Newspaper's Editorial Opinion Prediction in Sentiment Analysis using Deep Learning Methods

BY

Mst. Anika Momtaj
ID: 181-15-10808
AND

Md. Shihab Mahmud
ID: 181-15-10961
AND

Uchchhwas Saha
ID: 181-15-10842

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

Supervised & Co-Supervised By

Aniruddha Rakshit
Senior Lecturer
Department of CSE
Daffodil International University

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APPROVAL

This Project titled "**Newspaper's Editorial Opinion Prediction in Sentiment Analysis using Deep Learning Methods**", submitted by **Mst. Anika Momtaj , Md. Shihab Mahmud** and **Uchchhwas Saha, ID No: 181-15-10808, 181-15-10961 and 181-15-10842** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment 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 4 January 2022.

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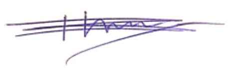

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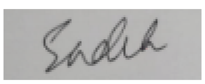

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Department of CSE
Faculty of Science & Information Technology
Daffodil International University

____

Shah Md. Imran **External Examiner**
Industry Promotion Expert
LICT Project, ICT Division, Bangladesh

DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Aniruddha Rakshit, Senior 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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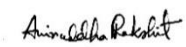

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Aniruddha Rakshit
Senior Lecturer
Department of CSE
Daffodil International University

Submitted by:

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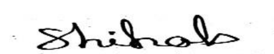
Mst. Anika Momtaj
ID: 181-15-10808
Department of CSE
Daffodil International University



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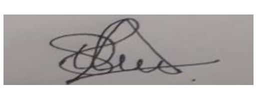
Md. Shihab Mahmud
ID: 181-15-10961
Department of CSE
Daffodil International University



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Uchchhwas Saha
ID: 181-15-10842
Department of CSE
Daffodil International University

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ABSTRACT

Sentiment analysis is a computational method that uses preliminary emotion analysis to retrieve feelings and key phrases from various texts (e.g., Positive, Negative, Neutral). It's necessary to extract useful information from big data, categorize it, and predict end-user behavior or emotions. Text classification is a research area of Natural Language Processing (NLP). Which is converted from unstructured data to meaningful categorical classes. All previous work is most likely based on traditional different classifiers such as KNN, SVM, and so on. In this study, we propose a method which is combined in two familiar deep learning models: Convolutional Neural Networks (CNN) and Bidirectional Long Short Term Memory (BiLSTM). CNN method retrieves greater characteristics by convolutional layers and max pooling layers and BiLSTM can capture long term dependencies by lexical items and it's better for text classification. Our own built datasets collected from various Bengali newspapers, such as Bangla Tribune, The Daily Sun etc. generate massive amounts of data. Our dataset size is 5996. The accuracy of the proposed model differs optimizer wise. We use three different optimizers: Adam, Adamax, RMSProp. With these three optimizers, the highest outcomes come from Adam optimizer. Accuracy of our first proposed model (BiLSTM CNN) with word2vec and Glove word embedding is 91.59% and 99.40%. In (CNN-BiLSTM) methods obtained outcomes are 92.60% and 94% and the final model (BiLSTM-CNN-BiLSTM) got their results 82.79% and 98.47%. The experimental results represent how the deep learning models effectively work. We say that the amount and quality of training examples have a significant impact on models performance.

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CHAPTER 1
Introduction

1.1 Introduction

In this decade, Sentiment analysis (SA) is a very popular research topic in the research area. Sentiment analysis is a field of Natural Language Processing (NLP) that can analyze or predict human emotion. There are four types of SA: Fine-grained sentiment, Emotion detection analysis, Aspect based and intent analysis. In this field, Used many opinions, reviews, ratings, etc. like Twitter comments, Facebook comments, blogging sites comments, newspaper editor opinions, and other social sites [1]. Text classification is a part of SA that is an automatic system to find out whether a text phase contains objective or opinion-forming content, and it can moreover decide the text or passages sentiment subjectivity and polarity [2]. There are many machine learning and deep learning methods used in this area. The SA categorization is mainly divided into two parts, positive and negative but from time to time it’s extended to be more positive, more negative, less positive, less negative, neutral etc. it totally depends on the datasets. Applying those methods, people can easily understand what the sentences are mainly about [3]. Suppose a customer buys something from a restaurant that has customer reviews or ratings of this restaurant but could not understand the main theme of this review, SA can easily analyze these reviews. The development of this area is driven by the rapid growth of social networks, e-commerce, and newspapers. Specifically in the field of newspapers, a huge number of reviews are published that reflect the perceptions of viewers about various aspects of news and others. The purpose of SA is to store opinions and emotions in user feedback that can be used to further decisions [4]. Using word vectors to transform data between text matrices. Word embedding techniques use both semantic and syntactic data on choosing words or give a poor dimensional yet nonstop vector. Categorical representations are mainly two approaches for representing emotional states [5]. We see many articles already published by SA. In our proposed paper, we try to use something different from other articles, and our paper is basically emotion detection analysis based. There are more published articles about newspaper reviews but our proposed work is

Newspaper Editorial opinion by the editor. An editor can opinion various news sources like sports news, science news, national news, international news etc. There are a lot of papers about newspapers related but editor opinion mining has few articles that's why we are working on editor opinion mining on this proposed paper. We collect our data from some Bangladeshi English newspapers like The daily star, Dhaka Tribune, The daily new nation etc. Firstly collected raw data then cleaned our data and classified it into five categories: excellent, positive, negative, deny and neutral and also labeled. We are proposing six different models in our proposed papers. we used two-word embedding, one is Glove word embedding and another one is word2vec. In our proposed work, we used 3 different methods using two-word embedding. We proposed a unique method that combined two different deep learning models: BiLSTM and CNN.

Sentiment analysis is important because it has numerous as well as effective applications on the basis of reviews or opinion mining. The process of extracting insights from social data is a process that organizations around the world are embracing. The primary goal of using SA is to find the real emotions of the various people who live in our society. There are different types of ways in SA to analyze people's emotions. In our proposed work, we used text sentiment analysis. Many works can be done in other ways like audio data, emoji data, pictures data, etc. Recently audio, emoji, pictures SA is a growing field of research. Some papers explain how to detect emojis or pictures by a sentence.

Text-based sentiment analysis is easier than others because when we use text data, machines can detect it easily. Suppose, "I eat rice" and "I don't eat rice", these two statements are easily detected by their polarity. But Other data like audio-visual data, emojis, tone, etc. can be hard to understand verbal communication, and also objects become much more confusing when attempting to evaluate a high amount of data containing both subjective and objective replies. Everyone gives their opinion independently. We can easily understand their opinion but sometimes some opinions are harder to understand. When we collect opinions through newspapers and train this opinion then sentences give the same outcome.

A lot of reasons behind that are that we choose opinion to classify sentiment or opinion-based SA in our proposed research works. We reviewed more papers about opinion mining, there are different types of opinion-based papers we can get but editor opinion mining articles couldn't get and this time SA is a hot topic to analyze sentiment classification that's why we chose this topic. There we used a new method that combined two deep learning methods. Everyone used existing models to implement their proposed work. In our work, we are trying to do something different from others.

There are many numerous approaches that can be experimented with Stanford NLP or text razor (an NLP API company). Writing R code to use sentiment and to packages. on the other hand, using python code and then using NLTK. It is entirely dependent on the data as well as the desired outcome (tokenization, POS, NLP, feature extraction, a combination of words, opinion explanation, and so on) from this evaluation.

1.2 Motivation

The method of evaluating whether a piece of writing is positive, negative, or neutral is known as sentiment classification. For text analysis, Natural Language Processing (NLP) is a part of machine learning (ML) that are combined in a sentiment analysis (SA) system. In our work, we used English Newspaper opinion text to classify Editor's opinions. SA is a significant as it has a wide range of useful applications based on reviews or opinion mining. Organization all over the world are embracing the process of extracting insights from Social data. The primary objectives of SA is to uncover the true feelings of people who live in our society. Everyone express their viewpoint in their own way. We can easily understand their viewpoint, but some opinions are more difficult to comprehend. When we gather opinions from newspapers and train them, the sentences produce the same result. We choose opinion to classify sentiment or opinion-based SA in our proposed research works for a various of reasons. We looked at more papers about opinion mining;
there are various types of opinion based papers available, but Editor opinion mining articles were not available, and this time SA is a hot topic for sentiment classification analysis, which is why we chose this topic.

1.3 Background and Context

Sentiment Analysis: A decision, a review, or a personal perspective are all examples of opinions. Each individual's viewpoint can be positive, negative or neutral [6]. This opinion classification has recently received attention, as opinion has become important in e-reputation measurement techniques.

1.3.1 Opinion Analysis Levels

Here different opinion analyses can be used at various levels of specificity, especially regarding:

- **Word level:** The analysis that defines a word's polarity is known as word-level, i.e., if it is a positive, negative, neutral, excellent, or deny word.
- **Sentence level:** The analysis that determines the polarity of a sentence is known as sentence level. It is frequently used in opinion analysis. It is a collection of words that, because it is particular to social networks, aims to define an opinion on a topic.
- **Document/passage level:** The analysis that determines the polarity of a document or passage is known as the document level. It is a more tough level than others because as the amount of words keeps increasing, so does the amount of noise words, which misrepresents reading and simplifies polarity prediction.

1.4 Expected Outcome

Our project has to do with research. As a result, our primary goal is to publish journal articles on projects that are related. A research paper allows for a lot of analysis to be done quickly. Our proposed work under the sentiment analysis (SA) domain. There are a lot of field about SA. In our work, we used text classification for newspaper's editorial opinion. The expected outcome is how the editors can gives their opinion in a separated news. We used deep learning methods to obtained this outcomes. We must train a machine and, as a result, the device must learn for any type of automated system. Following that, the mastering version is used in the backend of a machine in conjunction with a web or mobile application. Editors can comments any news independently and this comments, we used and classify what he/she told.

1.5 Report Layout

There are six chapters in total. Each chapter is discussed from various perspectives, and each chapter has several parts that are explained in detail. The following are the contents of this report paper:

Chapter 1

Some sections of this chapter include the following – 1.1 Discuss about Introduction part, 1.2 Discussing about the Motivations, 1.3 Opinions Analysis Levels, 1.4 Discuss the Rational Study of this article, 1.5 Expected Outcome.

Chapter 2

This chapter we discuss about, 2.1 Introduction, 2.2 Related Works and 2.3 Summary of the Research.

Chapter 3

In this chapter we described the full working flow of our work. Including Some sections, 3.1 Introduction, 3.2 Research Subject and Instrumentations, 3.3 Data Collection, 3.4 Dataset Partition, 3.5 Data Preprocessing, 3.6 Statistical Analysis, 3.7 Proposed Methodology and 3.8 Implementation Process

Chapter 4

This chapter covers with Experiment and Result Discussion of this research, 4.1 Introduction, 4.2 Experimental Result & Analysis, 4.3 Discussion.

Chapter 5

In This chapter we discussed about social impact in our society, 5.1 Impact of Society, 5.2 Ethical Aspects, 5.3 Sustainability Plan

Chapter 6

This Section discussed about, 6.1 Summary of The Study, 6.2 Conclusion, 6.3 Implication for Further Study.

CHAPTER 2

Background Studies

2.1 Introduction

We began this research by reading related literature reviews. Specifically, our experiments are based on sentiment analysis of English newspapers document sentences. Our proposed work will be done by deep learning methods. Deep learning is a part of machine learning method that uses artificial neural networks to learn representations. There are three types of machine learning: supervised, semi-supervised, and unsupervised. Before many newspaper related article published in different methods. Hopefully our proposed work is the first work to be done by those models.

2.2 Related Works

(Fan Liu et al.,2019) To classify multiple kinds of arrhythmias, this work suggests an attention-based hybrid LSTM-CNN model. The general trends and native functions of ECG can be extracted simultaneously by combining SB-LSTM and TD-CNN. The TAG in SB-LSTM, in particular, can enhance the effect of various trends in key parts of the ECG, Whereas the FAM and LAM un TD-CNN can give more weight to advanced features at particular areas. The proposed attention mechanisms, in particular, generate an 8% performance increase, which has been qualitatively visualized. Finally, their model achieves 99.3% ACC, 99.6% SEN, and 98.1% SPE, which outperforms three state-of-art methods [7]. (Ms. Gaurangi Patil et al., 2014) In this paper, they collect user opinions about political candidates via comments and tweets and then use Support Vector Machine (SVM) to categorize them as positively or negatively for sentiment analysis (SA) by categorizing the user’s comment as positive or negative for SA. Various outcomes indicate that SVM outperformances ANN when it comes to text categorization [8]. (Olga kolchyna et al., 2015) In this paper, the twitter dataset is collected using two different processes of sentiment analysis: the lexicon-based approach and the machine learning approach. The demonstrate that combining the two techniques often improves the accuracy of sentiment analysis for twitter. The test was run on a SemEval competition-2013, Task 2-B test dataset.

They also demonstrated that the use of cost-sensitive classifiers enhances the accuracy of complexity prediction only in the case of highly unbalanced datasets: on the benchmark twitter dataset, a cost sensitive SVM yielded a 7% improvement in performance over a conventional SVM. SVM accuracy is 91.17%, Naïve Bayes (NB) accuracy is 88.54%, and Decision trees accuracy is 89.9% [9]. (Suchita V Wawre et al., 2016) In this paper, experiments of online movie reviews were conducted using sentiment classification techniques, and two supervised machine learning approaches, SVM and NB, were compared for review sentiment classification. According to the results, the NB approach outperformed the SVM, and when the training dataset had a large number of reviews, the NB approach achieved high accuracies when compared to others. The outcomes of these two methods are as follows: NB 65.57%, SVM 45.71% [10]. (Sujata Rani et al., 2017) In this paper collect student feedback via a student response system (SRS) also from online learning portals like Coursera and student opinion using NRC Emotion Lexicon to improve learning and teaching [11]. (Elsherif Elmurngi et al., 2018) They gather online movie reviews using SA methods in order to identify fake reviews, and they compare five supervised machine learning algorithms for classification tasks of reviews using two separate datasets: NB, SVM, K-Nearest Neighbors (KNN-IBK), K*, and Decision Tree (DT-J48). Experimental results demonstrate that the SVM algorithm outperforms other algorithms in terms of accuracy, not only text classification but also in identifying fake reviews. NB has a 70.9% accuracy, SVM has a 76% accuracy, K* has a 69.4%, KNN has a 70.5% accuracy, and DT has a 69.9% [12]. (V.K. Singh et al., 2013) Presenting this paper, Four different methods described for document-level sentiment classification are used, including two machine learning classifiers (NB and SVM), and the SentiWordNet strategies for sentiment classification using three datasets of movie reviews. Since they use three different datasets the results vary from different approaches. The results of ML models are NB 83.8%, SVM 78.15%, SO-PMI-IR 84.327%, modified SentiWordNet Approach [13]. (Alvaro Ortigosa et al., 2013) this article shows that they use a classification approach implemented is SentBuk that take a hybrid model: if combines lexical-based and machine learning methods, and they use a dataset for, Facebook that includes message written by users. The results achieved using this method show that it is possible to perform analysis in Facebook with good accuracy, with an accuracy of 83.27% [14]. (Zeenia Singla et al., 2017) In this article. The NB , SVM, and DT methods were used to collect various product reviews. Models are evaluated using 10-Fold cross validation. The outcomes show that the SVM techniques has the highest predictive accuracy of the three models. While the NB model has low predictive accuracy [15]. (Hemalatha et al., 2013) In this paper, they collecting messages from social networking sites while data preparation unnecessary data such as repeated messages (tweets), repetitive letters, URLs, feelings icons, WH-Questions, special character, and the result shows how impactful it is to perform distant supervised learning using NB classifier and Maximum Entropy (ME) models [16]. (B. Le et al., 2015) This paper present that they developed a technique for selecting a new feature set based on information Gain, Bigram, and Object-Oriented extraction methods in SA on a social media site, as well as proposed a model based on NB and SVM. Using all techniques and preprocessing to remove noisy data, emoticons, hashtags, and so on. This model proven to be very effective and extract on the analysis of emotions [17]. (Mohammed H. Abd El-Jawad et al., 2018) They used preprocessing techniques to remove noisy data and compare its performance of various machine learning and deep learning algorithms, as well as introduce and test a new hybrid model against the other classification techniques such as Convolutional neural networks, DT, NB, and recurrent neural networks. According to the results, the hybrid model has the best accuracy of 83.60%, the highest sensitivity of 87.10% and the maximum specificity of 79.30% [18]. (BiswaRanjanSamal et al., 2017) In this paper, after trying to collect movie review datasets of various sizes, the data is cleaned before being used in supervised machine learning algorithms (MB, Logistic Regression, Linear Model) to train the model to classify the review. According to the results, SVC/SVM is the best classifier among others in terms of gaining 100% accuracy for a significant number of movie reviews [19]. (Megha Rathi et al., 2018) To analyze and classify the sentiments, the proposed research work created a hybrid classification model by combining the SVM, Adaboost Decision Tree and DT. The accuracy of this SVM is 82% in this paper, 67% in Adaboost Decision Tree, and 84% in DT [20]. (Rajkumar S. Jagdale et al., 2019) The dataset used in this paper was obtained from Amazon and contains reviews of different kinds of devices/products. After preprocessing and applying ML algorithms (NB, SVM) to categorize positive or negative reviews. NB, SVM produces the best outcomes for classifying product reviews. For Camera reviews, NB has an accuracy of 98.17% and SVM had an accuracy of 93.54% [21]. (Atiqur Rahman et al., 2019) This paper, after gathering data from movie reviews and preprocessing it with an NLP tool, they used different five classifiers to determine which classifiers provide the best outcomes: Bernoulli Naïve Bayes (BNB), DT, SVM, ME, and Multinomial Naïve Bayes (MNB). The results show that MNB has a higher accuracy (88.5%) than others [22]. (Jaspreet Singh et. Al., 2017) Here are three datasets of products reviews, camera reviews, and movie reviews from Amazon and IMDB. ML (NB, J48, BFTREE, OneR) classifiers were used to predict sentiment. After examining and comparing these four classification models, The NB was discovered to be quite fast in learning, whereas OneR appears to be less dim in producing the accuracy of 91.30% in precision , 97% in F-Measure, and 92.34% misclassified occurrences [23]. (Sreevidya p. et al., 2020) This paper present a scheme for deep learning-based multimodal SA, as well as the development of two parallel text-based and audio-based models. The deep neural features extracted from these specific modalities are merged together and fed into the final CNN layers, where the bimodal fusion is applied [24]. (Shahid Shayaa et al., 2018) In this paper, presenting a thorough systematic literature reviews with the goal of discussing both technical details of OMSA (Techniques and types) and non-technical aspects in the form of application fields [25]. (Kia Dashtipour et al., 2018) Deep learning models of two types (deep autoencoders and deep convolutional neural networks (CNNs)) are developed and implemented to a completely unique Persian movie reviews dataset in this paper. The proposed deep learning models are analyzed and compared to a cutting-edge shallow multilayer perceptron (MLP)- based ML model [26]. (Munir Ahmad et al., 2017) In this paper, various ML strategies, various types of research, and experiment on ML based tools and techniques for sentiment analysis and classification are consulted in order to generate interest is this field of research [27]. (Anuja P Jain et al., 2009) This paper proposed a text methodological approach for twitter data based on NLP techniques, followed by a feature extraction technique elicit sentiment-relevant features. In the suggested scheme, a model is also trained for SA using ML classifiers such as NB, SVM, and DT [28]. (Ali Feizollah et al., 2019) This paper utilizes tweets of halal products, such as halal tourism and halal cosmetics, to demonstrate how Twitter data is retrieved and the viewpoint of tweets on a specific topic is determined by calculating. The data was filtered using an algorithm, and a test was carried out to calculate and analyze the sentiment of the tweets using deep learning algorithms. CNN, LSTM and RNN were also used to enhance the accuracy and build predictive model. The word2vec feature extraction method, combined with a stack of the CNN and LSTM algorithms, obtained an accuracy of 93.78% in the outcomes [29]. (Qiongzia Huang et al., 2017) They propose a new model for deep sentiment representation in this paper by skillfully combining one-layer CNN and two-layer LSTMs. The CNN makes it easy to auto extract local features and decrees computational cost due to the convolution layer and pooling layer. Furthermore, because of its capacity to study syntax functionalities of linguistics, LSTM is proficient in learning sequence characteristics. As a result, our model performs well in sentiment classification.

