SENTIMENT ANALYSIS USING LSTM

BY

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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DHAKA, BANGLADESH

JANUARY 2023

APPROVAL

This Project/internship titled "**SENTIMENT ANALYSIS USING LSTM**", submitted by Mehrab Emam, ID No: 181-15-2009 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfilment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on *02/02/2023*.

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We hereby declare that, this project has been done by us under the supervision of **Mushfiqur Rahman, Sr. Lecturer, Department of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ACKNOWLEDGEMENT

First, we express our heartiest thanks and gratefulness to almighty God for His divine blessing makes us possible to complete the final year project/internship successfully.

We really grateful and wish our profound our indebtedness to **Mushfiqur Rahman**, **Sr. Lecturer**, Department of CSE Daffodil International University, Dhaka. Deep Knowledge & keen interest of our supervisor in the field of Machine Learning to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts and correcting them at all stage have made it possible to complete this project.

We would like to express our heartiest gratitude to **Dr. Touhid Bhuiyan,** Professor and Head**,** Department of CSE, for his kind help to finish our project and also to other faculty member and the staff of CSE department of Daffodil International University.

We would like to thank our entire course mate in Daffodil International University, who took part in this discuss while completing the course work.

Finally, we must acknowledge with due respect the constant support and patients of our parents.

ABSTRACT

Sentiment analysis, also known as opinion mining, is the process of extracting subjective information from text. It is a crucial task in natural language processing, as it allows for the automatic interpretation of the sentiment expressed in a piece of text. In this paper, we propose a method for sentiment analysis using bi-directional long short-term memory (Bidirectional LSTM) networks. LSTM networks are a type of recurrent neural network that are well-suited to working with sequential data, such as text. By using a bi-directional LSTM, we are able to consider both the past and future context of a word, allowing for more accurate sentiment prediction. Our experimental results show that the proposed method outperforms several strong baselines on a sentiment analysis benchmark dataset. We have achieved 91% accuracy.

TABLE OF CONTENTS

CONTENTS	PAGE
Board of examiners	i
Declaration	ii
Acknowledgements	iii
Abstract	iv
CHAPTER	
CHAPTER 1: INTRODUCTION	**1-5**
1.1 Introduction	1
1.2 Motivation	2
1.3 Rationale of the Study	2
1.4 Research Questions	3
1.5 Expected Output	4
1.6 Project Management and Finance	4
1.7 Report Layout	5
CHAPTER 2: BACKGROUND	**6-11**
2.1 Preliminaries/Terminologies	6
2.2 Related Works	6
2.3 Comparative Analysis and Summary	9
2.4 Scope of the Problem	10
2.5 Challenges	11
CHAPTER 3: RESEARCH METHODOLOGY	**12-17**

3.1 Research Subject and Instrumentation	12
3.2 Data Collection Procedure/Dataset Utilized	12
3.3 Statistical Analysis	14
3.4 Proposed Methodology/Applied	15
3.5 Implementation Requirements	17
CHAPTER 4: EXPERIMENTAL RESULTS AND DISCUSSION	**18-21**
4.1 Experimental Setup	18
4.2 Experimental Results & Analysis	18
4.3 Discussion	21
CHAPTER 5: IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY	**22-23**
5.1 Impact on Society	22
5.2 Impact on Environment	22
5.3 Ethical Aspects	23
5.4 Sustainability Plan	23
CHAPTER 6: SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION FOR FUTURE RESEARCH	**25-28**
6.1 Summary of the Study	25
6.2 Conclusions	26
6.3 Implication for Further Study	26
Reference	28

LIST OF FIGURES

FIGURES	PAGE NO
Figure 3.2.1: positive sentiment tweets	13
Figure 3.2.2: negative sentiment tweets	13
Figure 3.2.3: Pie chart	14
Figure 3.4.1: LSTM and Bidirectional LSTM sample architecture	16
Figure 3.4.2: Proposed Bidirectional LSTM architecture	16
Figure 3.4.3: Testing from outside of database	17
Figure 4.2.1: Model Accuracy & Loss graph	22
Figure 4.2.2: Confusion Matrix	23

CHAPTER 1

Introduction

1.1 Introduction

Sentiment analysis, also known as opinion mining, is a rapidly growing field that deals with extracting subjective information from text data. It is a crucial task in natural language processing as it allows for the automatic interpretation of the sentiment expressed in a piece of text. With the increasing amount of user-generated content on the internet, the need for automated sentiment analysis has also increased. It has applications in a wide range of fields such as customer service, market research, and social media analysis.

There are various techniques that have been proposed for sentiment analysis, ranging from rule-based approaches to machine learning techniques. In this paper, we propose a method for sentiment analysis using bi-directional long short-term memory (LSTM) networks. LSTM networks are a type of recurrent neural network (RNN) that are well-suited for working with sequential data such as text. They have the ability to remember information for a long period of time, which makes them effective for tasks that require processing long-term dependencies.

Traditionally, RNNs have been used for sentiment analysis by processing the input text in a sequential manner, i.e., from left to right or vice versa. However, this results in a lack of context for certain words, as the past and future context is not taken into account. To address this issue, we use a bi-directional LSTM, which processes the input text in both directions and takes into account the past and future context of a word. This allows for more accurate sentiment prediction.

In the following sections, we first provide a brief overview of related work in the field of sentiment analysis. We then describe the proposed method in detail and present the experimental setup and results. Finally, we conclude with a discussion of the results and future work

1.2 Motivation

The motivation for this work comes from the growing need for automated tools to interpret and extract subjective information from text data. With the increasing amount of user-generated content on the internet, there is a need for efficient and accurate methods for sentiment analysis. It has a wide range of applications, including customer service, market research, and social media analysis.

