect mobile applications they use each day to function together seamlessly. This is ideal for non-technical users because a single line of code to capture tweets doesn't have to be created.Zapier is a platform that enables you to link to different applications so that when certain conditions are met, you can take the required action. You can use this to get zero code lines of Twitter info.Tweet Download helps you to download posts, comments, and mentions from your page. It is especially ideal for marketers who wish to track the quality of their goods, what the consumers feel regarding their items etc. more.

5. Results and Discussion

Deep learningmethodologies play a crucial role when it comes to sentiment analysis. The customized deep learning framework was generated and utilized as mentioned in section 4.1. It was based on the twitter messages. The real data extracted from the twitter platform using Twitter developer API, Standard Search API, the Tweepy library, and various non-developer tools. The obtained results are mentioned in two forms. One form represents the graphical representation and the other is tabular form. The comparison of training accuracy vs validation accuracy and training loss vs validation loss represented in corresponding graphical representation as mentioned in the figure- 2 and 3. The evaluation metrics obtained are represented in the tabular form as mentioned in the table-1. The details of training loss, validation loss, training accuracy, and validation accuracy are represented in the tabular form as mentioned in the table-2.

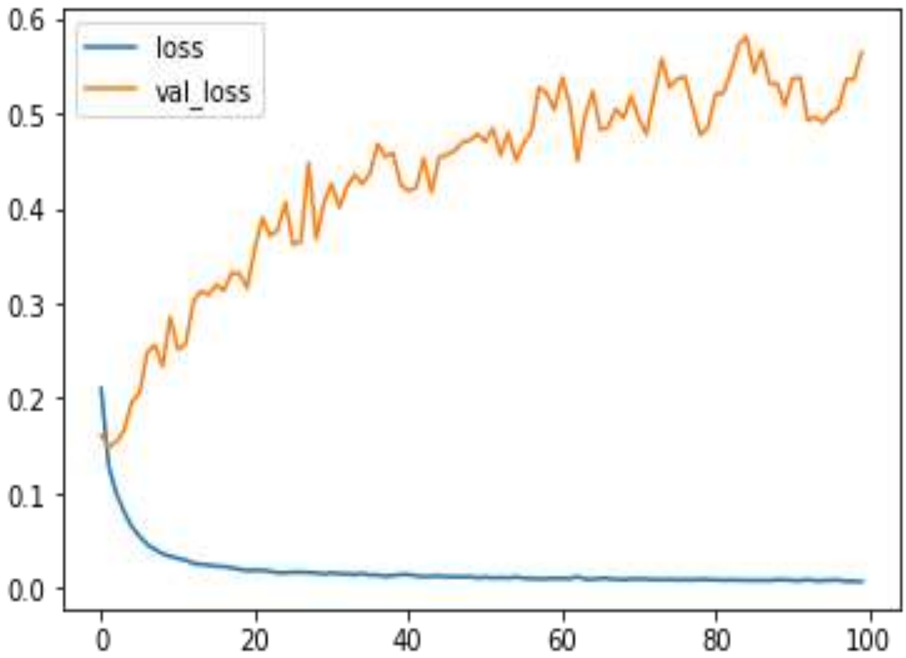

Figure 2.comparison of training loss vs validation loss.

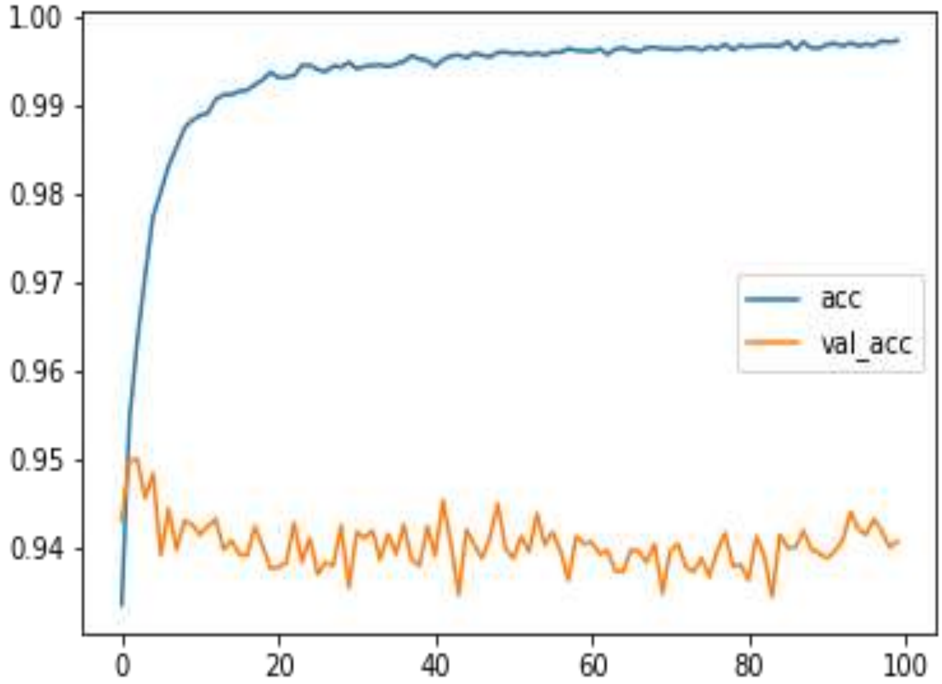

Figure 3. Accuracy of Training Data.

Table 1. The obtained evaluation metrics for the proposed framework.

Evaluation Metric	Value (in %)
Precision	79.64
Recall	78.79
F1_Score	79.21
Accuracy	94.07

Table 2:Details of loss and accuracy for training and validation sets.

Training Loss	0.1907
Validation Loss	0.5636
Trining Accuracy	0.9968
Validation Accuracy	0.9407

5.1. The Expected Outcomes

- *Prioritize the Action:* Sentiment analysis can easily filter out unread positivity and negativitymentions, indicating which tweets are serious and which are not.
- *Business Growth:*Twitter opinion research will also allow you to stay a step ahead of the rivals, recognizing the pain-points of certain companies in the business. Moreover, you will offer ideas on how to promote your company by evaluating feelings on tweets and keywords specific to your industry.
- *Feeling Detection:*We can detect or predict the user's feelings or emotions by analyzing the messages they are tweeting. IF they are happy, excited, sad, or angry.

6. Conclusion

In this research work, proposed a customized deep neural network for the sentimental analysis which performed better way in comparison with the existing methodologies with a limited number of layers and less computational capacity of the neural network. In the aspect of reducing computational capacity and improving the accuracy, the proposed framework was successful. Yet, it needs to be modified for better accuracy. For the future work aspect, the network can be enhanced such that the goal of reducing computational capacity with better accuracy. For future work, batch normalization operations can also be added which will enhance the accuracy of the framework. We able to show that sentimental analysis which is highly complex in nature able to solve utilizing Deep learning frameworks which proves that deep learning can better solution for the scenarios related to complex analysis.

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