Their proposed model's accuracy was 87.20% which is 4% higher than LSTM. It's obvious that our model outperforms all others [30]. (Kia Dashtipour et al., 2021) The paper presents a context-aware, deep-learning Persian approach to SA. The developed method exemplifies an engineering approach to deep learning that categorizes Persian film reviews. The previously proposed manual-feature-engineered SVM-based approach compares two profound learning algorithms, CNN and LSTM. According to simulation results, LSTM outperforms MLP, autoencoders, SVM, LR, and CNN algorithms. The simulation results show that profound learning outperforms state-of-art superficial ways to learning. The stacked-bidirectional-LSTM obtained highest accuracy of up to 95.61% for the film dataset, but not for the hotel dataset, where 2D-CNN performed better which is 89.76% [31]. (Amin Ullah et al., 2017) A new activity recognition method has been proposed using video data processing using a CNN and a DB-LSTM network. The experimental results demonstrate that the technique of recognizing by the three benchmark datasets, these were UCF-101, YouTube 11 Actions, and HMDB51, outperforms state-of-the-art action-detection methods significantly. The averaged accuracy these datasets was 92.84% and other CNN model result was 88.10% [32]. (Jin Wang et al., 2017) This paper proposes to predict VA test ratings using a CNN-LSTM regional model, which is made up of two parts:

the regional CNN and the LSTM. In the proposed regional CNN, a single sentence is used as region. Such regional information is sequentially integrated across LSTM VA prediction regions. The prediction process can be viewed as a combination of regional CNN and LSTM, both locally in sentences and across sentences. The predicted outcomes shown that the proposed model outperforms previous models based on lexicons , regression and NN [33]. (Soufian Jebbara et al.,2017), In this work a module architecture was presented, which addresses the analysis of feelings as a question of extraction. The proposed architecture divides the problem into three subtasks, each of which addresses a specific component. The architecture proposed divides the problem into three subtasks and covers each one with a specific component, achieving promising results, outperforming an 18% overall baseline accuracy and providing initial USAGE data. The current state of the art in aspect state-of-the-art relationship extraction exceeds 15% of F-Measure by our relationship extraction element [34]. (Shervin Minaee et al.,2019) A method based on LSTM and CNN ensemble is presented for the purpose of collecting temporary data information and trying to extract the data's spatial patterns. The experimental results show that both individual models can outperform this ensemble model [35]. (Artaches Ambartsoumian et al.,2018) In this paper, the effectiveness of SANs for sentimental analysis was investigated. By trying to compare its classification precision to six data sets and performance results such as training speed and memory usage, they show that SANs outperform RNN and CNN. BiLSTM self-attention models were found to be 3.4 times and 5.9 times faster to train than LSTM models. On the other hand, inferior times are 15.5% slower than LSTM and 41% faster than BiLSTM [36].

2.3 Summary of Research

The main goal of this study is to contribute to our efforts in the field of sentiment analysis (SA) through deep learning techniques. This project we proposed three different methods. We assembled 5996 data from different English newspapers. Our dataset is unique because this dataset built by manually. For the dataset, we needed to create three columns: first column for the Editorial comments, second one was category and last one is label. There three classes in our dataset, positive, negative and neutral. Then we preprocessed our dataset. In preprocessing, we removed punctuation marks, cleaning data etc. In modelling time, dataset divided by two parts: one is training dataset and another is testing dataset. After all the process completed then it's time to model training. Finally we got our desired outcomes for our proposed new models.

CHAPTER 3

Research Methodology

3.1 Introduction

Every research project has a distinct methodology, and ours is no exception. Now we'll go over the entire process of our work in detail. The research project's goal is to discover something new by employing a novel problem-solving technique. The methodology part of all this is included in the application. We'll go over each component of the model that we used in our work. For this study, we used two deep learning method, one is Bidirectional BiLSTM and another is CNN. In deep learning knowledge, BiLSTM and CNN are used to solve the sentimental analysis data processing problem. We need to know what we're working on and why before we run the deep learning model. To get an accurate result, we'll need a proper dataset once more. Before running any algorithm, it is critical to create and preprocess datasets thoroughly. This section explains how the various components of our approach work together to produce excellent results. The ability to work and supply the aristocracy is enhanced by proper narration and justification of method. The method's graphical sketch and mathematical equations, as well as their representation, aid in comprehending the entire endeavor. Working in the future necessitates a thorough understanding of methodology, which is a critical component. Anyone looking at a work flow can easily get a number of ideas if mathematical terms and graphical waves are completely functional. Again, a good working flow chart is required for a good research paper. Anyone can easily understand a transparent or white background workflow chart and learn about the models in a short amount of time. Anyone looking at a transparent or white background workflow chart will have no trouble learning about the models in a short time. The method's foot space are described in detail in this section. Here, a sub phase of a few middle sections assists in recognize the gist of the model with the use of that will be very helpful in understanding the methodology part. The entire work process is outlined below, and it serves as a summary of the entire research project.

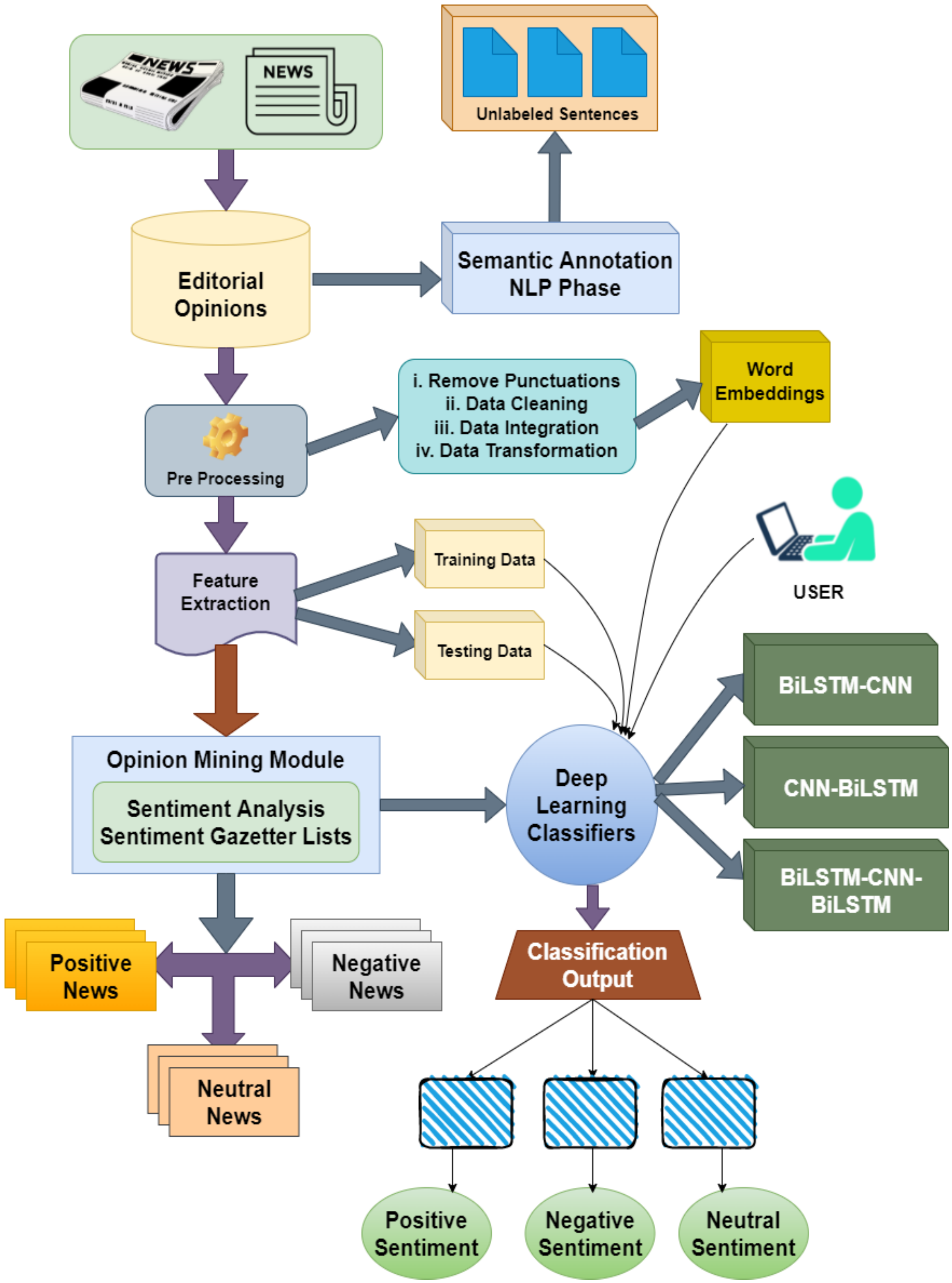


Figure 3.1.1 Work Process for our Methodology

3.2 Research Subject and Instrumentations

We proposed out thesis tittle is “”. Nowadays Sentiment Analysis is a very hot topic in research field. In our research methodology, we used some deep learning models because there some mathematically functions that we used in our proposed model. It will be extremely difficult for us to work with a deep learning model because it requires a high-configuration PC, GPU, and other apparatus. The following is a list of the necessary equipment and technology to get our model up and running –

Software and Hardware:

- Intel Core i3 7^{th} generation with 8GB RAM.
- 1TB HDD
- 256GB SSD
- Google Colab with GPU

Development Tools:

- Windows 10
- Python 3.7
- 1.15.2 version of TensorFlow Backend
- NumPy
- NLTK
- Pandas

3.3 Data Collection

Data collection could even be viewed as a scientific method of obtaining data from observations. The majority of researchers have made their datasets freely available online, but we created our own. Gathering raw data is the first step, followed by categorizing and labeling this dataset. We gather editorial opinions from a variety of newspapers, including the Bangla Tribune, The Daily Sun, and others. There are 2172 positives, 1992 negatives and 1832 neutrals data in this dataset, which totals 5996 data. The dataset is one-of-a-kind in that it was created specifically for sentiment classification analysis. We can use three columns in this dataset: the first is Comments, followed by Category, and finally Label.

Table 3.3.1 Sample of our dataset

Sentence	Category
That Petro Bangla only received two bids ----------------------------- would be a good way to assuage the fears of international organizations and protect Bangladesh's economic outlook in the long run.	Positive
By making threats to take over Bangabhaban and re-issuing the threat to besiege ---------------- have been the Islamic thing to do.	Negative
We believe that Bangladesh is changing. Even amidst the -------------- This is the spirit that will infuse the Dhaka Tribune.	Neutral

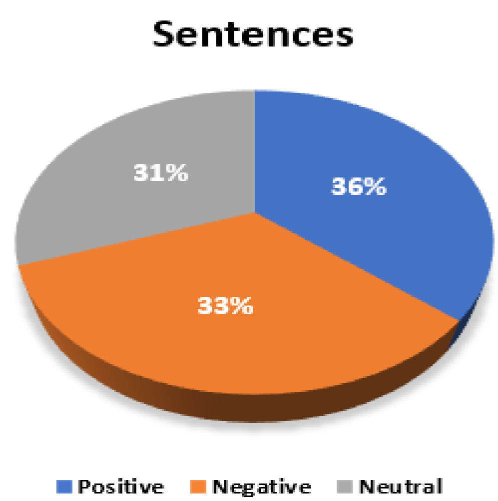


Figure 3.3.2 Pie chart: Percentage of our own build dataset

3.4 Data Partition

In our dataset, different types of topics were added like political-related, sports-related, national, international news etc. Below we showed a graph of the data partition of each topic.

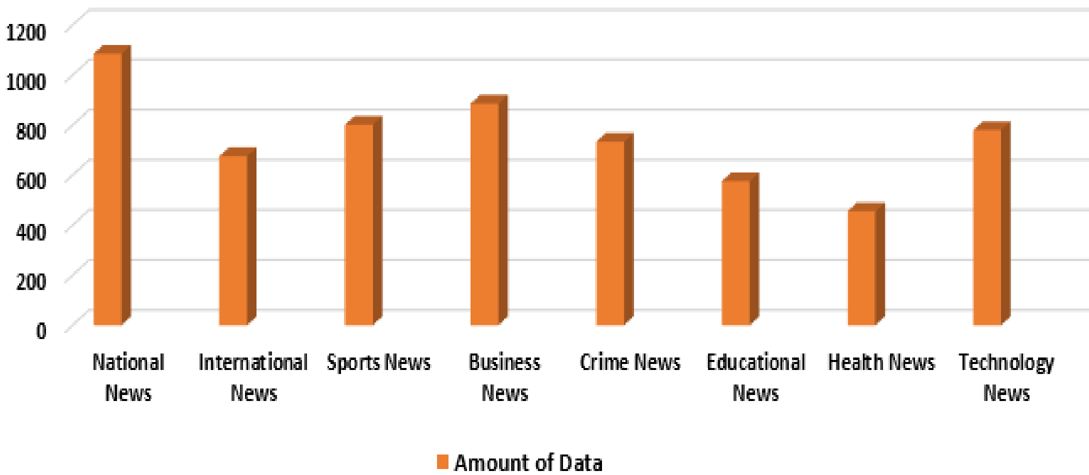


Figure 3.4.1 Data Partition of various news

Table 3.4.2 Amount of all different news

Name of News	Amount of Data	Training Dataset	Testing Dataset
National News	1086	870	216
International News	676	540	136
Sports News	802	642	160
Business News	886	708	178
Crime News	734	587	147
Educational News	576	460	116
Health News	456	364	92
Technology News	780	624	156

3.5 Data Preprocessing

Data preprocessing means changing from main data to well-formed data. In the dataset, when we collect raw data there are some errors, missing data, incomplete sentences, grammar mistakes etc. This preprocessing method helps to solve these problems. Below we listed which preprocessing methods we used –

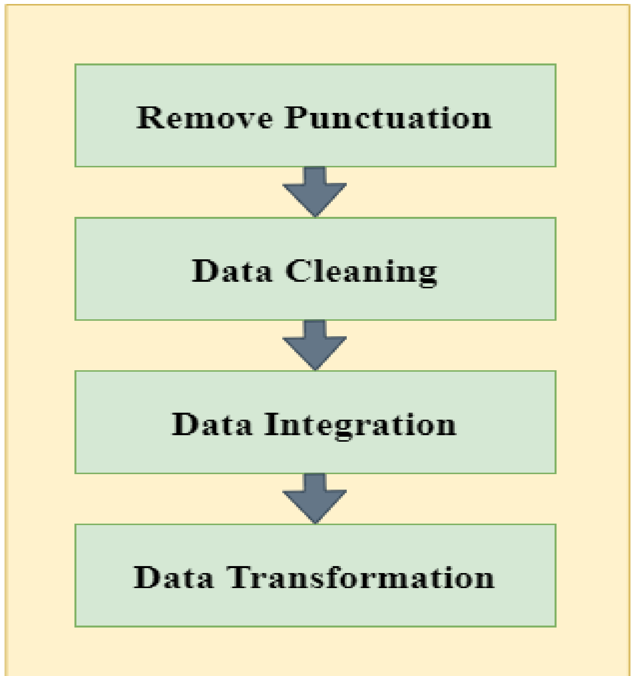


Figure 3.5.1 Dataset preprocessing

3.5.a Remove Punctuation

In our dataset there are many punctuation marks we find such as “[(),!@$^&*#+<|>-/’]” and remove all types of punctuation.

3.5.b Data Cleaning

Data is cleaned by the processes of missing data filled in, or missing rows being deleted, noisy data is relieved or inconsistent data is resolved.

3.5.c Data Integration

Different types of data representations can be stored together and resolve some conflicts data.

3.5.d Data Transformation

Data transformation is being used to implement the information, so that it can be used smoothly for a method to be created.

3.5.1 Tokenization

Tokenization is mainly used for splitting a sentence, document, or passage into separate words. In this separate word also called a 'token'. Tokenization is important because a token can be easily defined by machines [37]. Below gave an example for more clarification - we took a part of a sentence to our dataset.

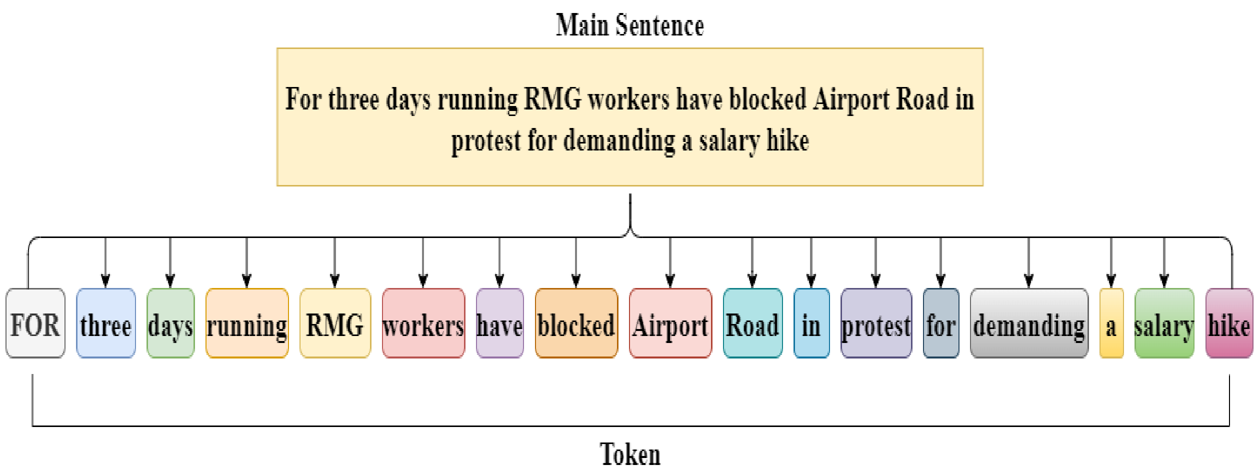


Figure 3.5.1.1 Tokenization Process

3.6 Statistical Analysis

In this work we collected almost 5996 datasets for different news. There were various news like national, sports, crime etc. It was own built dataset because all of the datasets were inputted manually. There are 2172 positives, 1992 negatives and 1832 neutrals data. Here we used 4796 sample for training and 1200 sample for validation.