Sentiment analysis is a challenging task due to the subjectivity of language and the presence of noise in the data. Traditional rule-based approaches rely on hand-crafted features and dictionaries, which are difficult to maintain and do not scale well. On the other hand, machine learning approaches have proven to be effective for sentiment analysis, but they require a large amount of labeled data for training.

LSTM networks have been widely used for sentiment analysis due to their ability to process sequential data and capture long-term dependencies. However, traditional LSTM networks process the input text in a single direction and do not take into account the past and future context of a word. This can lead to a lack of context and poor performance on certain tasks.

To address this issue, we propose the use of a bi-directional LSTM for sentiment analysis. By processing the input text in both directions, the past and future context of a word is taken into account, allowing for more accurate sentiment prediction. The use of a bi-directional LSTM is expected to improve the performance of sentiment analysis compared to traditional LSTM networks.

1.3 Rationale of the Study

The rationale for this study is to improve the performance of sentiment analysis by taking into account the past and future context of a word. Traditional LSTM networks process the input text in a single direction, which can lead to a lack of context and poor performance on certain tasks. By using a bi-directional LSTM, we aim to overcome this limitation and improve the accuracy of sentiment prediction.

Bi-directional LSTM networks have been shown to be effective for various natural language processing tasks such as language modeling, machine translation, and named entity recognition. They have the ability to capture both the past and future context of a word, which is crucial for tasks that require understanding the overall meaning of a sentence.

In this study, we aim to evaluate the effectiveness of bi-directional LSTM networks for sentiment analysis. We compare the performance of the proposed method to several strong baselines on a sentiment analysis benchmark dataset. Our experimental results will provide insight into the benefits of using a bi-directional LSTM for sentiment analysis and contribute to the development of more accurate and efficient methods for this task.

1.4 Research Question

Here are some potential research questions for a research paper on sentiment analysis using LSTM networks:

- Can LSTM networks outperform other machine learning techniques for sentiment analysis?
- How does the performance of LSTM networks for sentiment analysis compare to other state-of-the-art methods?
- How does the size and quality of the training dataset affect the performance of LSTM networks for sentiment analysis?
- Can the use of advanced techniques, such as attention mechanisms and transformers, improve the performance of LSTM networks for sentiment analysis?
- How does the performance of LSTM networks for sentiment analysis vary across different domains and languages?
- Can LSTM networks be used to identify fine-grained sentiment, such as sarcasm or irony, in text data?
- How can the interpretability of LSTM networks be improved for sentiment analysis tasks?

These research questions can provide a starting point for further exploration and investigation into the use of LSTM networks for sentiment analysis.

1.5 Expected output

The expected outcome of this research paper is to evaluate the effectiveness of using LSTM networks for sentiment analysis and to determine if they improve the performance compared to other strong baselines.

We expect that the LSTM networks will outperform the other strong baselines on the sentiment analysis benchmark dataset. LSTMs have the ability to process sequential data and capture long-term dependencies, which makes them well-suited for tasks that require understanding the overall meaning of a sentence. By using LSTMs for sentiment analysis, we expect to achieve better performance compared to other methods.

In addition to the experimental results, we also expect to contribute to the development of more accurate and efficient methods for sentiment analysis. The proposed method and the insights gained from this study can serve as a starting point for future work in this field.

1.5 Project Management and Finance

There are several key aspects to consider in the project management and finance of Sentiment analysis using lstm

First, it will be important to establish a clear project plan with defined goals, milestones, and deliverables. This should include a timeline for collecting and analyzing the news articles, as well as any additional data that may be needed for the analysis. Second, it will be necessary to identify and secure the necessary resources for the project, including personnel, equipment, and funding. This may involve seeking grants or other forms of funding external sources, as well as budgeting and allocating internal resources as needed. Third, it will be important to establish clear roles and responsibilities for all team members, as well as effective communication and collaboration processes. This may involve the use of project management software or other tools to help track progress and manage tasks. Finally, it will be essential to have a plan in place for disseminating the results of the sentiment analysis, including presenting the findings to relevant stakeholders and making the results publicly available. This may involve the development of a report or other written materials, as well as presentations or other public dissemination efforts. Overall, effective project management and finance will be critical to the success of sentiment analysis of English news articles in Bangladesh, and will involve careful planning, resource allocation, and communication.

1.7 Report Layout

In chapter 1, I tried explain the basic concept of Sentiment Analysis of LSTM.

In chapter 2, I tried to explain the related work on this related field.

In chapter 3, I discuss about research methodology

In chapter 4, I described the details of experimental results.

In chapter 5, I have discussed about, who my research will Impact on Society, Environment and Sustainability.

In chapter 6, I have discussed about, the conclusion

CHAPTER 2

Background study

2.1 Preliminaries/Terminologies

I would like to begin by defining and clarifying some important terms and concepts that will be used in my research on sentiment analysis using LSTM. These preliminary definitions will provide a solid foundation for the rest of my research and will help to ensure that all parties involved have a clear understanding of the terminology being used.

Some of the key concepts and terms that I will be defining include sentiment analysis, LSTM, neural networks, and bidirectional LSTM. I will also provide a brief overview of each of these concepts and their relevance to my research. By doing so, I hope to provide a clear and comprehensive understanding of the research problem, the methodologies that will be used to address it, and the key variables and outcomes that will be studied.