3.7 Proposed Methodology

In deep learning, there are many models and various types of models of different types of motives. Bidirectional Long short term memory (BiLSTM) and Convolution Neural

Networks (CNN) will be very useful for our proposed work. Basically we combined two deep learning models. Below we given our model structure with graphical view -

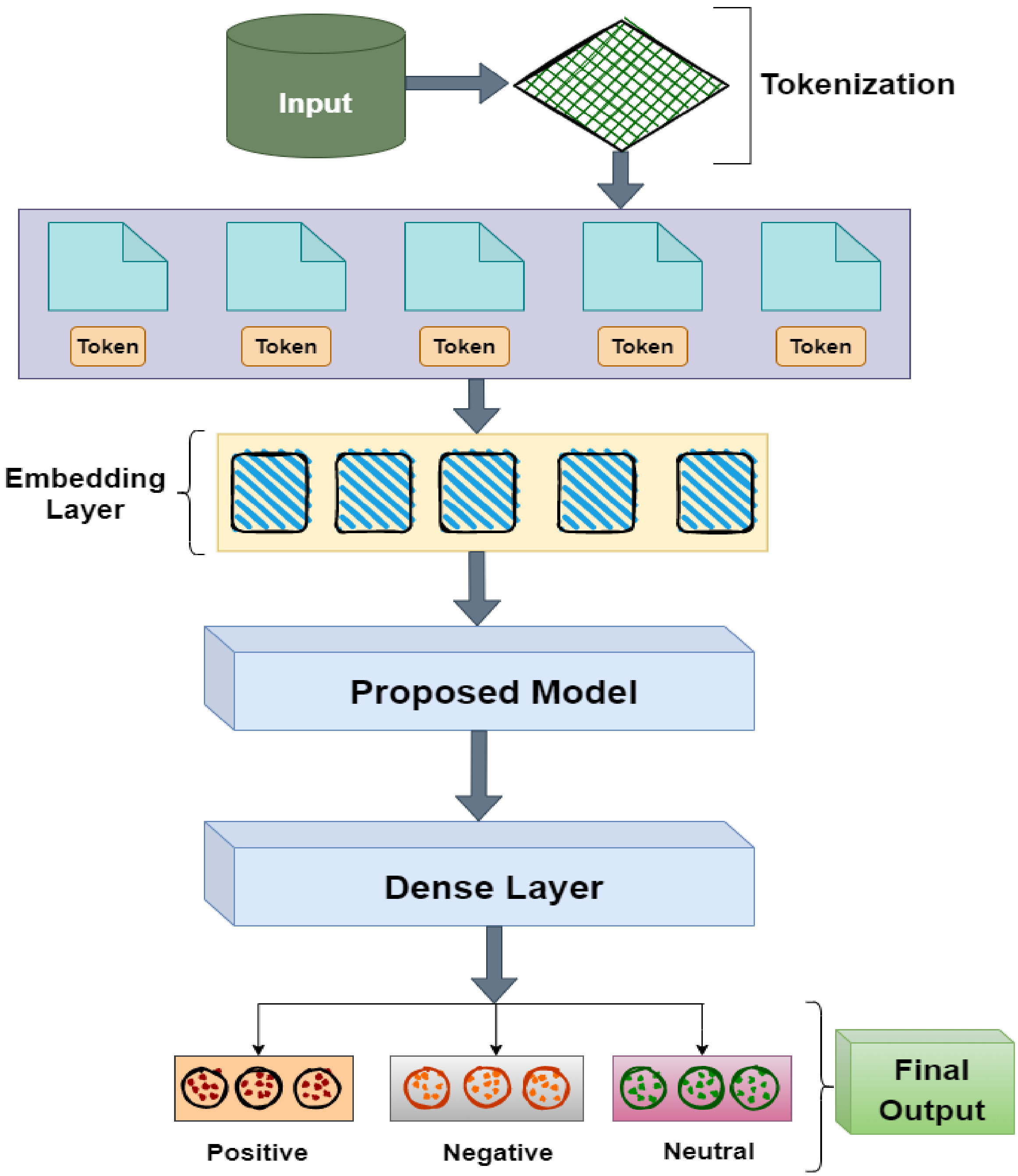


Figure 3.7.1 Architecture of our Proposed Method

3.7.a BiLSTM-CNN

A Bidirectional LSTM or BiLSTM is a sequential processing technique that is made up of two LSTMs, one is forward directional and another is backward directional. CNN is a heavy powerful term in text classification on sentiment analysis and it is very excellent in opinion analysis. It is very useful for long articles and its characteristics are still difficult to extract. After adding the embedding layer then used two bidirectional layers with dropout value 0.5 and lastly added three convolution layers with 32 filters, the kernel size is 3 and the activation function was “relu”. The error function was “categorical_crossentropy,” which was required to assemble the method. The “Adam” optimizer used this model and the layer dropout was 0.5. Finally we trained this model, the epoch was 50 and the batch size was 256.

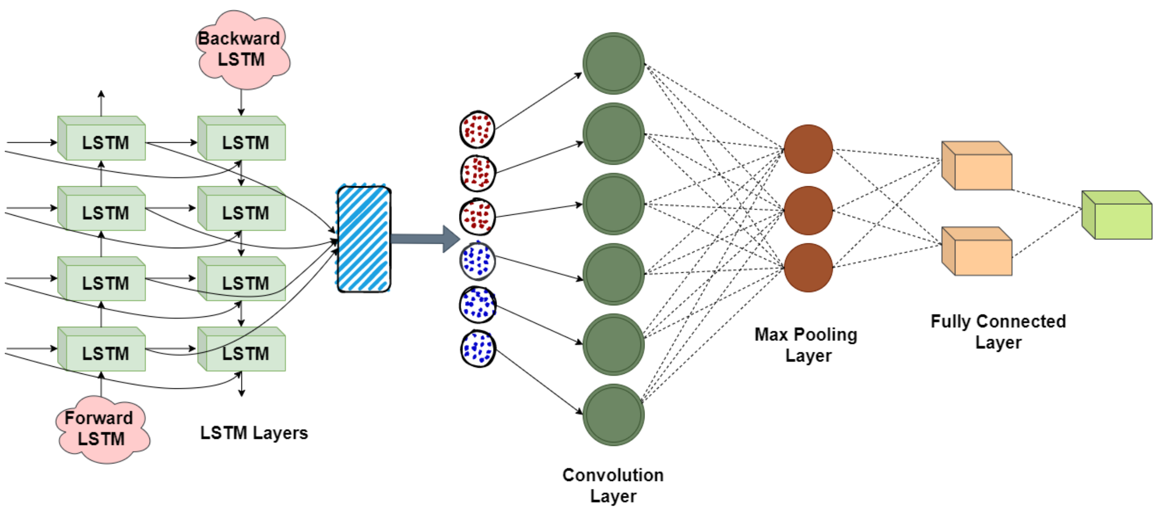


Figure 3.7.a.1 Architecture of BiLSTM-CNN Network

3.7.b CNN-BiLSTM

A CNN-BiLSTM is a CNN and bidirectional LSTM structures that are combined. It is a combination model of CNN and BiLSTM and also with word embedding called glove. Firstly using an embedding layer then use a spatialDropout1D whose value was 0.2 and two CNN layers were added after the embedding layer. There were two CNN layer conv1D which filters 32 , kernel size is 3 and the activation was ‘relu’. To generate the character-level functionalities, the CNN element is used. The model uses a convolution and a max pooling layer for each phase to retrieve a new feature representation from its per extracted features such as character embeddings and characteristics of a particular.. After adding two CNN layers then the two BiLSTM layers were added. In BiLSTM layers, To describe the class of each outcome, the SoftMax activation function converts the vector into probability. The error function was “categorical_crossentropy,” which was required to assemble the method. The “Adam” optimizer used this model and the layer dropout was 0.5. Finally we trained this model, the epoch was 50 and the batch size was 256.

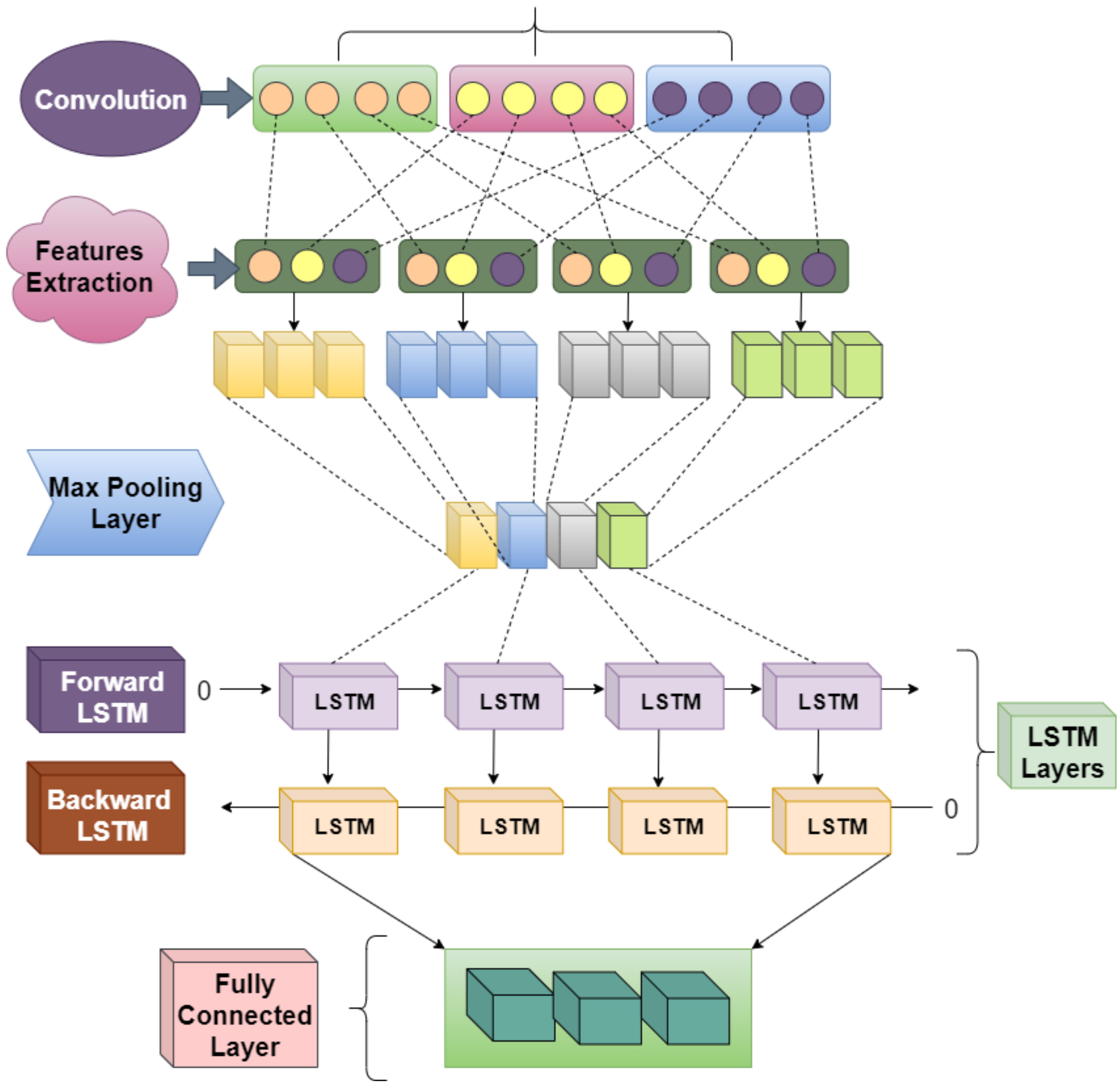


Figure 3.7.b.1 Architecture of CNN-BiLSTM Network

3.7.c BiLSTM-CNN-BiLSTM

This model is combined by two LSTM methods and one CNN method. First of all, this model started with an embedding layer and spatialDropout1D value was 0.2 then at a time two bidirectional layers were added, whose dropout value was 0.5. This layer maintains the data's series. It enables the detection of links among both input patterns and the output. This Layer's entry is the combination of the maximum pooling outcomes. There were two CNN layer conv1D which filters 32 , kennel_size is 3, pool_size 2 and the activation was 'relu'. There was a max pooling layer which is a fully connected layer. After adding these two layers of CNN architecture then finally we were added two bilstm layers. The error function was "categorical_crossentropy," which was required to assemble the method. The "adam" optimizer used this model and lastly trained this model with 50 epochs and the batch_size was 256.

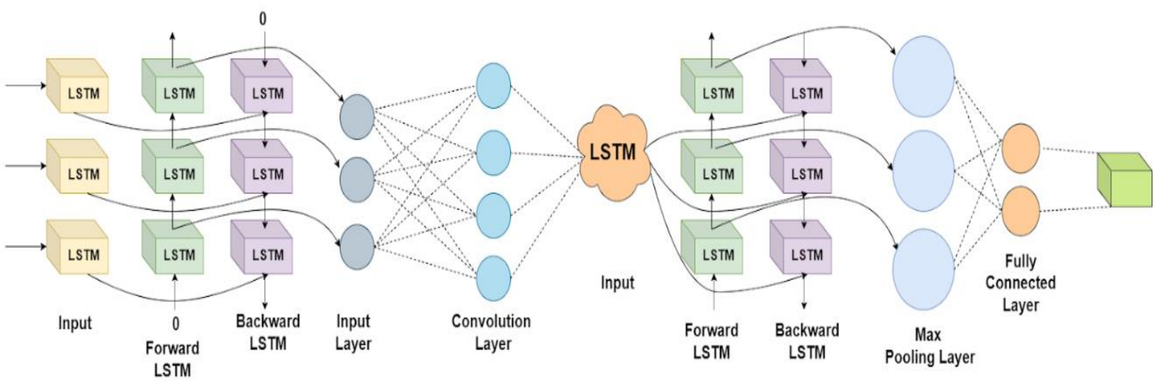


Figure 3.7.c.1 Architecture of BiLSTM-CNN-BiLSTM Network

3.8 Implementations Necessity

In deep learning, there are several models and various kinds of models for different types of motives. In our proposed work we used two models as a combined. This two models are very useful for sentiment analysis both Bengali and English sentences. Our datasets are mainly passage size which is collected from various newspapers. This models are working as sentence by sentence through layers wise. This sentences breaking into word then we got our final output.

3.9 Parameter tuning for models

This table shows which parameters in our models we can use to get the best outcome. GridSearchCV is used in parameter settings to determine the best configuration of our models. We used the same parameters of all methods. These parameters are also the same with two word embedding (Word2vec and glove).

Table 3.9.1 Parameter Tuning used in our models

Models	Epochs	Batch Size	MaxLen
BiLSTM-CNN	50	256	1000
CNN-BiLSTM	50	256	1000
BiLSTM-CNN-BiLSTM	50	256	1000

CHAPTER 4

Experimental Results and Discussion

4.1 Introduction

We want over the various algorithms used in this project in detail before moving on to this chapter. Now, in this chapter, we'll talk about the outcomes of the various algorithms. Before said that we used two word embedding techniques, Word2vec and Glove. Our proposed models was BiLSTM-CNN, CNN-BiLSTM, BiLSTM-CNN-BiLSTM. This section we discussion our models outcomes and others result analysis. To minimize the optimization and loss of the model, we used three optimizer: Adam, Adamax and RMSProp. It may be able to send us a good accuracy after a food model train. In this three optimizer, Adam optimizer is very important for train period of others optimizers. Adam is important because it calculates all parameters. For deep learning algorithm model train, a well-configured computer or laptop is essential. A GPU is required for dataset training.
First, we use direct PC to train our proposed model. As a result, running the model takes a long time, and the results obtained are unsuitable for our proposed models. So, for this project, we used Google Colab to train our models. It provides users with a free GPU service.

4.2 Descriptive Analysis

A confusion matrix is used to assess the accuracy of deep learning classification technique. To show how many instances have been assigned to each class, a confusion matrix is drawn.

Accuracy: It refers to the proportion of correct predictions made by the model.

$$\text{Accuracy} = \frac{Correct\ Predictions}{Total\ Predictions}$$

Precision: first let us know about precision[38]. It is basically the ratio of true positives upon the true sum of true positive pulse false positive. Out of the total positive predicted by the model the percentage of actual results. It is mostly used for information retrieval. We can write like this-

$$\text{Precision} = \frac{TP}{TP+FP} \times 100\%$$

Recall: The ratio of the true positive and the true positive, false negative value is called the Recall. It is the measurement of the completeness of the model.

$$\text{Recall} = \frac{TP}{TP+FN} \times 100\%$$

F1-Score: The balance between both recall and precision is called the F1 score. Both false positive and the false negative is considered in the f1 score.

$$\text{F1-Score} = \frac{2 \times precision \times recall}{precision + recall} \times 100\%$$

Sensitivity: It is calculated of total number of correct positives predictions divided by the total number of positives [39]. It is same as recall that's why it's called recall or true positive rate.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \times 100\%$$

Specificity: It is calculated of total number of correct negatives predictions divided by the total number of negatives. It is called true negative rate.

$$\text{Specificity} = \frac{TN}{TN+FP} \times 100\%$$

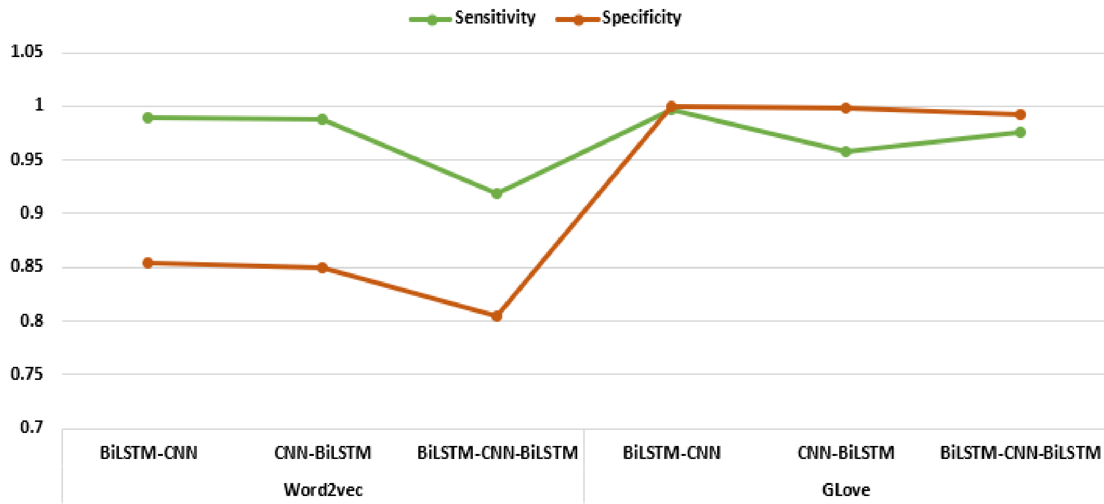


Figure 4.2.1 Sensitivity and specificity Analysis of our models

False Positive Rate (FPR): The number of incorrect positive predictions divided by the total number of negatives, called false positive rate.

$$\text{FPR} = \frac{FP}{TN+FP} \times 100\%$$

False Negative Rate (FNR): a false negative is an outcome where the model incorrectly predicts the negative class.

$$\text{FNR} = \frac{FN}{FN+TP} \times 100\%$$

Negative Predictive Value (NPV): It is the proportion of subject who were truly diagnosed as negative to the total number of people who had negative test results.

$$\text{NPV} = \frac{TN}{TN+FN} \times 100\%$$

False Discovery rate (FDR): The number of false discoveries are divided by the total number of discoveries.

$$FDR = \frac{FP}{TP+FP} \times 100\%$$

Mean Absolute Error (MAE): It is measured as the average sum of the absolute difference between predicted and actual errors.

Root Mean Squared Error (RMSE): It is the standard deviation of predictions errors.

Cohen's Kappa Score (CKS): It is a measure of how well two raters agree on categorizing N times into C mutually exclusive categories.

Table 4.2.2 Matrix calculation of Adam Optimizer

Proposed Models	FPR	FNR	NPV	FDR	MAE	MSE	RMSE	CKS
Word2vec-BiLSTM-CNN	0.145	0.009	0.991	0.158	0.127	0.048	0.219	0.873
Word2vec-CNN-BiLSTM	0.150	0.011	0.990	0.167	0.152	0.051	0.227	0.888
Word2vec-BiLSTM-CNN- BiLSTM	0.194	0.080	0.927	0.212	0.206	0.085	0.292	0.742
Glove-BiLSTM-CNN	0.000	0.002	0.997	0.000	0.010	0.002	0.054	0.990
Glove-CNN-BiLSTM	0.001	0.041	0.952	0.001	0.159	0.047	0.218	0.909
Glove-BiLSTM-CNN-BiLSTM	0.006	0.023	0.973	0.006	0.029	0.009	0.090	0.976

4.3 Experimental Results and Analysis

We all know that no machine can produce 100% accurate results. The model we used for our project produced good results, but it was not always 100% accurate [40]. It occasionally produced incorrect outcomes in a short period of time.

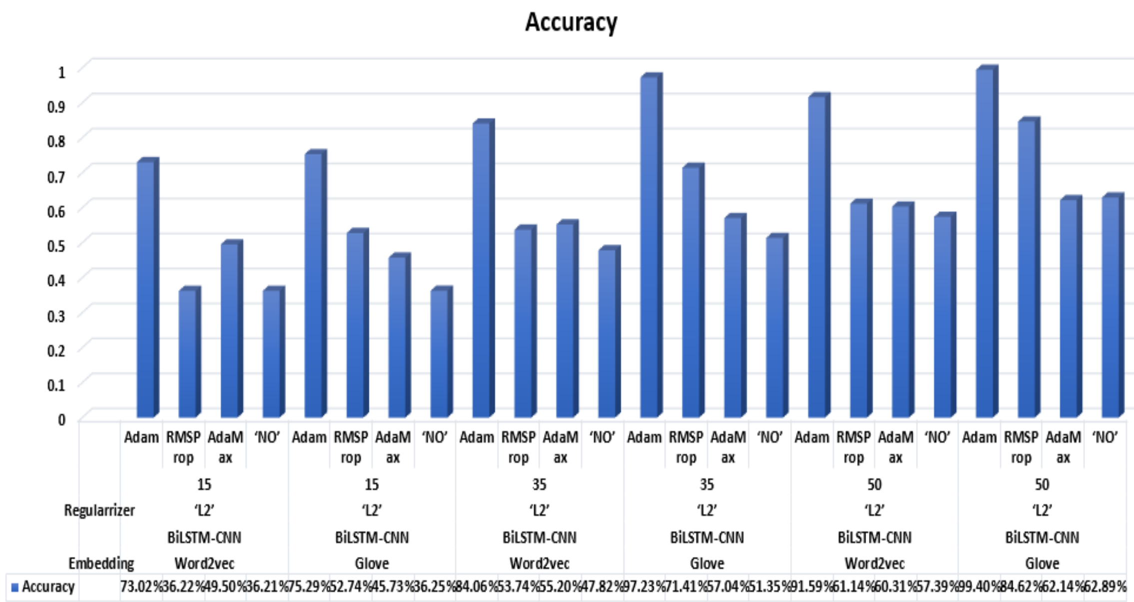


Figure 4.3.1 Accuracy of BiLSTM-CNN in different optimizers and epochs

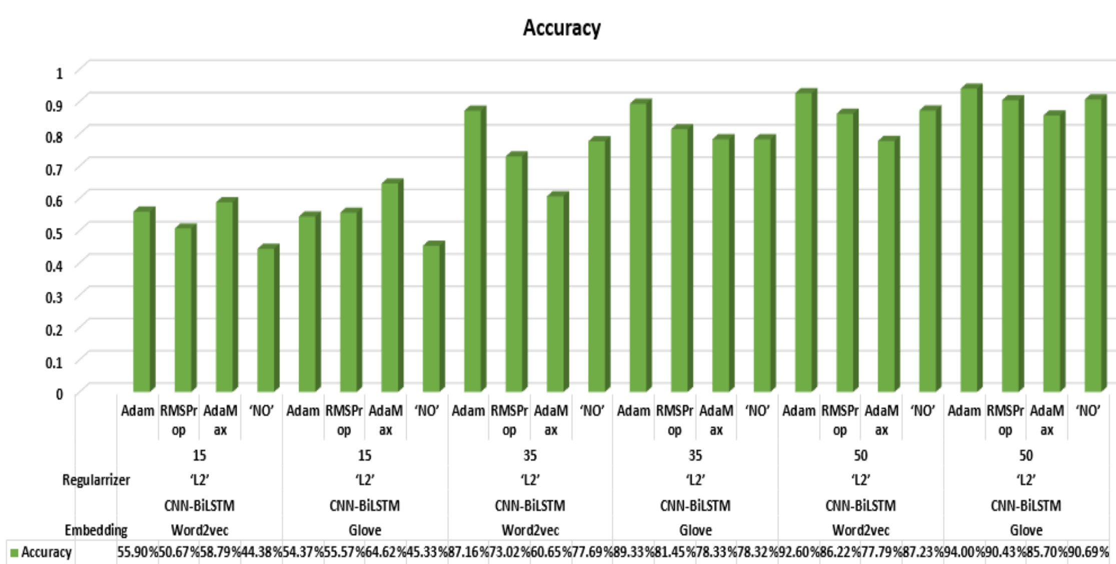


Figure 4.3.2 Accuracy of CNN-BiLSTM in different optimizers and epochs

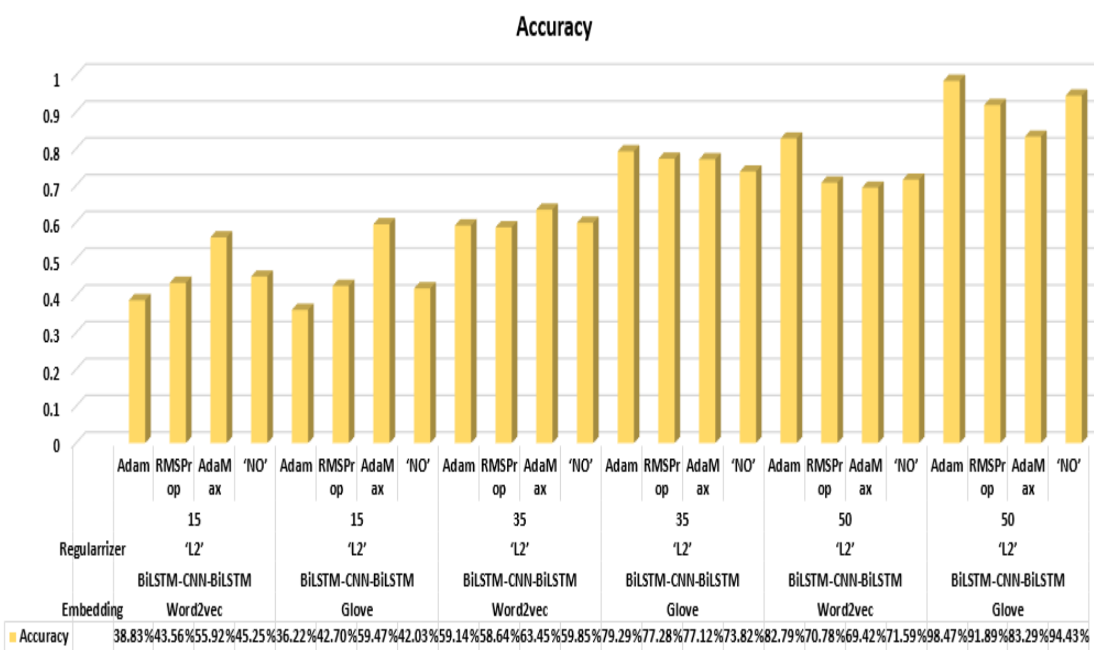


Figure 4.3.3 Accuracy of BiLSTM-CNN-BiLSTM in different optimizers and epochs

Word Cloud: Word cloud is mainly known as cloud of words.

Figure 4.3.4 Word cloud for our datasets

National News (Positive)

National News (Negative)

National News (Neutral)

International News (Positive)

International News (Negative)

International News (Neutral)

Sports News (Positive)

Sports News (Negative)

Sports News (Neutral)

Business News (Positive)

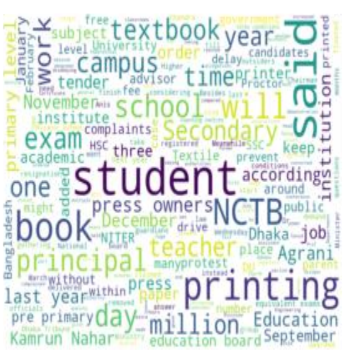
Business News (Negative)

Business News (Neutral)

Crime News (Positive)

Crime News (Negative)

Crime News (Neutral)



Educational News (Positive)

Educational News (Negative)

Educational News (Neutral)

Health News (Positive)

Health News (Negative)

Health News (Neutral)

Technology News (Positive)

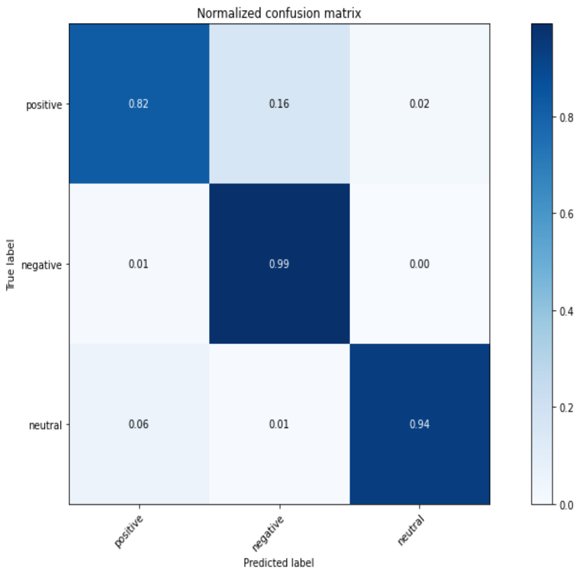
Technology News (Negative)

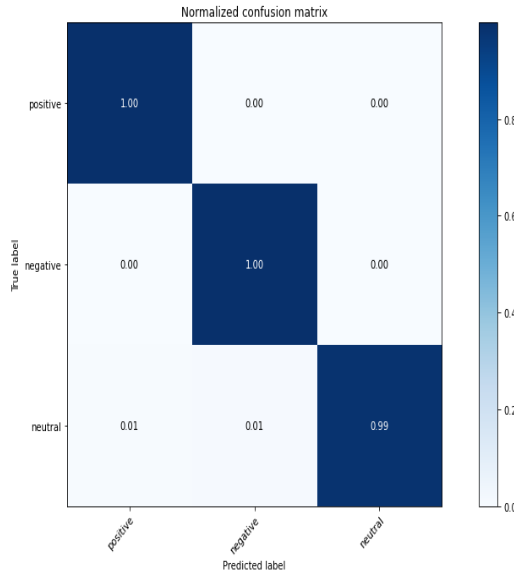
Technology News (Neutral)

Figure 4.3.5 Word cloud for different news

4.3.1 Adam Optimizer

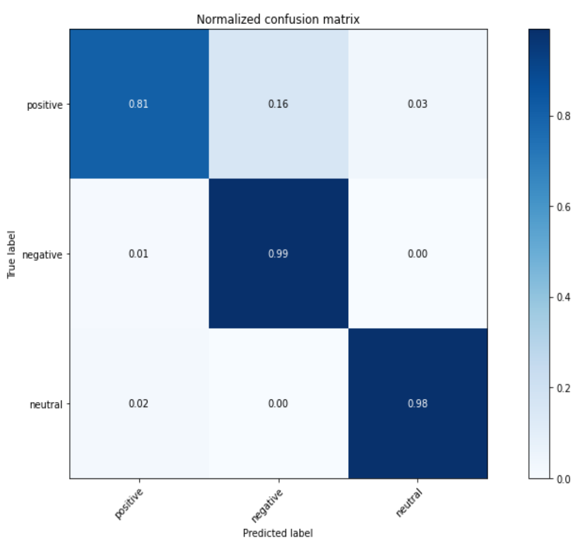
Confusion matrix: It’s a N×N dimensional matrix.in confusion matrix there are two things one is actual value and other is predicted value. Confusion matrix can give us an idea if our classification model is getting right and if there are any kind of errors it is making.

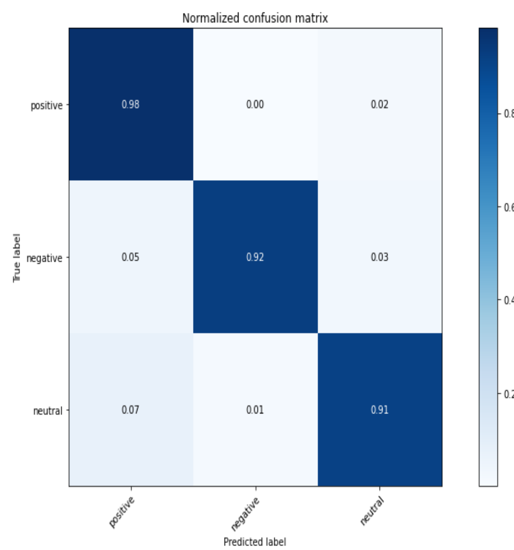




a. Confusion matrix of Word2vec-BiLSTM-CNN

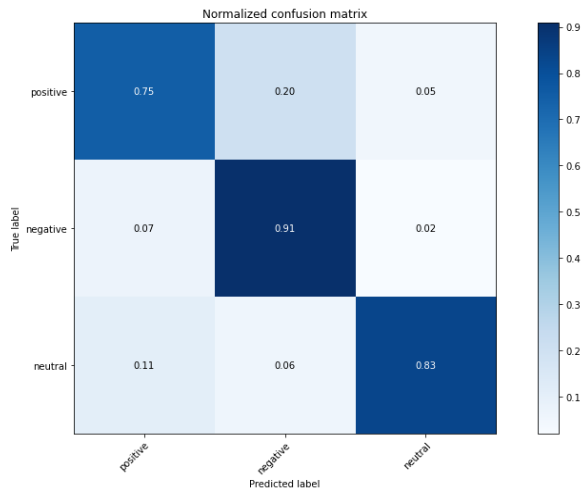
b. Confusion matrix of Glove-BiLSTM-CNN



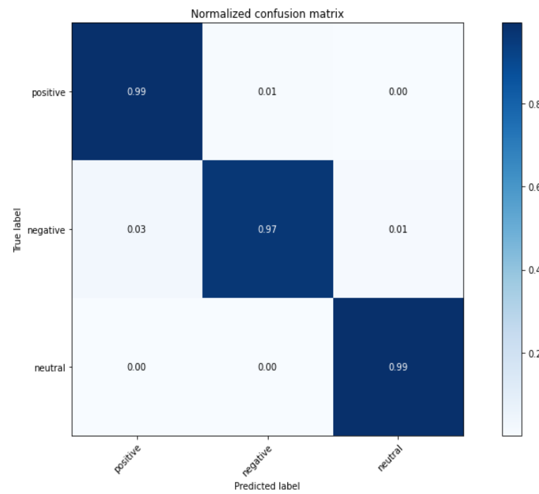


c.Word2vec-CNN-BiLSTM

d. Glove-CNN-BiLSTM



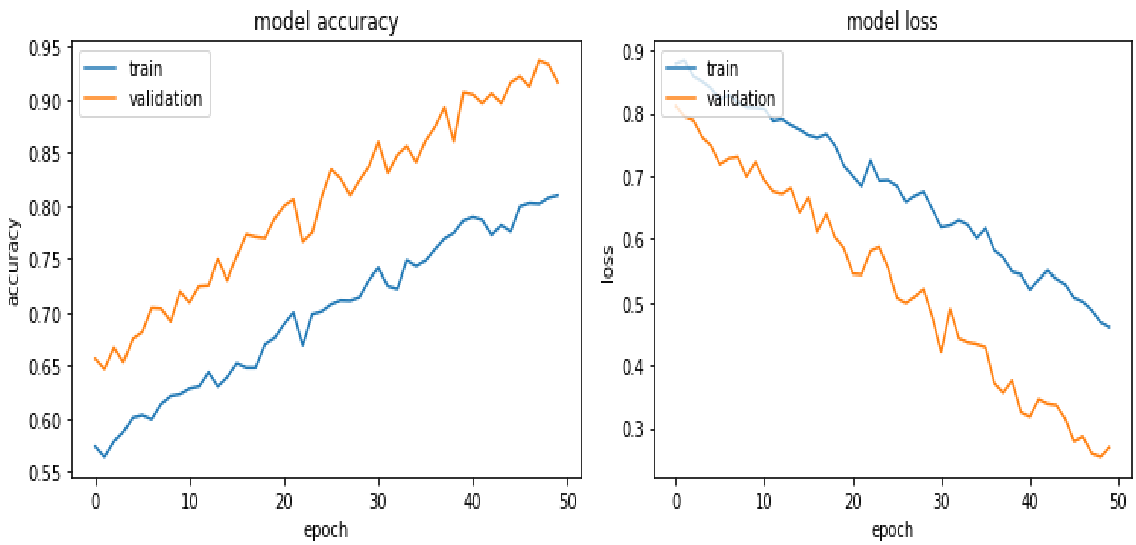
e. word2vec-BiLSTM-CNN-BiLSTM



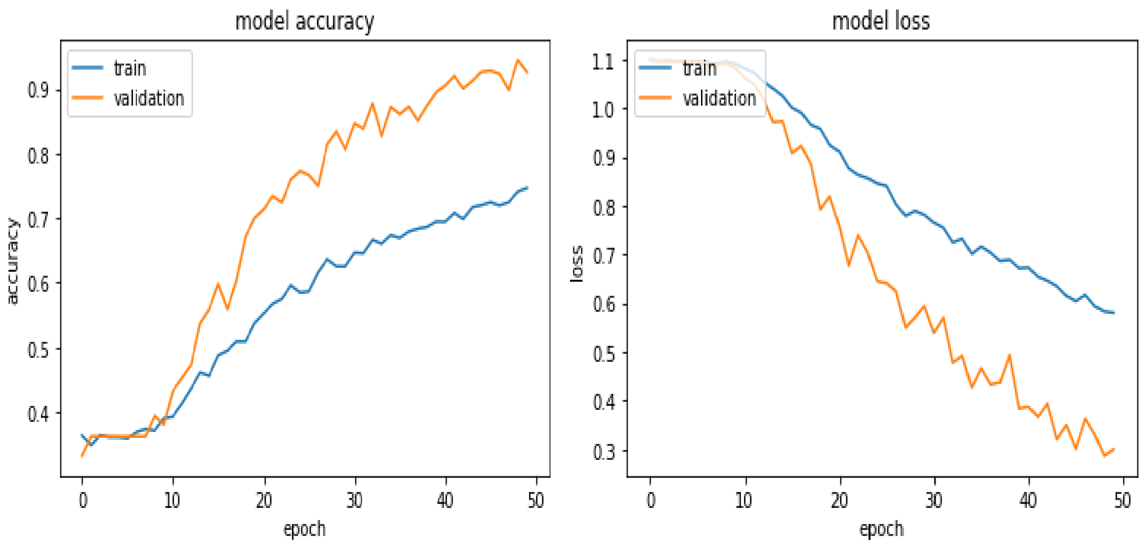
f. Glove-BiLSTM-CNN-BiLSTM

Figure 4.3.1.1 Confusion matrix for Adam Optimizer

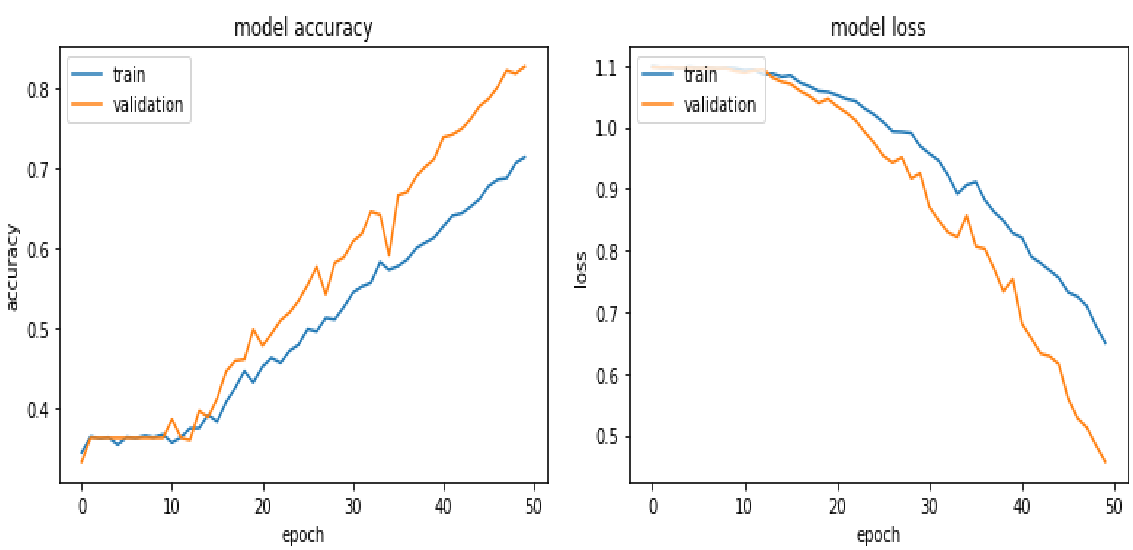
Accuracy and Loss (Adam Optimizer) : The loss value indicates how badly or well a model performs after each optimization iteration. An accuracy metric is used to quantify the algorithm's effectiveness in a meaningful way. The accuracy of an approach is typically determined after the parameter estimation and is expressed as the percentage.