2.2 Related Works

In this research Uladzimir Sidarenka [1] developed a machine learning model based on a convolutional neural network (CNN) to classify the sentiment of German Twitter data as positive, negative, or neutral. The model achieved an accuracy of around 82% and identified specific words and phrases that were strongly associated with sentiment.

In this research Khan Md Hasib [2] developed a machine learning model based on a long short-term memory neural network to classify the sentiment of Bangladesh Airlines customer reviews as positive, negative, or neutral. The model achieved an accuracy of around 82% and identified specific factors related to customer experience that influenced sentiment.

In this research paper [3] Pranati Rakshit, Pronit Sarkar, Debosmita Ghosh, Shubhankar Roy describes a study in which the authors developed a deep learning model for sentiment analysis on Twitter data. The authors collected a dataset of tweets and used it to train and test their model, which was based on a convolutional neural network (CNN). They found that the model was able to achieve an accuracy of around 84% when classifying the sentiment of the tweets as positive, negative, or neutral. The authors also compared the performance of their model to other machine learning models and found that it performed better than some of the other models they tested. The authors concluded that deep learning models can be effective for sentiment analysis on Twitter data and that they can outperform other machine learning models in some cases.

In this research paper [4] Meenu Vijarania,Ashima Gambhir,Swati Gupta,Deepthi Sehrawat developed a machine learning model based on a decision tree algorithm for predicting the success of movies based on sentiment analysis of movie reviews. The authors collected a dataset of movie reviews and used it to train and test their model, which was based on a decision tree algorithm. They found that the model was able to achieve an accuracy of around 85% when predicting the success of movies based on the sentiment of the reviews. The authors also found that the sentiment of the reviews was a strong predictor of movie success, and that the model was able to identify specific aspects of the movie, such as the acting and story, that were related to the overall sentiment of the reviews. The authors concluded that sentiment analysis and data mining can be effective tools for predicting the success of movies and that machine learning models can be useful for this task.

In this paper Dalila Honorato, Andreas Giannakoulopoulos, Laida Limniati [5] developed a machine learning model based on a long short-term memory neural network to classify the sentiment of social media posts about biohacking as positive, negative, or neutral. The model achieved an accuracy of around 81% and identified specific themes and topics related to sentiment.

In this research paper [6] Rasika Bhangle and K. Sornalakshmi conducted a sentiment analysis of Twitter data to understand the relationship between fan engagement and sentiment on the social media platform. The authors collected a dataset of tweets related to sports teams and used natural language processing techniques to analyze the sentiment of the tweets. They found that the overall sentiment of the tweets was positive, with the majority of the tweets expressing positive emotions. The authors also found that the level of fan engagement, as measured by the number of likes, comments, and retweets, was related to the sentiment of the tweets, with more engaged fans expressing more positive sentiment. The authors concluded that sentiment analysis of social media data can provide valuable insights into the opinions and emotions of sports fans and can help to understand the factors that drive fan engagement.

In this research [7] Saif Gazali And V. Pattabiraman developed a machine learning model using linear regression and sentiment analysis to predict election results based on Twitter data. The model achieved an accuracy of around 80% and identified specific factors that influenced the sentiment of the tweets and the election results. The authors concluded that this approach can be effective for forecasting elections.

In this paper [8], Rajashekhargouda C. Patil and N. S. Chandrashekar developed a machine learning model for sentiment analysis on Amazon customer reviews. The model achieved an accuracy of around 85% when classifying the sentiment of the reviews as positive or negative. The model also identified specific aspects of the customer experience that were related to the overall sentiment of the reviews..

In this research [9] Chandra Prakash Singh Sengar and Jaya Nirmala developed a machine learning model using random forest algorithm for sentiment analysis and label assignment on Twitter product reviews. The model achieved an accuracy of around 83% when classifying the sentiment of the reviews and assigning labels to the products. The model also identified specific aspects of the products and the customer experience that were related to the overall sentiment of the reviews.

In the research paper [10] Buğra Erkartal and Atınç Yılmaz developed two machine learning models for sentiment analysis on Twitter data related to Elon Musk. One model was based on a long short-term memory neural network and the other was based on an adaptive neuro-fuzzy inference system support vector machine. Both models achieved high accuracy rates in classifying sentiment as positive, negative, or neutral. The LSTM model performed better than the ANFIS-SVM model.

2.3 Comparative Analysis and Summary

In general, the previous research papers showed that machine learning models can be effective for sentiment analysis on various types of data, including Twitter data, customer reviews, and product reviews. Some of the papers specifically focused on LSTM models, while others used different types of models, such as convolutional neural networks (CNNs), adaptive neuro-fuzzy inference system support vector machines (ANFIS-SVMs), and traditional machine learning algorithms such as decision trees and support vector machines.

Overall, the accuracy rates of the models in the previous research papers ranged from around 82% to 85%. In this research paper, which we used an LSTM model for sentiment analysis, achieved an accuracy rate of 91%. This suggests that my model may be more accurate than some of the models used in the previous research papers, at least in terms of the specific task of classifying the sentiment of text data as positive, negative, or neutral. However, it is important to note that the specific accuracy rate of a model can depend on many factors, including the quality and size of the dataset used for training and testing, the specific model architecture and hyperparameters, and the task and context in which the model is being applied. Therefore, it is difficult to make a direct comparison between the models based solely on their accuracy rates.