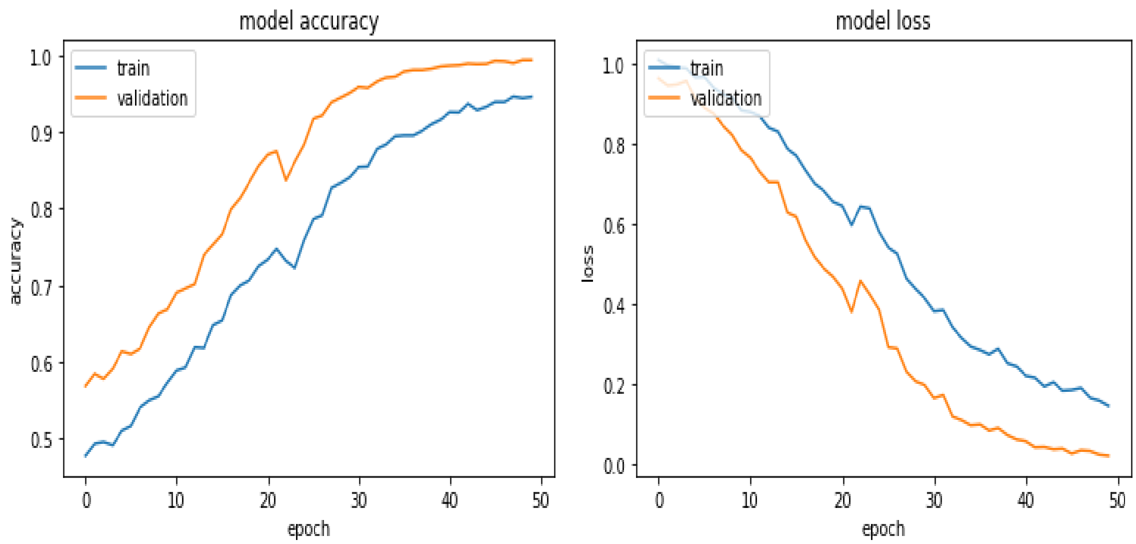
A. Word2vec-BiLSTM-CNN



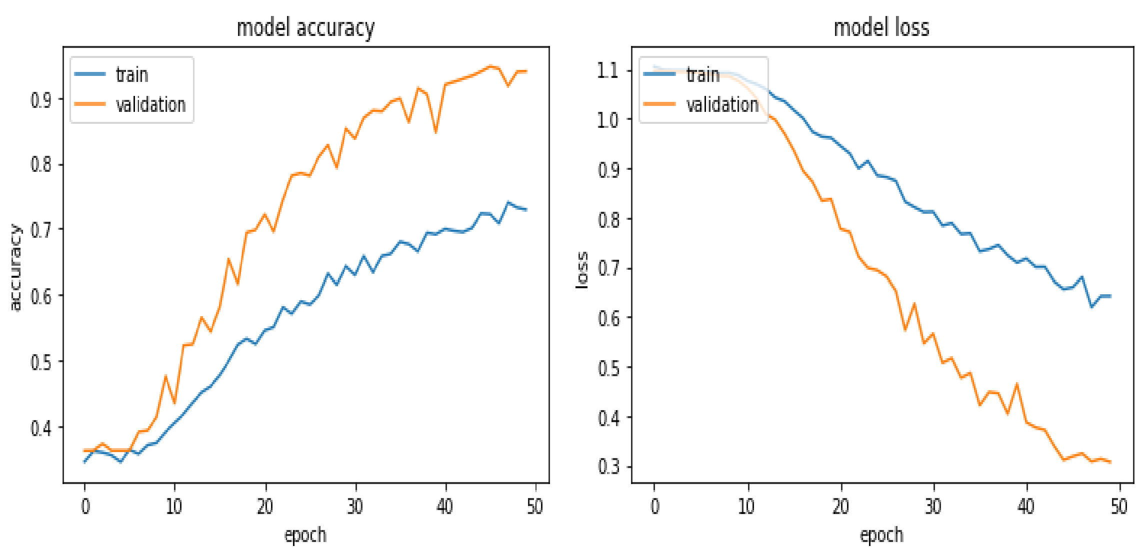
B. Word2vec-CNN-BiLSTM



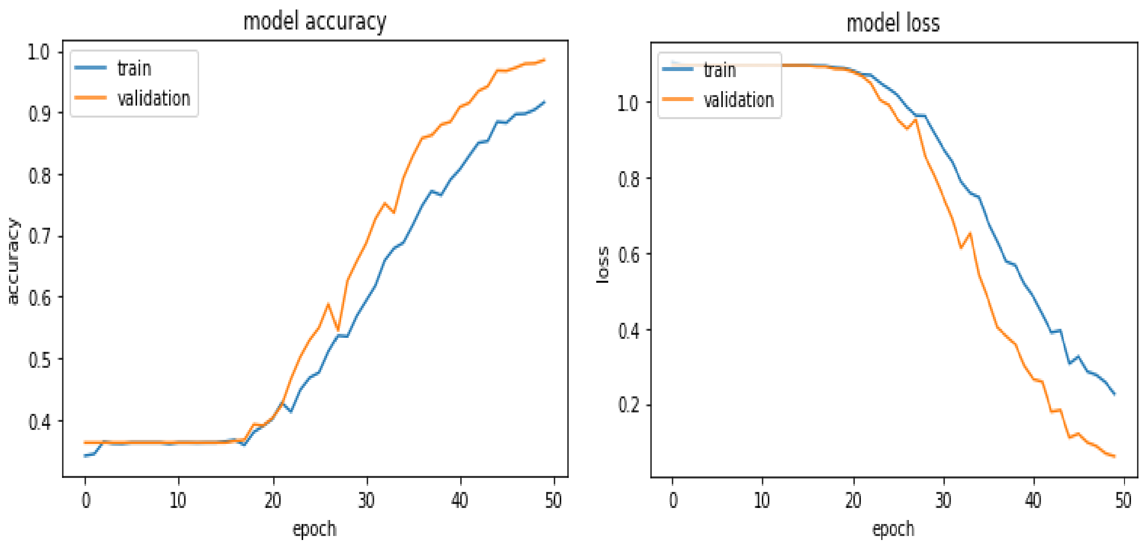
C. Word2vec-BiLSTM-CNN-BiLSTM



D. Glove-BiLSTM-CNN



E. Glove -CNN- BiLSTM



F. Glove-BiLSTM-CNN-BiLSTM

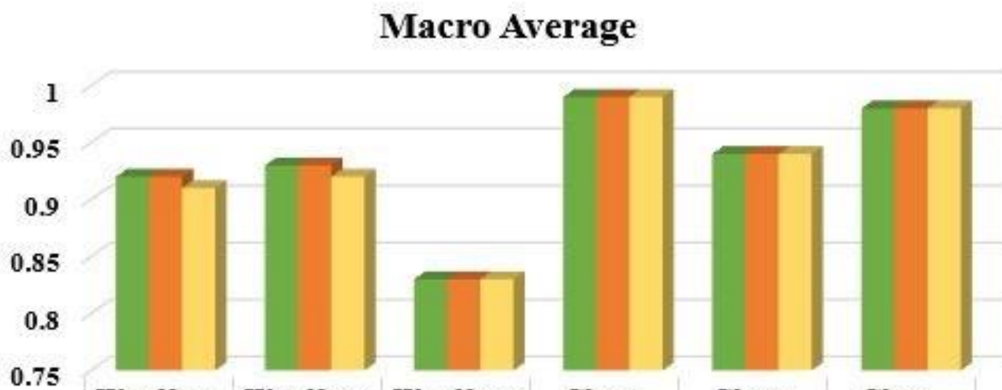
Figure 4.3.1.2 Graphical results of our models

Table 4.3.1.3 Precision, recall, f1-score for the standard matrix values

Word Embedding	Model	Category	Precision	Recall	F1-Score
Word2vec	BiLSTM-CNN	Positive	0.92	0.82	0.87
		Negative	0.85	0.99	0.91
		Neutral	0.98	0.94	0.96
	CNN-BiLSTM	Positive	0.97	0.81	0.88
		Negative	0.85	0.99	0.91
		Neutral	0.97	0.98	0.98
	BiLSTM-CNN-BiLSTM	Positive	0.80	0.75	0.78
		Negative	0.76	0.91	0.83

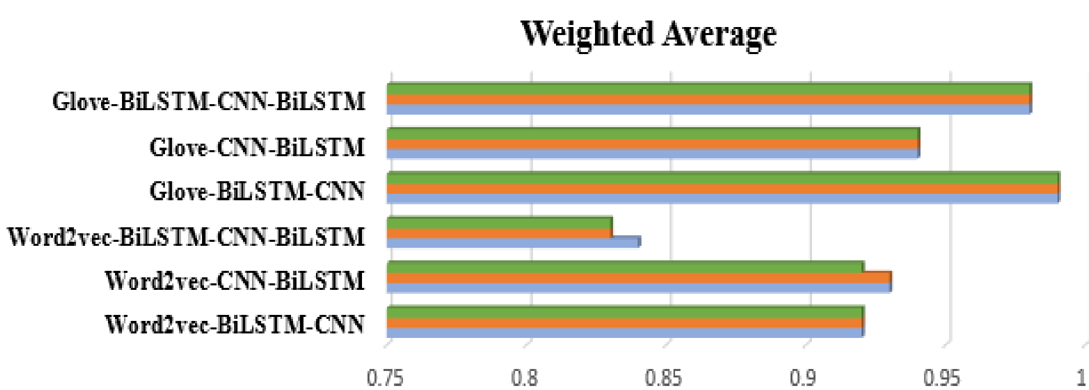
		Neutral	0.93	0.83	0.88
Glove	BiLSTM-CNN	Positive	0.99	1.00	1.00
		Negative	0.99	1.00	0.99
		Neutral	1.00	0.99	0.99
	CNN-BiLSTM	Positive	0.89	0.98	0.93
		Negative	0.98	0.92	0.95
		Neutral	0.96	0.91	0.94
	BiLSTM-CNN-BiLSTM	Positive	0.97	0.99	0.98
		Negative	0.99	0.97	0.98
		Neutral	0.99	0.99	0.99

Weighted Average and Macro Average (Adam Optimizer): When evaluating loss, macro estimate gives each predicted outcome the weight, but if data is somehow unequally distributed and want to give a few predictions as much weight, users utilize 'weighted' average.



	Word2vec-BiLSTM-CNN	Word2vec-CNN-BiLSTM	Word2vec-BiLSTM-CNN-BiLSTM	Glove-BiLSTM-CNN	Glove-CNN-BiLSTM	Glove-BiLSTM-CNN-BiLSTM
Precision	0.92	0.93	0.83	0.99	0.94	0.98
Recall	0.92	0.93	0.83	0.99	0.94	0.98
F1-Score	0.91	0.92	0.83	0.99	0.94	0.98

Figure 4.3.1.4 Results of macro average of our model

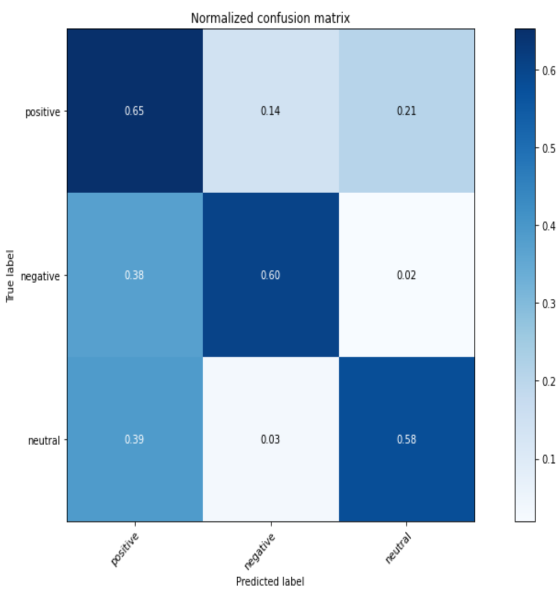


	Word2vec-BiLSTM-CNN	Word2vec-CNN-BiLSTM	Word2vec-BiLSTM-CNN-BiLSTM	Glove-BiLSTM-CNN	Glove-CNN-BiLSTM	Glove-BiLSTM-CNN-BiLSTM
F1-Score	0.92	0.92	0.83	0.99	0.94	0.98
Recall	0.92	0.93	0.83	0.99	0.94	0.98
Precision	0.92	0.93	0.84	0.99	0.94	0.98

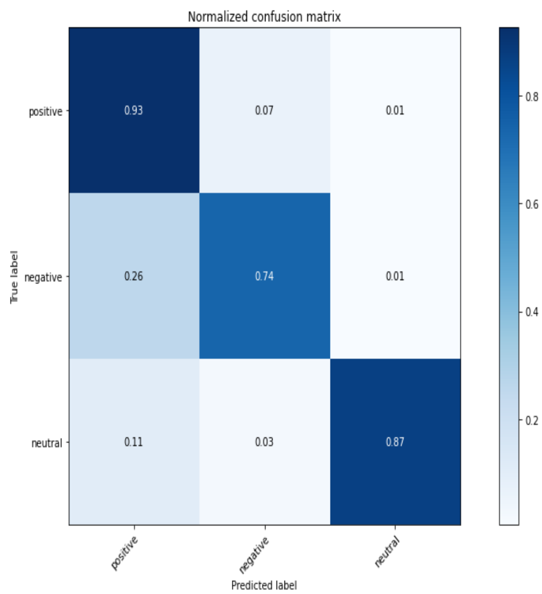
Figure 4.3.1.5 Results of weighted average of our model

4.3.2 RMSProp Optimizer

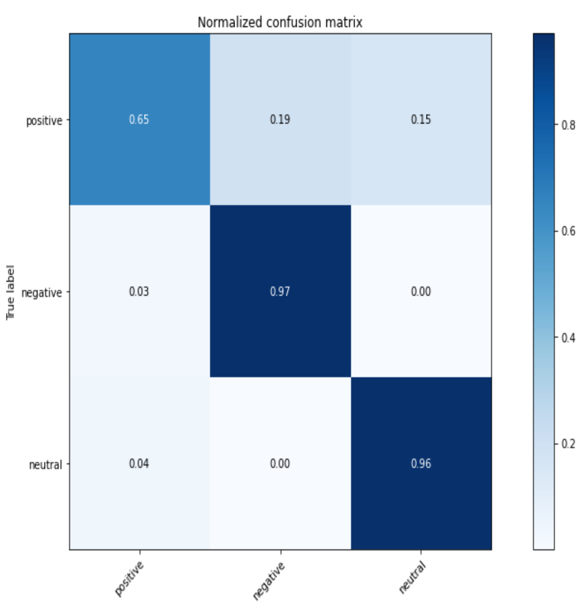
RMSProp is a gradient-based optimization technique used in deep learning. RMSProp solves the aforementioned problem by correcting the slope using a moving estimate of squared gradients. Normalization equalizes step length, lowering it for big slopes to avert bursting and increasing it for narrow slopes to avoid receding.

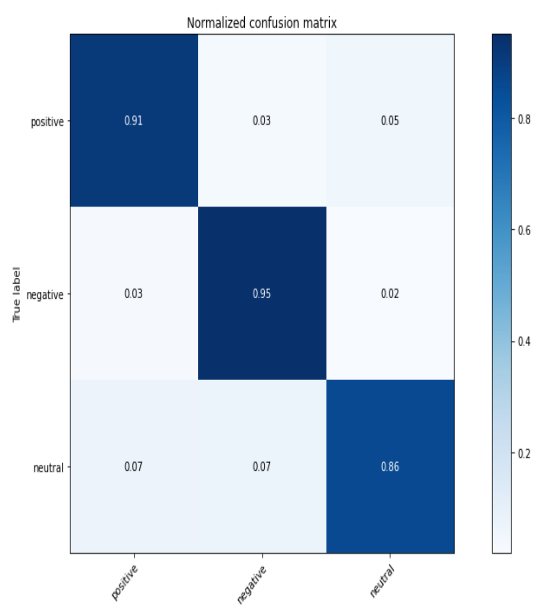


a. Word2vec-BiLSTM-CNN

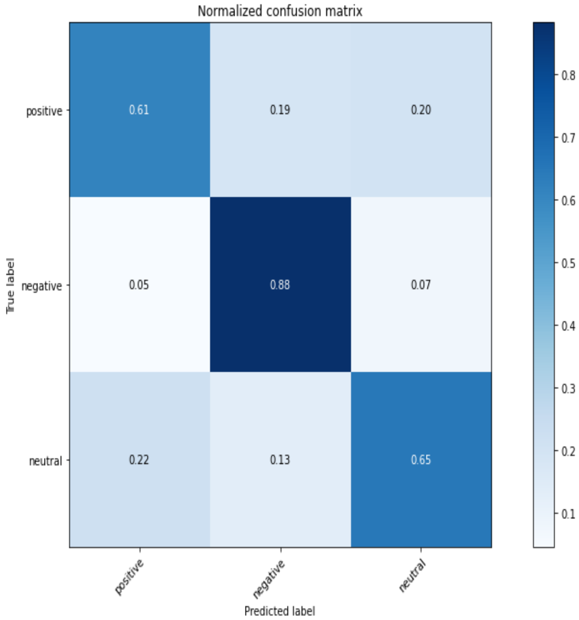


b. Glove-BiLSTM-CNN

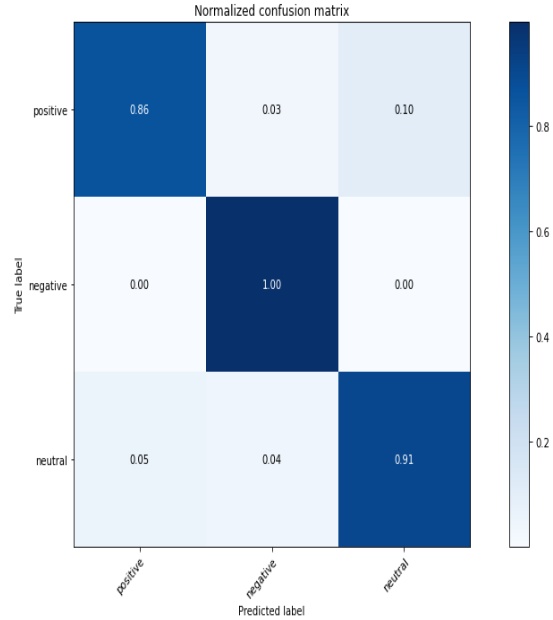




c.Word2vec-CNN-BiLSTM



d. Glove-CNN-BiLSTM

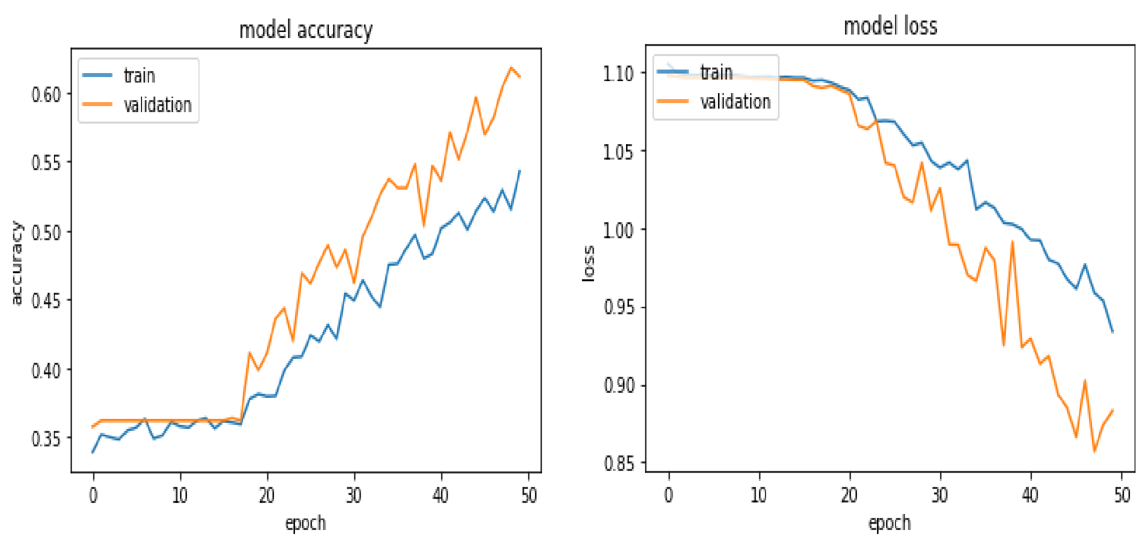


e.Word2vec-BiLSTM-CNN-BiLSTM

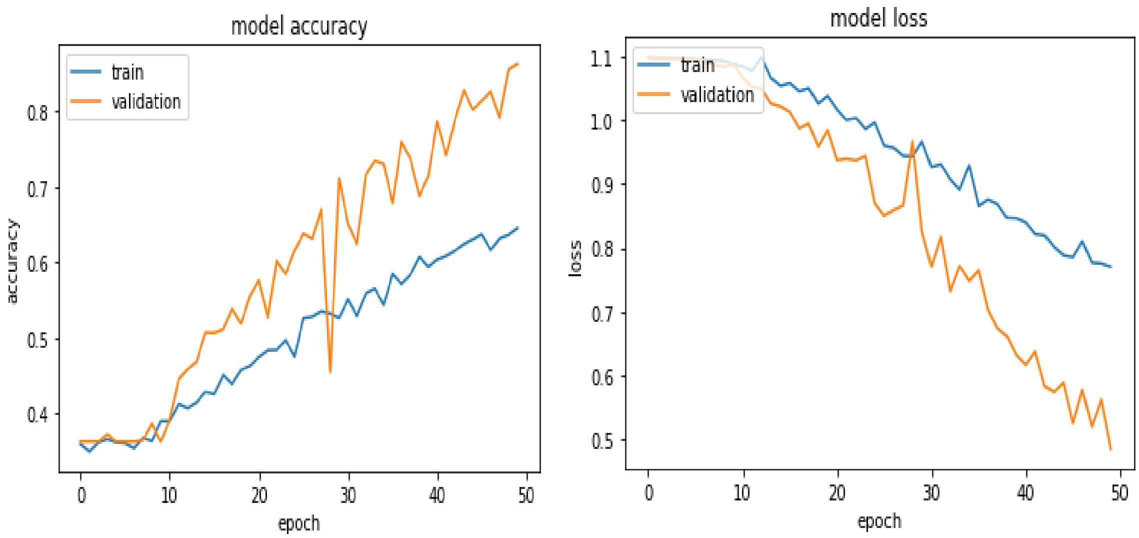
f. GLove-BiLSTM-CNN-BiLSTM

Figure 4.3.2.1 Confusion matrix of RMSProp optimizer

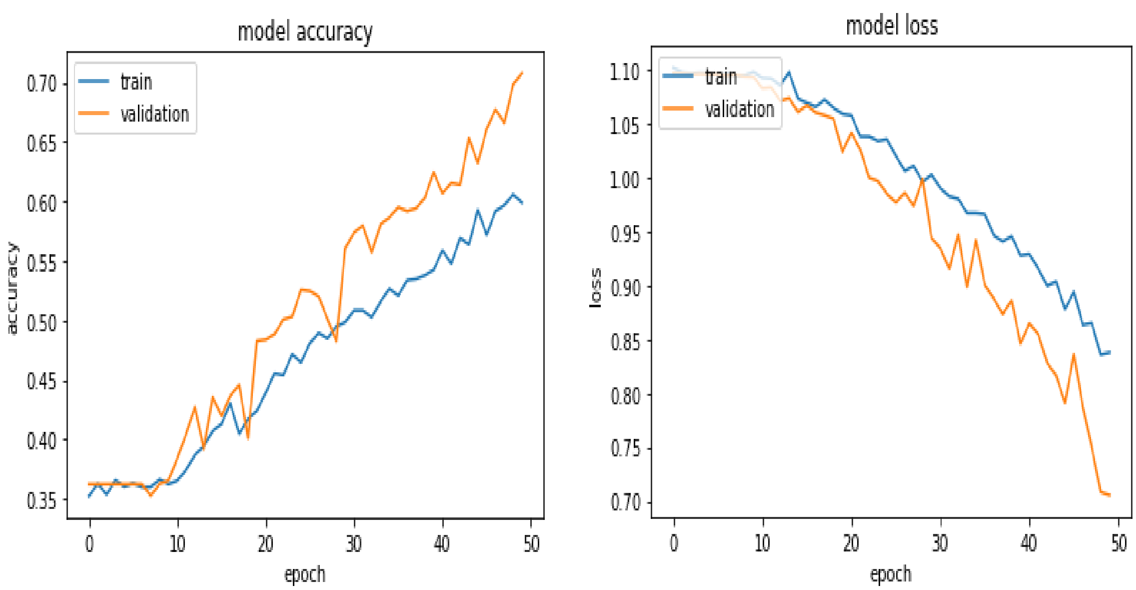
Model Accuracy and Loss (RMSProp Optimizer):



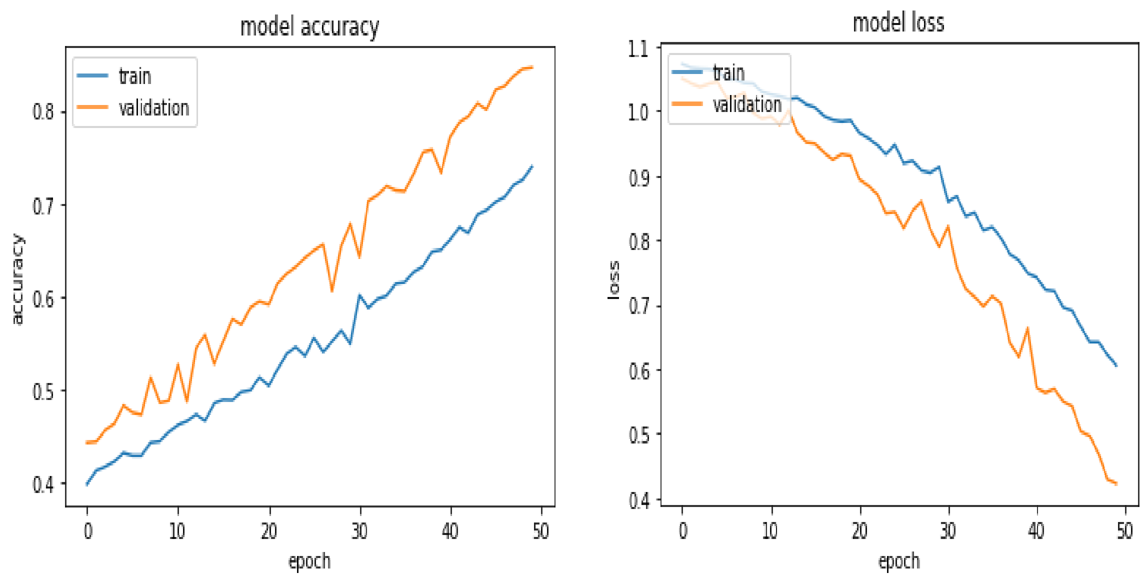
(a) word2vec-BiLSTM-CNN



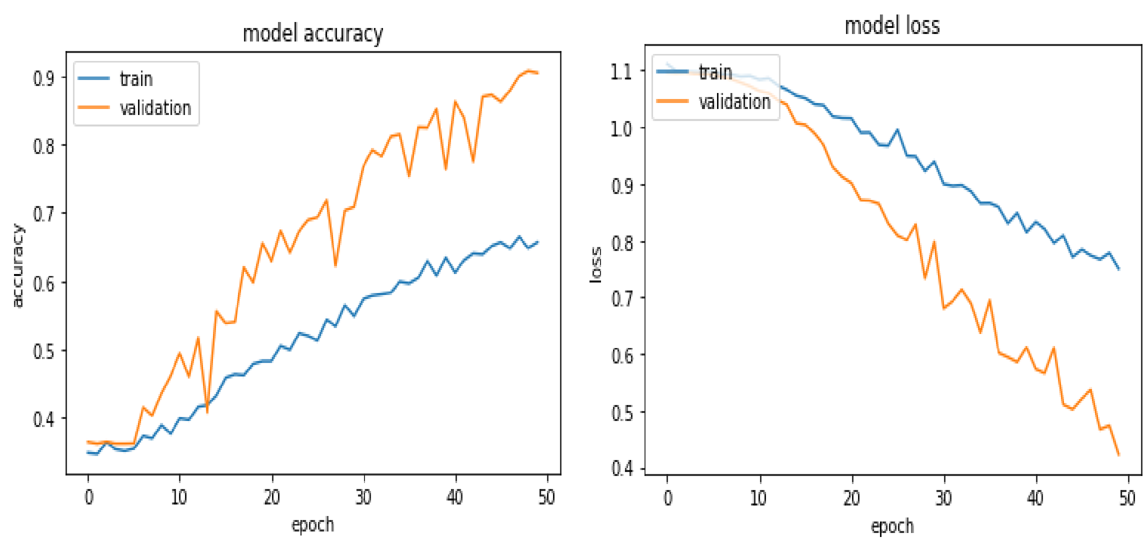
(b) word2vec-CNN-BiLSTM



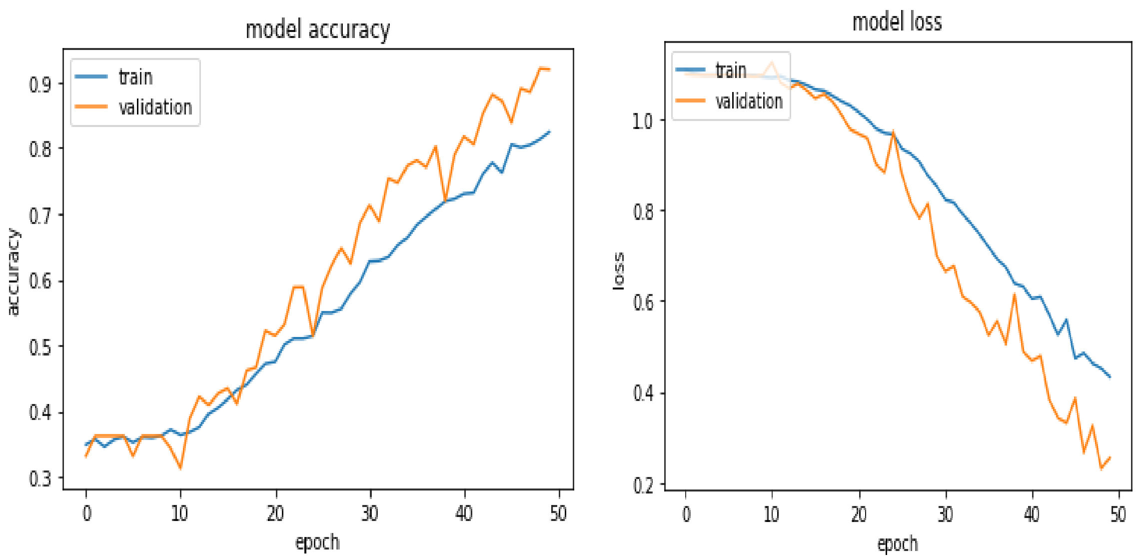
(c) word2vec-BiLSTMCNN-BiLSTM



(d) Glove-BiLSTM-CNN



(e) Glove-CNN-BiLSTM



(f) Glove-BiLSTM-CNN-BiLSTM

Figure 4.3.2.2 Accuracy and Loss of all models

Table 4.3.2.3 Precision, recall and f1-score of confusion matrix

Word Embedding	Model	Category	Precision	Recall	F1-Score
Word2vec	BiLSTM-CNN	Positive	0.46	0.65	0.54
		Negative	0.76	0.60	0.57
		Neutral	0.74	0.58	0.65
	CNN-BiLSTM	Positive	0.91	0.65	0.76
		Negative	0.82	0.97	0.89
		Neutral	0.87	0.96	0.92
	BiLSTM-CNN-BiLSTM	Positive	0.69	0.61	0.65
		Negative	0.71	0.88	0.79

		Neutral	0.73	0.65	0.68
GLove	BiLSTM-CNN	Positive	0.72	0.93	0.81
		Negative	0.88	0.74	0.80
		Neutral	0.99	0.87	0.92
	CNN-BiLSTM	Positive	0.89	0.91	0.90
		Negative	0.89	0.95	0.92
		Neutral	0.93	0.86	0.89
	BiLSTM-CNN-BiLSTM	Positive	0.94	0.86	0.90
		Negative	0.92	1.00	0.96
		Neutral	0.90	0.91	0.90

Table 4.3.2.4 Sensitivity and Specificity score of RMSProp optimizer

Word Embedding	Models	Sensitivity	Specificity
Word2vec	BiLSTM-CNN	0.653	0.797
	CNN-BiLSTM	0.960	0.821
	BiLSTM-CNN-BiLSTM	0.935	0.812
GLove	BiLSTM-CNN	0.795	0.912
	CNN-BiLSTM	0.971	0.964
	BiLSTM-CNN-BiLSTM	0.997	0.964

Table 4.3.2.5 Performance measure matrix of models

Proposed Models	FPR	FNR	NPV	FDR	MAE	MSE	RMSE	CKS
Word2vec-BiLSTM-CNN	0.202	0.346	0.616	0.178	0.379	0.175	0.419	0.416
Word2vec-CNN-BiLSTM	0.178	0.039	0.970	0.228	0.234	0.089	0.299	0.792
Word2vec-BiLSTM-CNN- BiLSTM	0.187	0.064	0.950	0.233	0.307	0.139	0.373	0.562
Glove-BiLSTM-CNN	0.087	0.204	0.739	0.065	0.196	0.079	0.281	0.768
Glove-CNN-BiLSTM	0.035	0.028	0.969	0.033	0.210	0.071	0.267	0.856
Glove-BiLSTM-CNN-BiLSTM	0.035	0.002	0.997	0.038	0.118	0.045	0.212	0.878

Table 4.3.2.6 Performance of macro average

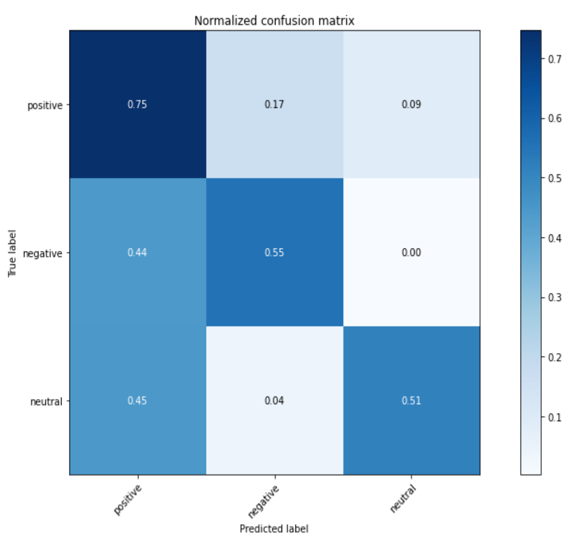
Word Embeddings	Models	Precision	Recall	F1-Score
Word2vec	BiLSTM-CNN	0.65	0.61	0.62
	CNN-BiLSTM	0.87	0.86	0.85
	BiLSTM-CNN-BiLSTM	0.71	0.71	0.71
Glove	BiLSTM-CNN	0.86	0.84	0.84
	CNN-BiLSTM	0.90	0.91	0.90
	BiLSTM-CNN-BiLSTM	0.92	0.92	0.92

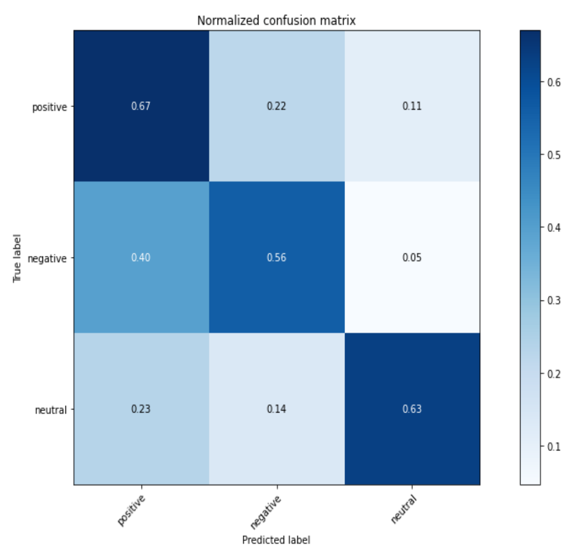
Table 4.3.2.7 Performance of weighted average

Word Embeddings	Models	Precision	Recall	F1-Score
Word2vec	BiLSTM-CNN	0.65	0.61	0.62
	CNN-BiLSTM	0.87	0.86	0.86
	BiLSTM-CNN-BiLSTM	0.71	0.71	0.70
Glove	BiLSTM-CNN	0.87	0.85	0.85
	CNN-BiLSTM	0.91	0.90	0.90
	BiLSTM-CNN-BiLSTM	0.92	0.92	0.92

4.3.3 AdaMax Optimizer

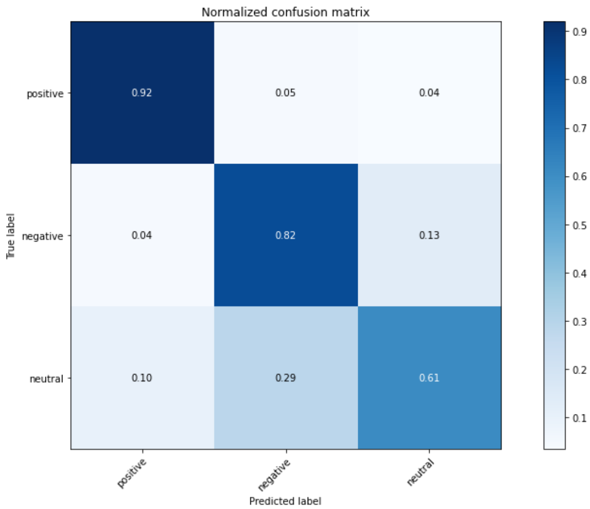
AdaMax is an expansion of Adam's gradient descent strategy that summarizes the strategy to the infinite norm and may lead to more effective optimization on some problems. It's a customized Adam version based on the infinity norm. The parameters indicated in the paper are the defaults. In some cases, AdaMax outperforms Adam, especially in models with embeddings.