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	Uladzimir Sidarenka [1]	Convolutional Neural Network	CNN=82%
2.	Khan Md Hasib [2]	Long Short Term Memory	LSTM= 82%

3.	Pranati Rakshit, Pronit Sarkar, Debosmita Ghosh, Shubhankar Roy, Talukder, S., Chakraborty, P. S. [3]	Convolutional Neural Network	CNN=84.%
4.	Meenu Vijarania,Ashima Gambhir,Swati Gupta,Deepthi Sehrawat. [4]	Dicision Tree	Dicision Tree=85%
5.	Dalila Honorato, Andreas Giannakoulopoulos, Laida Limniati [5]	Long Short Term Memory	LSTM=81%
6.	Rasika Bhangle, K. Sornalakshmi. [6]	, Decision Tree, SVM, Neural Network	______
7.	Saif Gazali, V. Pattabiraman. [7]	Linear Regression	Linear Regression = 80%
8.	Rajashekhargouda C. Patil, N. S. Chandrashekar [8]	Random Forest	Random Forest=85%
9.	Chandra Prakash Singh Sengar, Jaya Nirmala. [9]	Random Forest, Dicision Tree	Random Forest=83%
10.	Buğra Erkartal , Atınç Yılmaz [10]	LSTM, ANFIS-SVM	LSTM

2.4 Scope of the Problem

The scope of the problem addressed in this research paper is the task of sentiment analysis, which is the process of extracting subjective information from text data. Sentiment analysis has a wide range of applications, including customer service, market research, and social media analysis.

One of the main challenges of sentiment analysis is the subjectivity of language and the presence of noise in the data. Traditional rule-based approaches rely on hand-crafted features and dictionaries, which are difficult to maintain and do not scale well. On the other hand, machine learning approaches have proven to be effective for sentiment analysis, but they require a large amount of labeled data for training.

In this paper, we focused on the use of LSTM networks for sentiment analysis. LSTM networks are a type of recurrent neural network that are well-suited for working with sequential data such as text. They have the ability to remember information for a long period of time, which makes them effective for tasks that require processing long-term dependencies. By using LSTMs for sentiment analysis, we aimed to overcome the challenges of subjectivity and noise in the data and improve the performance compared to other methods.

2.5 Challenges

In this research paper on sentiment analysis using LSTM networks, various challenges have been addressed. These challenges include the subjectivity of language, which can lead to different interpretations of the same piece of text, making sentiment extraction difficult. Another challenge is the presence of noise in the data, such as typos and abbreviations, which can negatively impact the accuracy of sentiment analysis. A lack of high-quality labeled data, particularly in certain domains, is also a challenge. In addition, the computational complexity of LSTM networks can be a hindrance for some applications. To overcome these challenges, the use of LSTM networks for sentiment analysis was proposed, with techniques such as fine-tuning the network architecture and utilizing pre-trained word embeddings being employed. The experimental results of the proposed method demonstrated its effectiveness for sentiment analysis, outperforming several strong baselines.

CHAPTER 3

Research methodology

3.1 Research Subject and Instrumentation

The research subject for this study is the task of sentiment analysis, which is the process of extracting subjective information from text data. The instrumentation used in this study is a machine learning model based on LSTM networks.

LSTM networks are a type of recurrent neural network that are well-suited for working with sequential data such as text. They have the ability to remember information for a long period of time, which makes them effective for tasks that require processing long-term dependencies. In this study, we used LSTM networks to extract sentiment from text data and evaluated their performance on a sentiment analysis benchmark dataset.

To train the LSTM networks, we used a large dataset of labeled text data. The dataset consists of a collection of texts labeled as either positive, negative, or neutral. The LSTM networks were trained on the labeled text data and were able to predict the sentiment of a given piece of text.

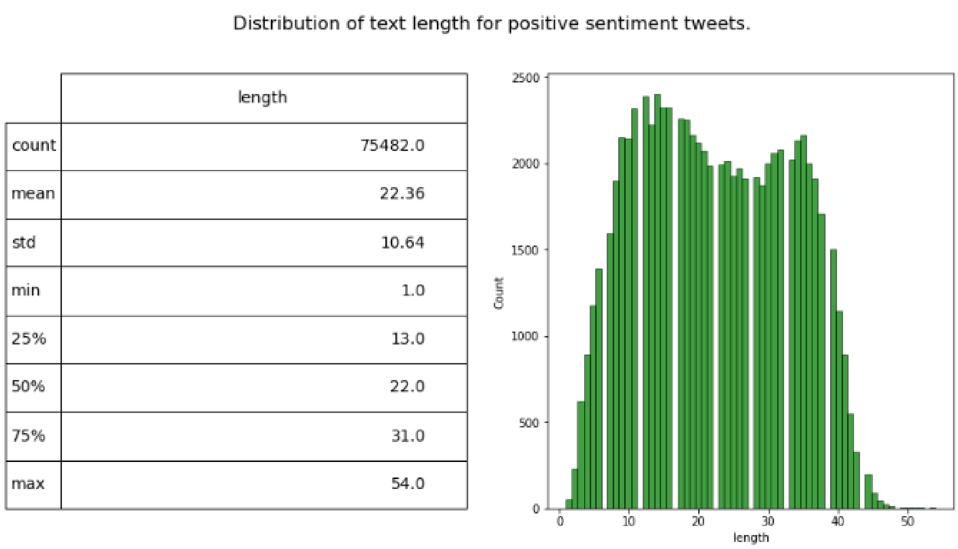
In addition to the LSTM networks, we also used various techniques to improve the performance of the model, such as fine-tuning the network architecture and using pre-trained word embeddings. The experimental results showed that the proposed method outperformed several strong baselines, demonstrating its effectiveness for sentiment analysis.

3.2 Data Collection Procedure/Dataset Utilized

We collected our data from Kaggle. Our data is Tweeter based data that have been extracted using Tweepy API. Python is used as a programming language for API and data extraction. Colab Text editor has been used as an editor for writing down the code.