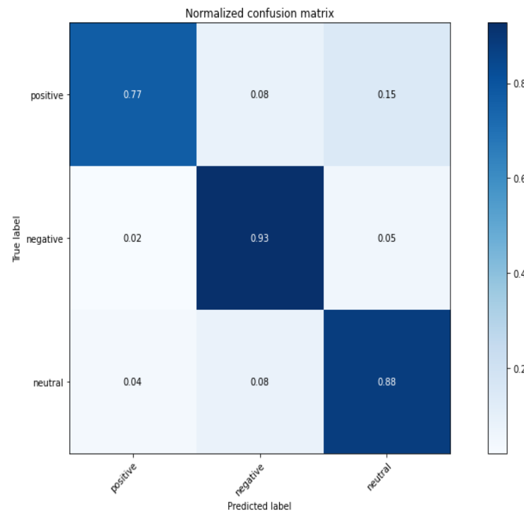




a. Word2vec-BiLSTM-CNN

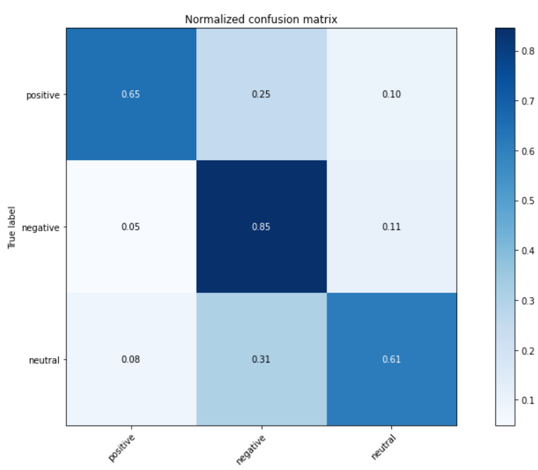
b. Glove-BiLSTM-CNN

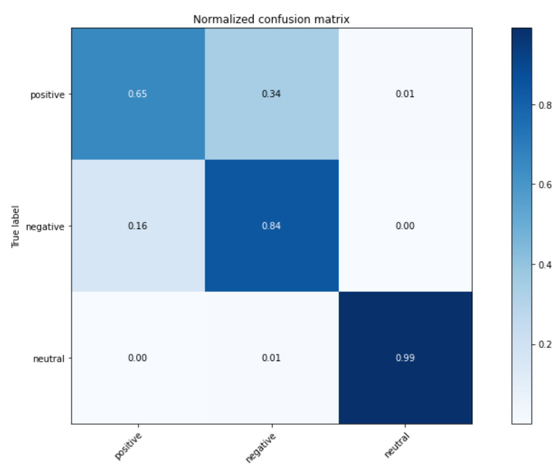




c. Word2vec-CNN-BiLSTM

d. Glove-CNN-BiLSTM



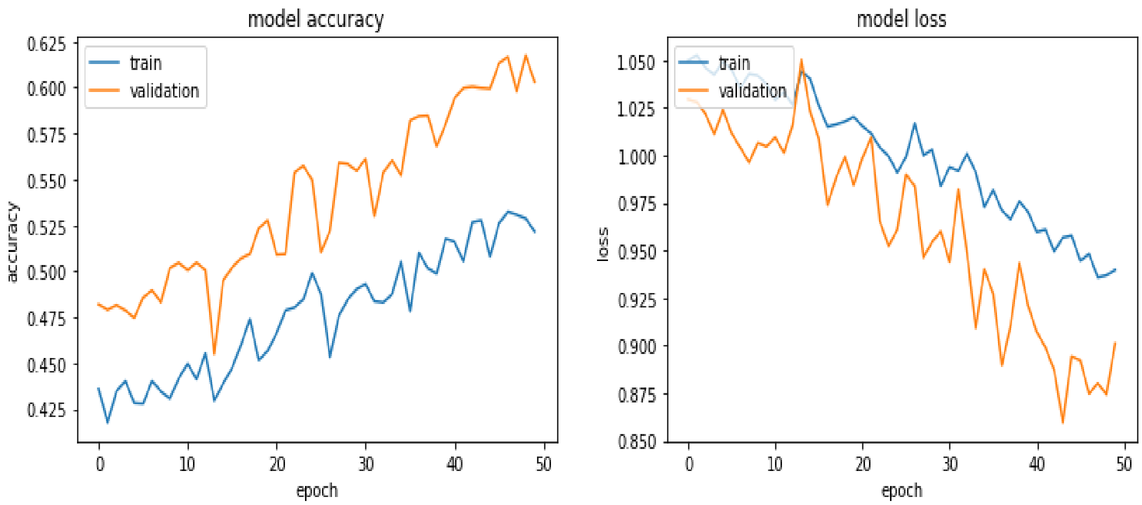


e. Word2vec-BiLSTM-CNN-BiLSTM

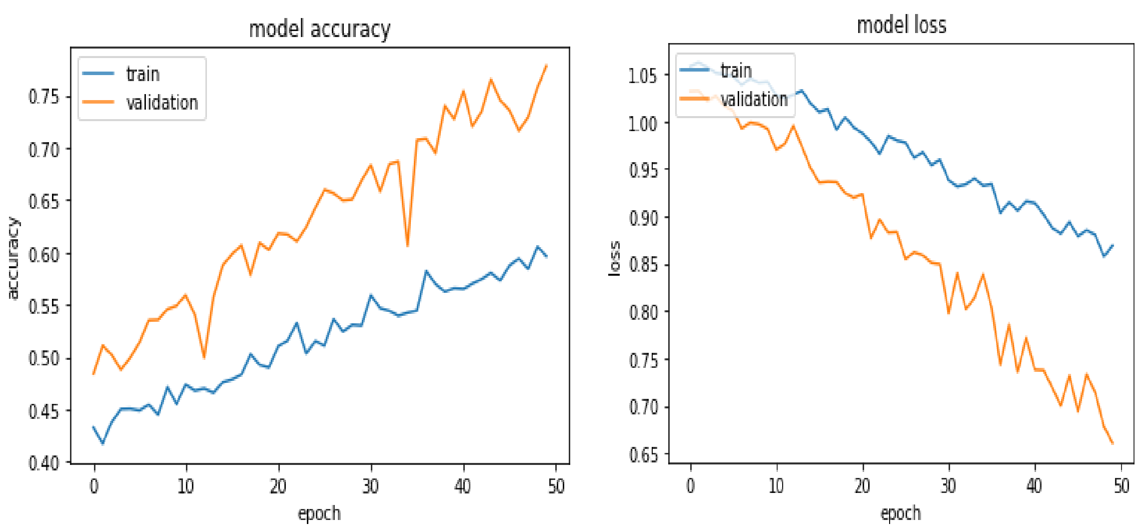
f. Glove-BiLSTM-CNN-BiLSTM

Figure 4.3.3.1 confusion matrix of AdaMax optimizer

Accuracy and Loss:

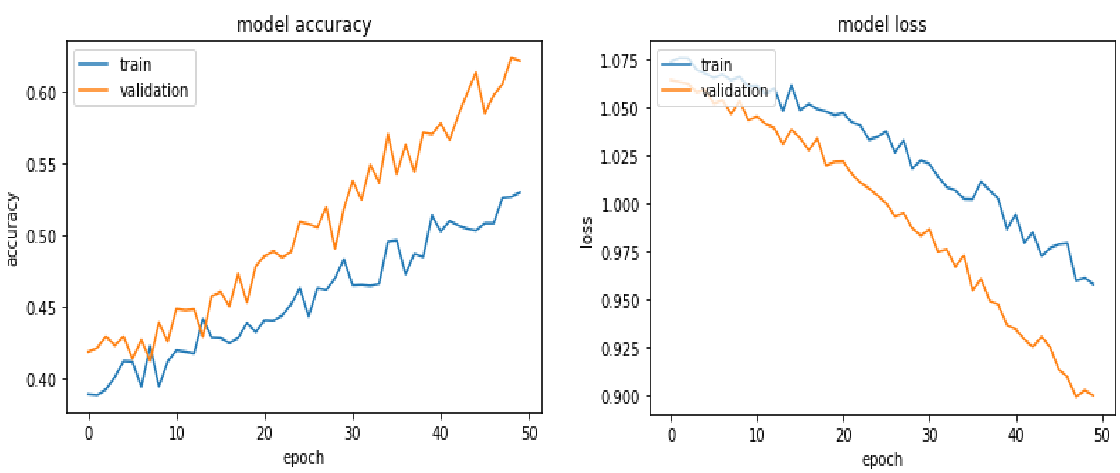


a. word2vec-BiLSTM-CNN

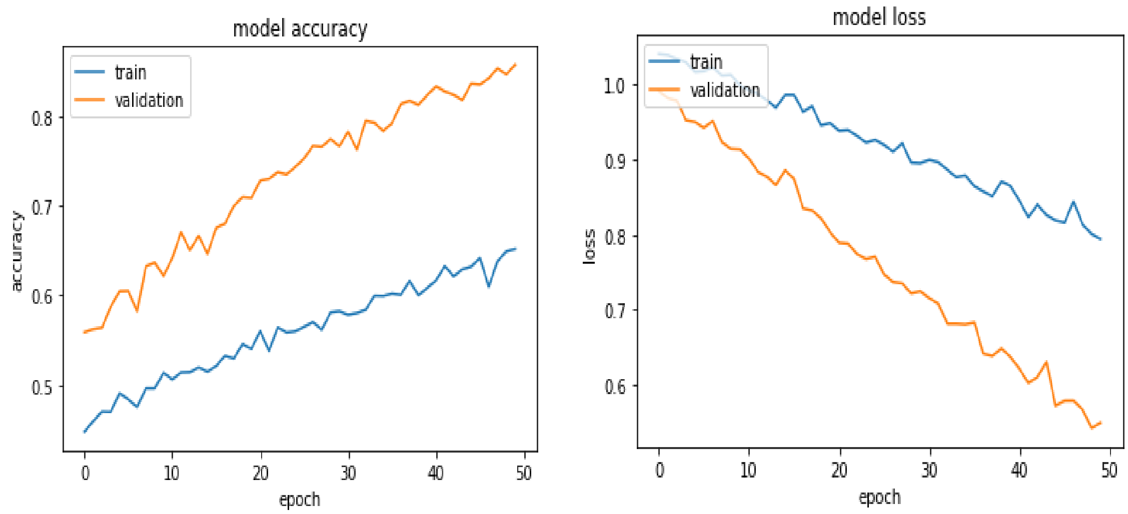


b. word2vec-CNN-BiLSTM

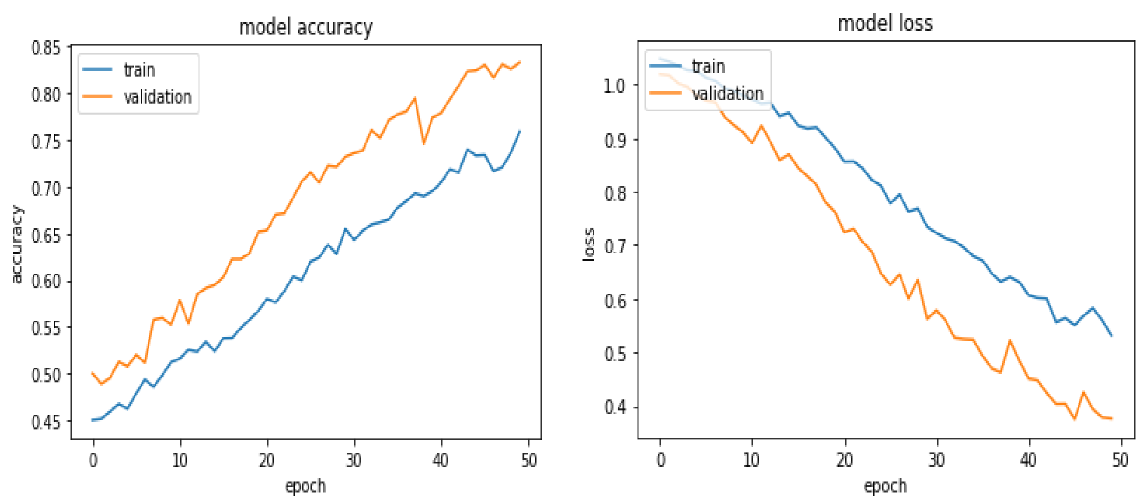
c. word2vec-BiLSTM-CNN-BiLSTM



d. Glove-BiLSTM-CNN



e. Glove-CNN-BiLSTM



f. Glove-BiLSTM-CNN-BiLSTM

Figure 4.3.3.2 Accuracy and Loss of all models

Table 4.3.3.3 Precision, recall and f1-scores of models

Word Embedding	Model	Category	Precision	Recall	F1-Score
Word2vec	BiLSTM-CNN	Positive	0.45	0.75	0.57
		Negative	0.71	0.55	0.62
		Neutral	0.86	0.51	0.64
	CNN-BiLSTM	Positive	0.86	0.92	0.89
		Negative	0.68	0.82	0.74
		Neutral	0.81	0.61	0.70
	BiLSTM-CNN-BiLSTM	Positive	0.82	0.65	0.73
		Negative	0.57	0.85	0.68
		Neutral	0.77	0.61	0.68
Glove	BiLSTM-CNN	Positive	0.52	0.67	0.59
		Negative	0.58	0.56	0.57
		Neutral	0.82	0.63	0.71
	CNN-BiLSTM	Positive	0.92	0.77	0.84
		Negative	0.83	0.93	0.88
		Neutral	0.83	0.88	0.85
	BiLSTM-CNN-BiLSTM	Positive	0.82	0.65	0.72
		Negative	0.69	0.84	0.76
		Neutral	0.99	0.99	0.99

Table 4.3.3.4 Sensitivity and specificity of models

Word Embedding	Models	Sensitivity	Specificity
Word2vec	BiLSTM-CNN	0.647	0.754
	CNN-BiLSTM	0.957	0.943
	BiLSTM-CNN-BiLSTM	0.934	0.753
Glove	BiLSTM-CNN	0.648	0.699
	CNN-BiLSTM	0.958	0.998
	BiLSTM-CNN-BiLSTM	0.819	0.693

Table 4.3.3.5 Standard matrix calculation

Proposed Models	FPR	FNR	NPV	FDR	MAE	MSE	RMSE	CKS
Word2vec-BiLSTM-CNN	0.245	0.352	0.556	0.181	0.381	0.178	0.422	0.405
Word2vec-CNN-BiLSTM	0.056	0.042	0.948	0.046	0.304	0.125	0.353	0.668
Word2vec-BiLSTM-CNN- BiLSTM	0.246	0.065	0.945	0.281	0.331	0.148	0.385	0.544
Glove-BiLSTM-CNN	0.300	0.351	0.585	0.248	0.380	0.177	0.421	0.432
Glove-CNN-BiLSTM	0.001	0.041	0.095	0.001	0.159	0.047	0.218	0.909
Glove-BiLSTM-CNN-BiLSTM	0.306	0.180	0.843	0.344	0.179	0.079	0.281	0.749

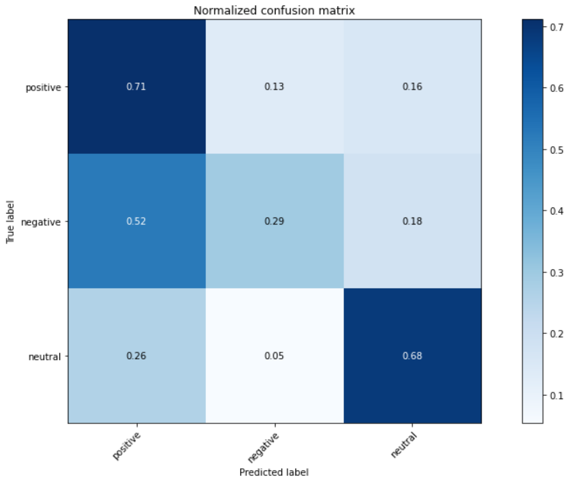
Table 4.3.3.6 macro average of models

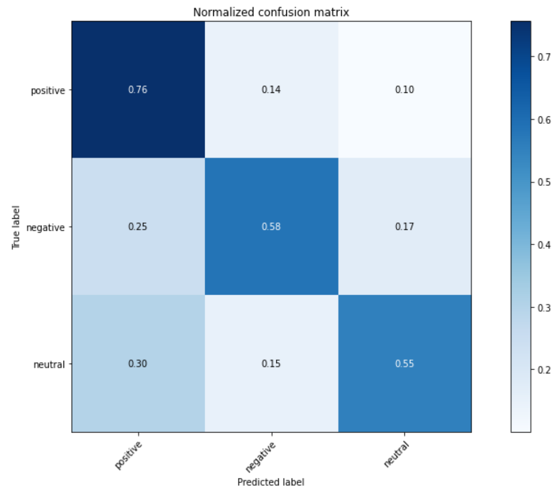
Word Embeddings	Models	Precision	Recall	F1-Score
Word2vec	BiLSTM-CNN	0.67	0.60	0.61
	CNN-BiLSTM	0.78	0.78	0.78
	BiLSTM-CNN-BiLSTM	0.72	0.70	0.70
Glove	BiLSTM-CNN	0.64	0.62	0.62
	CNN-BiLSTM	0.86	0.86	0.86
	BiLSTM-CNN-BiLSTM	0.83	0.83	0.83

Table 4.3.3.7 weighted average of models

Word Embeddings	Models	Precision	Recall	F1-Score
Word2vec	BiLSTM-CNN	0.68	0.60	0.61
	CNN-BiLSTM	0.78	0.78	0.77
	BiLSTM-CNN-BiLSTM	0.73	0.69	0.70
Glove	BiLSTM-CNN	0.65	0.62	0.63
	CNN-BiLSTM	0.86	0.86	0.86
	BiLSTM-CNN-BiLSTM	0.84	0.83	0.83