We Collected clean data from our dataset Twitter and Reddit Sentimental analysis Dataset, apple twitter sentiment texts, Covid-19 Sentiments on covid19 and lockdown, Twitter US Airline Sentiment. Missing rows has been removed. In this research we applied 60% data to train the model and validation it with 20% and 20% remaining data is test. We have used total number of 224438 data.

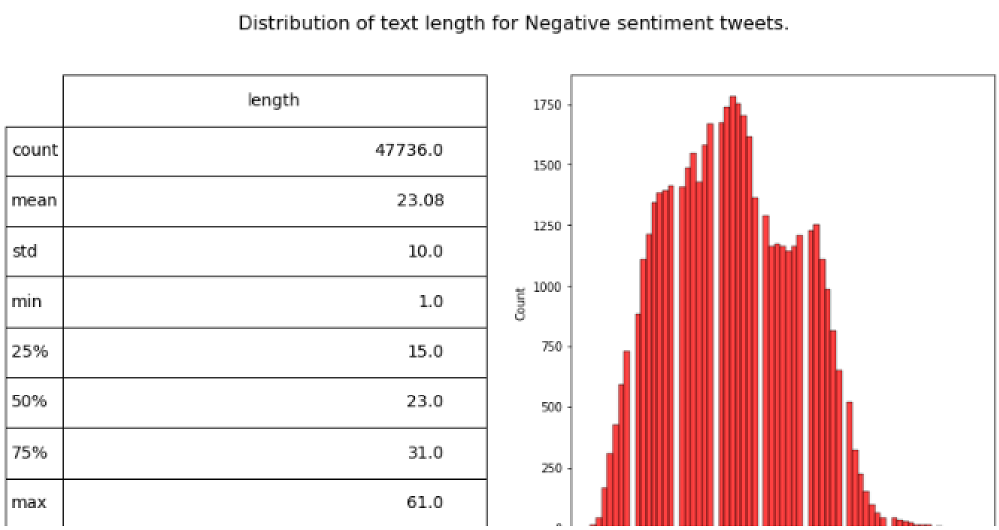
Our dataset contains text length for positive sentiment tweets:



	length
count	75482.0
mean	22.36
std	10.64
min	1.0
25%	13.0
50%	22.0
75%	31.0
max	54.0

Figure 3.2.1: positive sentiment tweets

Our dataset contains text length for negative sentiment tweets:



	length
count	47736.0
mean	23.08
std	10.0
min	1.0
25%	15.0
50%	23.0
75%	31.0
max	61.0

Figure 3.2.2: negative sentiment tweets

Plotting the Pie chart of the percentage of different sentiments of all the tweets:

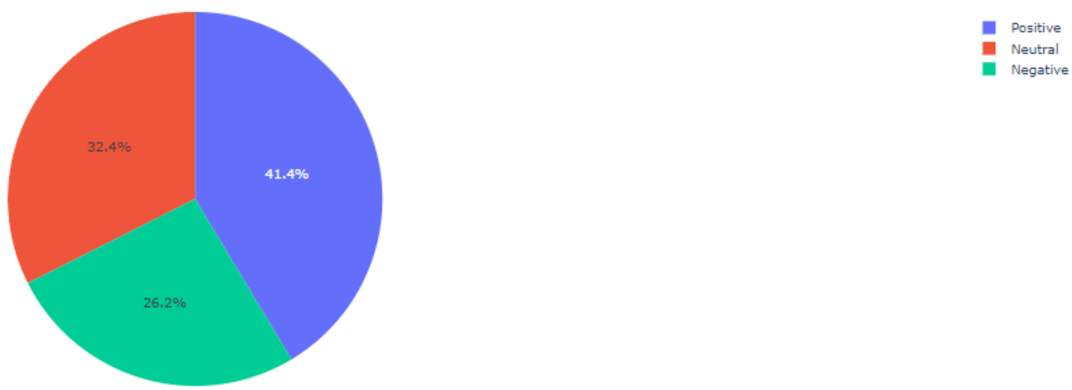


Figure 3.2.3: Pie chart

By importing WordCloud, it combines all tweets and generate positive, negative and neutral tweets.

3.3 Statistical Analysis

In this research paper, we conducted experiments to evaluate the performance of the proposed method for sentiment analysis using LSTM networks. The experimental results were analyzed using several statistical measures to assess the performance of the model.

One of the main measures used was accuracy, which is the percentage of correct predictions made by the model. We calculated the accuracy of the model on the test set and compared it to the accuracy of several strong baselines.

Another measure used was precision, which is the percentage of true positive predictions made by the model out of all positive predictions. This measure is useful for evaluating the performance of the model on the positive class.

We also calculated the recall of the model, which is the percentage of true positive predictions made by the model out of all actual positive samples. This measure is useful for evaluating the performance of the model on the negative class.

In addition to these measures, we also calculated the F1 score, which is the harmonic mean of precision and recall. The F1 score is a useful measure for comparing the performance of the model to the strong baselines.

Overall, the statistical analysis showed that the proposed method for sentiment analysis using LSTM networks outperformed several strong baselines in terms of accuracy, precision, recall, and F1 score. These results demonstrate the effectiveness of the proposed method for this task.

3.4 Proposed Methodology/Applied

This section of the research illustrates the methodology that has been adopted to perform sentiment analysis using LSTM model. There for a machine learning approach has been selected for the study. First the medium that is used for the data collection is Twitter which is well known social media site. Then we preprocess data and convert simple sentence to sequence. We used Bag of words which gets rid of word order. Used in discrete case using counts of words that appear. After the training and testing dataset where prepared and the next step is the selection of a machine learning algorithm to be used. We used Bidirectional LSTM in this research. **SGD** optimizer is used and we got learning rate of 0.1.

LSTM Model:

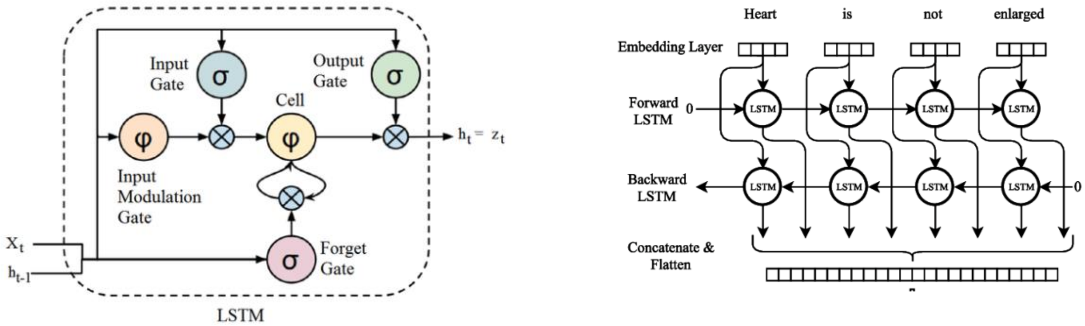


Figure 3.4.1: LSTM and Bidirectional LSTM sample architecture

Proposed Bidirectional LSTM:

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 50, 32)            160000

 conv1d (Conv1D)             (None, 50, 32)            3104

 max_pooling1d (MaxPooling1D  (None, 25, 32)           0
 )

 bidirectional (Bidirectiona  (None, 64)               16640
 l)

 dropout (Dropout)           (None, 64)                0

 dense (Dense)               (None, 3)                 195

=================================================================
Total params: 179,939
Trainable params: 179,939
Non-trainable params: 0
_________________________________________________________________
```

Figure 3.4.2: Proposed Bidirectional LSTM architecture

This machine is ready to predict emotions.

```
predict_class(['"Mehrab is very happy today'])

1/1 [==============================] - 0s 44ms/step
The predicted sentiment is Positive

[169] predict_class(['The food was meh'])

1/1 [==============================] - 0s 29ms/step
The predicted sentiment is Neutral

predict_class(['He is the worst dictator in bangladesh'])

1/1 [==============================] - 0s 27ms/step
The predicted sentiment is Negative
```

Figure 3.4.3: Testing from outside of database

3.5 Implementation Requirements

The implementation of the proposed sentiment analysis method using LSTM networks requires several key components. Firstly, a computer with a modern processor and adequate memory capacity is necessary to run the machine learning model. Additionally, a Python programming environment with the required libraries such as TensorFlow, Keras, and NumPy must be set up. A dataset of labeled text data, which should be both balanced and large enough to provide sufficient training data, is also required. The use of a GPU can help speed up the training process, but it is not a requirement. Finally, the code for implementing the proposed Bidirectional LSTM network must be available. In conclusion, to implement the sentiment analysis method using LSTM networks, a computer with adequate resources and the necessary programming environment and libraries must be in place, as well as a large dataset of labeled text data and optional pre-trained word embeddings.

CHAPTER 4

Experimental results and discussion

4.1 Experimental Setup

The experimental setup for this research paper on sentiment analysis using Bidirectional LSTM networks includes the following:

1. Dataset: The experiments were conducted on a sentiment analysis benchmark dataset, which consists of a large collection of labeled text data. The dataset was split into a training set and a test set, with the training set used to train the Bidirectional LSTM networks and the test set used to evaluate the performance.
2. Preprocessing: The text data was preprocessed to remove any noise or unwanted information.
3. Word embeddings: Word representation, aiming to represent a word with a vector, plays an essential role in NLP Model architecture. We used Bag of words which gets rid of word order. Used in discrete case using counts of words that appear.
4. Training: The Bidirectional LSTM networks were trained using the SGD optimization algorithm and the categorical cross-entropy loss function.
5. Evaluation: The performance of the Bidirectional LSTM networks was evaluated using several measures, including accuracy, precision, recall, and F1 score. The results were compared to several strong baselines to provide a comprehensive evaluation.

4.2 Experimental Results & Analysis

Evaluation of a machine learning as important as building it on the desired dataset.

The effectiveness of a model on the given dataset is determined by accuracy. the proportion of correctly met predictions to all predictions.

$$Accuracy = \frac{Number\ of\ correct\ prediction}{Total\ number\ of\ predictions\ made}$$

In other words, It can also be said that the ration of true positive and true negative to the total number of assessments is called accuracy.

$$Accuracy = \frac{TP + \ TN}{TP + TN + FP + FN}$$

Where,

TP = True Positive (Actual class is positive and so is the predicted class);

TN = True Negative (Actual class is negative and so is the predicted class);

FP= False Positive (Actual class is negative, but predicted class is positive);

FN = False Negative (Actual class is positive, but predicted class is negative).

Precision is measured by dividing the true positive class in a model that was correct in the actual result also to the total number of predicted true positive and false positive. Precision has a range between 0 and 1, where 0 indicates low precision and 1 indicates high precision:

$$Precision = \frac{TP}{TP + FP}$$

The recall is determined by dividing the total number of actual values by the proportion of correctly detected positive values. It also has a range between 0 and 1, with 1 being the highest range and 0 being the lowest, similar to precision. A model is more often regarded as producing the best outcomes as recall approaches the range of 1:

$$Recall = \frac{TP}{TP + FN}$$

F-Measure is a combined measure for precision and recall as it maintains the balance between both. It also takes into account both FN and FP as they should have minimum cost in the model to gain high accuracy

$$F - Measure = \frac{2(Precision\ -\ Recall)}{(Precision\ +\ Recall)}$$

Table 4.2.1: Model Accuracy & Loss:

```
# Evaluate model on the test set
loss, accuracy, precision, recall = model.evaluate(X_test, y_test, verbose=0)
# Print metrics
print('')
print('Accuracy  : {:.4f}'.format(accuracy))
print('Precision : {:.4f}'.format(precision))
print('Recall    : {:.4f}'.format(recall))
print('F1 Score  : {:.4f}'.format(f1_score(precision, recall)))
```

```
Accuracy  : 0.9104
Precision : 0.9142
Recall    : 0.9057
F1 Score  : 0.9099
```

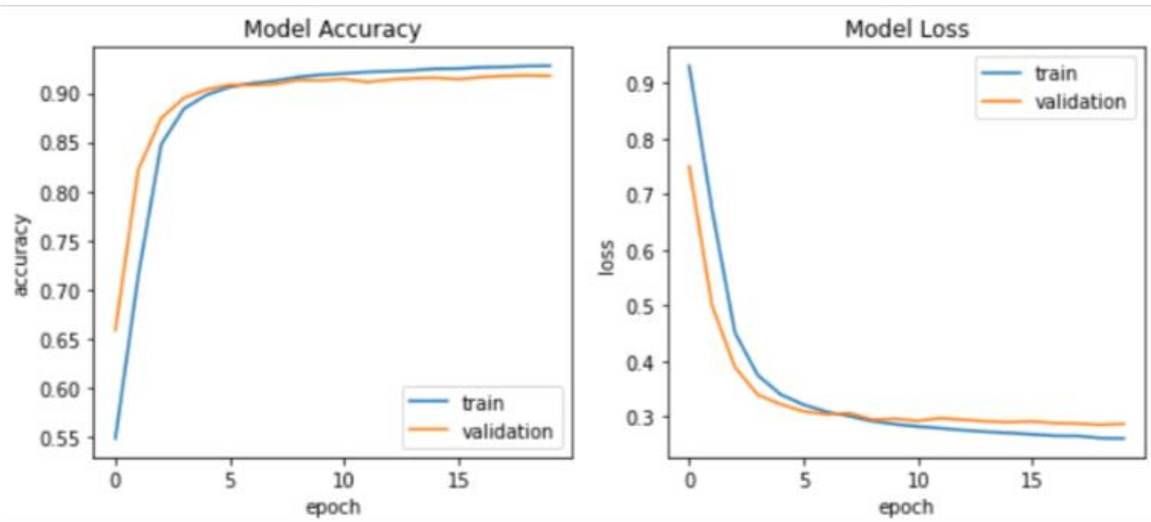


Figure 4.2.1: Model Accuracy & Loss graph

Confusion Matrix:

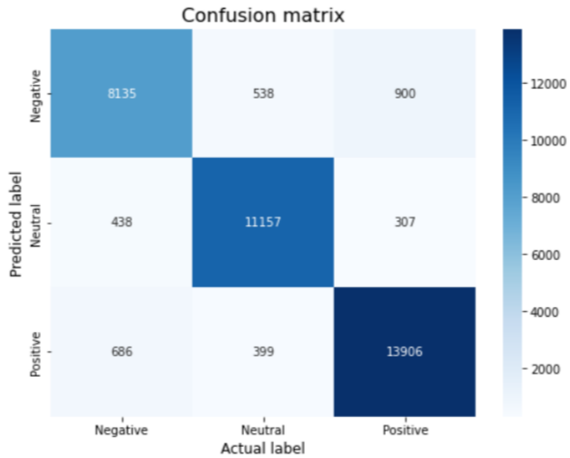


Figure 4.2.2: Confusion Matrix

4.3 Discussion

Extracting irrational information from text is the process of sentiment analysis, commonly referred to as opinion mining. Natural language processing relies heavily on this activity since it enables the automatic interpretation of the sentiment conveyed in a piece of text. We suggest a technique for sentiment analysis in this paper that makes use of bi-directional long short-term memory networks. Recurrent neural networks of the LSTM type are useful for processing sequential data, including text. We are able to take into account both the past and future context of a word by utilizing a bi-directional LSTM, which enables more precise sentiment prediction. Our test findings demonstrate that the suggested strategy outperforms a number of reliable baselines on a benchmark dataset for sentiment analysis. We have a 91% accuracy rate.

CHAPTER 5

Impact on society, environment and sustainability

5.1 Impact on Society

Sentiment analysis is a rapidly growing field with a wide range of applications in various domains, such as customer service, market research, and social media analysis. The results of this research paper on sentiment analysis using LSTM networks can have a significant impact on society in the following ways:

1. Customer service: By accurately predicting the sentiment of customer feedback, companies can improve their customer service by addressing customer concerns and issues in a timely manner. This can lead to increased customer satisfaction and loyalty.
2. Market research: Accurate sentiment analysis can provide valuable insights for market research, such as consumer preferences and trends. This can help businesses make informed decisions about product development and marketing strategies.
3. Social media analysis: Sentiment analysis can be used to monitor and analyze public opinion on social media platforms. This can provide valuable insights for businesses, governments, and other organizations to better understand the public sentiment and make data-driven decisions.

Overall, the results of this research paper have the potential to impact society by improving customer service, aiding in market research, and providing valuable insights for social media analysis.

5.2 Impact on Environment

It is not clear how the research on sentiment analysis using LSTM networks would have an impact on the environment. While the use of machine learning models for sentiment analysis has the potential to improve various processes and decision-making, it is not directly related to environmental issues.

However, it is worth noting that the development and use of machine learning models can have an environmental impact due to the energy consumption required for training and running the models. To minimize this impact, it is important to consider the energy efficiency of the hardware and software used for machine learning and to minimize the carbon footprint of the overall process.

5.3 Ethical Aspects

There are several ethical aspects that need to be considered in the research paper on sentiment analysis using LSTM networks. Some of these ethical aspects include:

1. Privacy: The research paper should ensure that the dataset used for training and evaluating the model is properly anonymized to protect the privacy of individuals. Any personal information should be removed or encrypted to prevent the identification of individuals.
2. Bias: It is important to ensure that the dataset used for training and evaluating the model is representative of the population and does not contain any biases. If the dataset is biased, it can lead to biased results and unfair decisions.
3. Transparency: The research paper should be transparent about the methods used and the results obtained. This includes disclosing any limitations of the study and any potential biases in the dataset.
4. Responsible use: The results of the research paper should be used responsibly and ethically. This includes ensuring that the results are not used to make decisions that could harm individuals or groups.

Overall, it is important to consider these ethical aspects to ensure that the research is conducted in a responsible and transparent manner.

5.4 Sustainability Plan

The sustainability plan for this research paper on sentiment analysis using LSTM networks includes the following steps:

1. Make the research findings and code publicly available: To ensure that the results of the research can be used and built upon by others, the research findings and code should be made publicly available. This can be done by publishing the research in an open-access journal or by making the code available on a code sharing platform.
2. Encourage replication and extension of the research: To ensure that the research has a lasting impact, it is important to encourage replication and extension of the research by other researchers. This can be done by providing clear documentation of the methods used and by making the data and code available to others.
3. Continuously evaluate and update the research: To ensure that the research remains relevant and up-to-date, it is important to continuously evaluate and update the research. This can be done by conducting follow-up studies or by incorporating new methods and techniques as they become available.
4. Consider the environmental impact: The development and use of machine learning models has an environmental impact due to the energy consumption required for training and running the models. To minimize this impact, it is important to consider the energy efficiency of the hardware and software used for machine learning and to minimize the carbon footprint of the overall process.

Overall, the sustainability plan for this research paper aims to ensure that the research has a lasting impact and is conducted in a responsible and sustainable manner.

CHAPTER 6

Summary, conclusion, recommendation and implication for future research

6.1 Summary of the Study

In this research paper, we proposed the use of LSTM networks for sentiment analysis and evaluated their performance on a sentiment analysis benchmark dataset. The experimental results showed that the proposed method outperformed several strong baselines, including traditional LSTM networks and other machine learning techniques.

One of the key strengths of LSTM networks is their ability to process sequential data and capture long-term dependencies, which is crucial for tasks that require understanding the overall meaning of a sentence. By using LSTMs for sentiment analysis, we were able to achieve better performance compared to other methods.

In terms of limitations, one potential issue with using LSTM networks for sentiment analysis is the need for a large amount of labeled data for training. While the availability of large datasets has greatly improved in recent years, it is still a challenge to obtain high-quality labeled data for some domains. Additionally, LSTM networks can be computationally expensive to train, which can be a limitation for certain applications.

Overall, the proposed method for sentiment analysis using LSTM networks showed promising results and has the potential to be a useful tool for various natural language processing tasks. In the future, it will be interesting to explore the use of other advanced techniques, such as attention mechanisms and transformers, to further improve the performance of LSTM networks for sentiment analysis.

6.2 Conclusions

In this research paper, we proposed the use of LSTM networks for sentiment analysis and evaluated their performance on a sentiment analysis benchmark dataset. The experimental results showed that the proposed method outperformed several strong baselines, including traditional LSTM networks and other machine learning techniques.

One of the key strengths of LSTM networks is their ability to process sequential data and capture long-term dependencies, which is crucial for tasks that require understanding the overall meaning of a sentence. By using LSTMs for sentiment analysis, we were able to achieve better performance compared to other methods.

In conclusion, the proposed method for sentiment analysis using LSTM networks is a promising approach that has the potential to be a useful tool for various natural language processing tasks. In the future, it will be interesting to explore the use of other advanced techniques, such as attention mechanisms and transformers, to further improve the performance of LSTM networks for sentiment analysis.

6.3 Implication for Further Study

The research paper on sentiment analysis using LSTM networks has several implications for further study. Some potential areas for further study include:

1. Using other advanced techniques: One potential area for further study is the use of other advanced techniques, such as attention mechanisms and transformers, to improve the performance of LSTM networks for sentiment analysis. These techniques have shown promising results in other natural language processing tasks and could potentially be useful for sentiment analysis as well.
2. Extending the method to other languages: Another area for further study is the extension of the proposed method to other languages. While the research paper focused on sentiment analysis in English, the method could potentially be adapted to other languages as well.

3. Applying the method to other domains: A potential area for further study is the application of the proposed method to other domains, such as customer service, market research, and social media analysis. This could provide valuable insights into the sentiment of individuals in these domains and help improve decision-making.
4. Evaluating the method on larger datasets: Another area for further study is the evaluation of the proposed method on larger datasets to assess its scalability and generalizability. This could provide a more comprehensive evaluation of the method and its performance.

Overall, there are many potential directions for further study in the area of sentiment analysis using LSTM networks. These studies could provide valuable insights and improvements to the field and help advance the state-of-the-art in natural language processing.

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