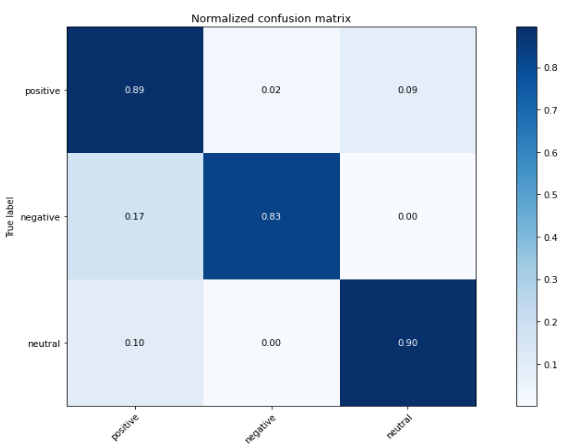
4.3.4 Without Optimizer

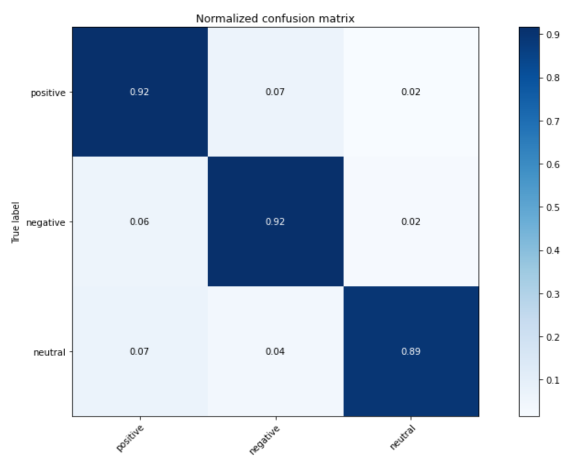




a. Word2vec-BiLSTM-CNN

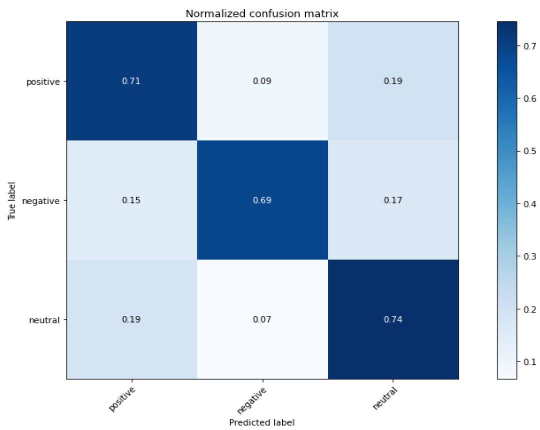
b. Glove-BiLSTM-CNN



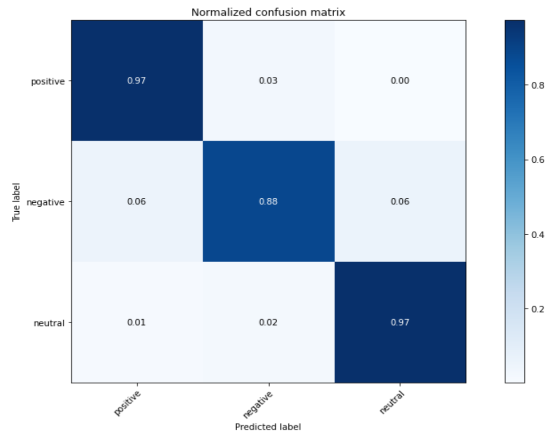


c. Word2vec-CNN-BiLSTM

d. Glove-CNN-BiLSTM



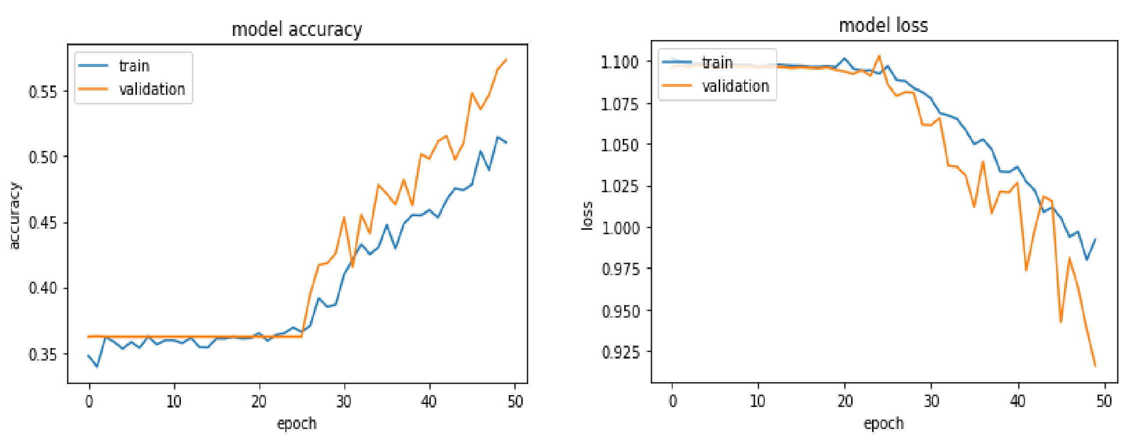
e. Word2vec-BiLSTM-CNN-BiLSTM



f. Glove-BiLSTM-CNN-BiLSTM

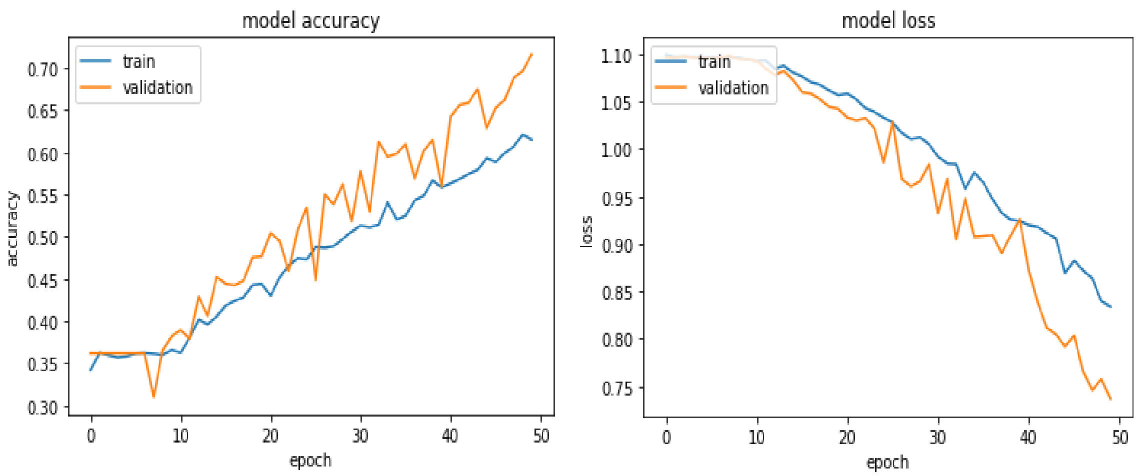
Figure 4.3.4.1 Graphical results of Confusion matrix

Accuracy and Loss:

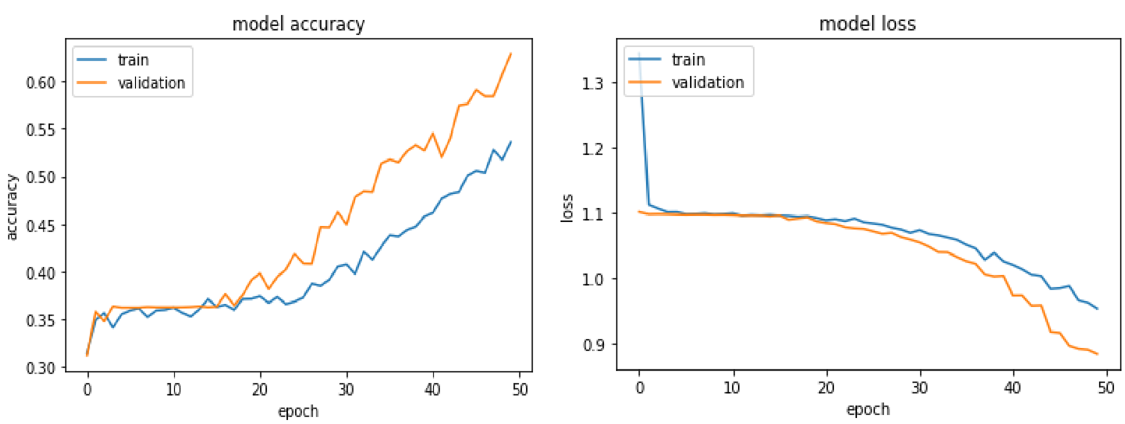


A. Word2vec-BiLSTM-CNN

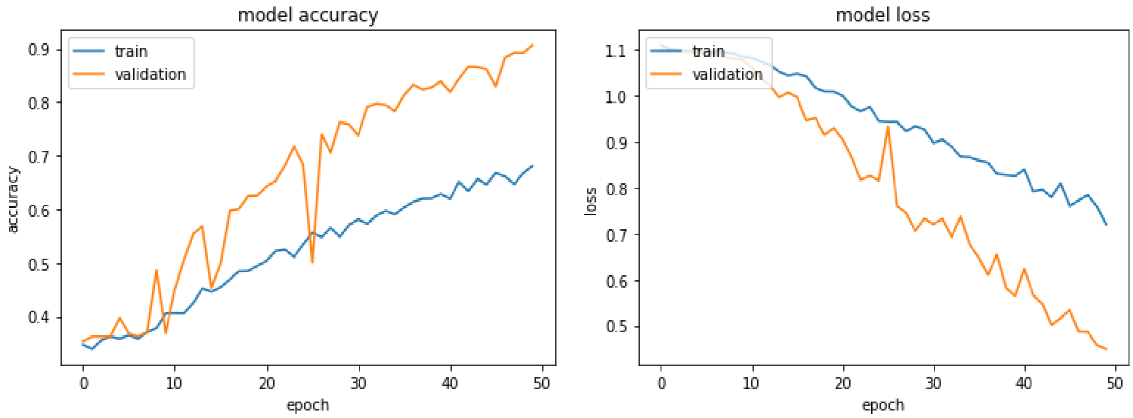
B. Word2vec-CNN-BiLSTM



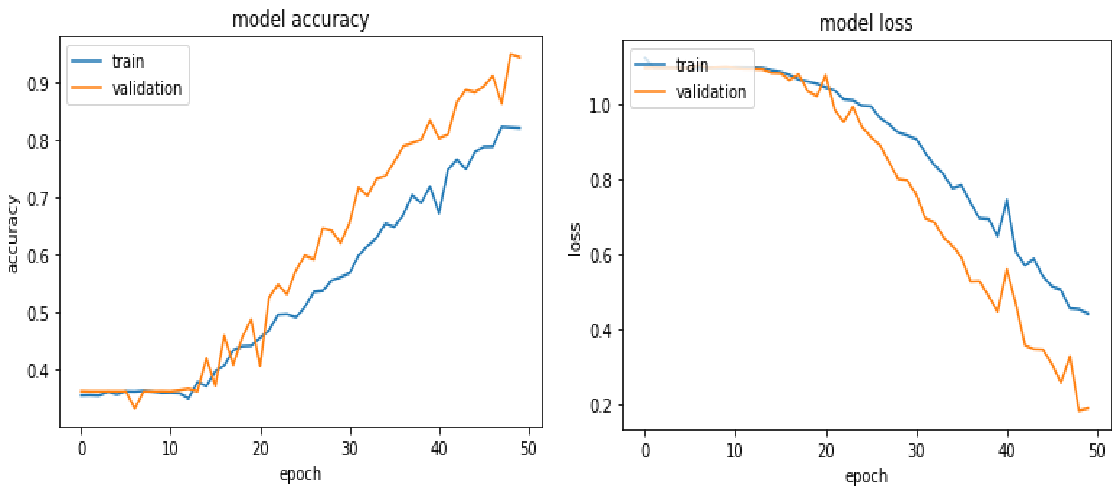
C. Word2vec-BiLSTM-CNN-BiLSTM



D. Glove-BiLSTM-CNN



E. Glove-CNN-BiLSTM



F. Glove-BiLSTM-CNN-BiLSTM

Figure 4.3.4.2 Accuracy and loss calculation

Table 4.3.4.3 Precision, recall and f1-score calculation

Word Embedding	Model	Category	Precision	Recall	F1-Score
Word2vec	BiLSTM-CNN	Positive	0.48	0.71	0.57
		Negative	0.59	0.29	0.39
		Neutral	0.70	0.68	0.69
	CNN-BiLSTM	Positive	0.77	0.89	0.82
		Negative	0.96	0.83	0.89
		Neutral	0.92	0.90	0.91
	BiLSTM-CNN-BiLSTM	Positive	0.68	0.71	0.69
		Negative	0.79	0.69	0.73
		Neutral	0.70	0.74	0.72
Glove	BiLSTM-CNN	Positive	0.58	0.76	0.65
		Negative	0.64	0.58	0.61
		Neutral	0.70	0.55	0.62
	CNN-BiLSTM	Positive	0.87	0.92	0.89
		Negative	0.88	0.92	0.90
		Neutral	0.96	0.89	0.93
	BiLSTM-CNN-BiLSTM	Positive	0.94	0.97	0.95
		Negative	0.95	0.88	0.91
		Neutral	0.95	0.97	0.96

Table 4.3.4.4 Sensitivity and specificity results

Word Embedding	Models	Sensitivity	Specificity
Word2vec	BiLSTM-CNN	0.595	0.671
	CNN-BiLSTM	0.847	0.970
	BiLSTM-CNN-BiLSTM	0.839	0.871
Glove	BiLSTM-CNN	0.769	0.788
	CNN-BiLSTM	0.943	0.925
	BiLSTM-CNN-BiLSTM	0.950	0.970

Table 4.3.4.5 Matrix calculation without optimizer

Proposed Models	FPR	FNR	NPV	FDR	MAE	MSE	RMSE	CKS
Word2vec-BiLSTM-CNN	0.328	0.404	0.360	0.157	0.381	0.180	0.425	0.355
Word2vec-CNN-BiLSTM	0.029	0.152	0.826	0.025	0.247	0.090	0.301	0.807
Word2vec-BiLSTM-CNN- BiLSTM	0.128	0.160	0.822	0.115	0.323	0.142	0.377	0.571
Glove-BiLSTM-CNN	0.211	0.230	0.703	0.159	0.377	0.174	0.417	0.443
Glove-CNN-BiLSTM	0.074	0.056	0.938	0.069	0.221	0.075	0.274	0.860
Glove-BiLSTM-CNN-BiLSTM	0.029	0.050	0.940	0.025	0.092	0.030	0.176	0.916

Table 4.3.4.6 macro average calculation

Word Embeddings	Models	Precision	Recall	F1-Score
Word2vec	BiLSTM-CNN	0.59	0.56	0.55
	CNN-BiLSTM	0.88	0.87	0.87
	BiLSTM-CNN-BiLSTM	0.72	0.71	0.72
Glove	BiLSTM-CNN	0.64	0.63	0.63
	CNN-BiLSTM	0.91	0.91	0.91
	BiLSTM-CNN-BiLSTM	0.94	0.94	0.94

Table 4.3.4.7 weighted average calculation

Word Embeddings	Models	Precision	Recall	F1-Score
Word2vec	BiLSTM-CNN	0.59	0.57	0.56
	CNN-BiLSTM	0.88	0.87	0.87
	BiLSTM-CNN-BiLSTM	0.72	0.72	0.72
Glove	BiLSTM-CNN	0.64	0.63	0.63
	CNN-BiLSTM	0.91	0.91	0.91
	BiLSTM-CNN-BiLSTM	0.94	0.94	0.94

4.3.4.8 The Model's Predicted Testing Outcome

	Sentence	Actual Category	Predict Category
	Bombs away Hartals are bad for business. We have heard this line over and over as ------ who seek to take advantage of others' penchant for violence.	Negative	
Word2vec-BiLSTM-CNN	Bombs away Hartals are bad for business. We have heard this line over and over as ------ who seek to take advantage of others' penchant for violence.	Negative	Neutral
Word2vec-CNN-BiLSTM	Bombs away Hartals are bad for business. We have heard this line over and over as ------ who seek to take advantage of others' penchant for violence.	Negative	Negative
Word2vec-BiLSTM-CNN-BiLSTM	Bombs away Hartals are bad for business. We have heard this line over and over as ------ who seek to take advantage of others' penchant for violence.	Negative	Negative
Glove-BiLSTM-CNN	Bombs away Hartals are bad for business. We have heard this line over and over as ------ who seek to take advantage of others' penchant for violence.	Negative	Negative
Glove-CNN-BiLSTM	Bombs away Hartals are bad for business. We have heard this line over and over as ------ who seek to take advantage of others' penchant for violence.	Negative	Negative
Glove-Bilstm-CNN-BiLSTM	Bombs away Hartals are bad for business. We have heard this line over and over as ------ who seek to take advantage of others' penchant for violence.	Negative	Negative

4.4 Discussion

We Proposed three models in out project. We used deep learning algorithms to combined our proposed models. We combined Bidirectional Long Short Term Memory (BiLSTM) and Convolutional Neural Networks (CNN) with word embedding techniques and created out proposed model. Without optimizer out results was poor and we were worried about it. But when we used optimizer, the result was so good and we were satisfied. Adam optimizer obtained best outcomes in all methods. We measure all types of loss functions during training stage and wait until all iterations are complete before calculating the final loss function. We separated the data into test and train groups before starting the model training.

CHAPTER 5

Impact on Society, Environment and Sustainability

5.1 Impact of Society

Our findings will have a significant impact on society. In this study we have worked with opinion classification using deep learning methods. Now is the age of information technology, and information technology has pervaded all aspects of our society. Our method has some impact for society. Every day we talk to each other but we can not understand their real emotion. Our models can help this type of text classification.

5.2 Ethical Aspects

Our work models or type does not violate any human basic rights or secrecy from an ethical standpoint. We have collected our data from different newspapers and this all newspapers are always available in online. As a result, the data we process cannot be used to identify or harm anyone. We have not completed any work or gathered data by injuring or intimidating people in the course of our duties. Because our work relies on data, we've taken extra precautions when gathering and storing data. While completing our work, we did not claim the work of any other organizations or person as our own. While working, we used our own computers. We haven't used anyone else's equipment, and we haven't stolen anyone else's information or data. We conducted our research while maintaining honesty, legal observance, integrity, legality, and transparency.

5.3 Sustainability Plan

Our primary goal is to use deep learning algorithms to classify the editor's opinions. Many changes in the company or organization can be made in the long term by using our program. Only certain datasets will work with our model. So, in order to advance and sustain this work in the future, we'll need a large number of datasets relating to various English Sentences. In the future, as the required English dataset is enhanced and improved, this model can be applied to educational, military, industrial, and business sectors, among others. Our proposed new model will help in future for another big datasets or others.

CHAPTER 6

Conclusion and Future Work

6.1 Summary of the Study

For this project, our total work related on sentiment analysis. We have done our work for editorial opinion classification using deep learning algorithms. Our work is very helpful for opinion classification. We got good outcomes for all models in our own built datasets. From the time we started collecting data to the time we finished the projects, it took us three months. To complete this, we had to go through a series of steps one by one. The entire work step has now been summarized and is listed below

Step 1: Editorial Opinion Datasets collected from various newspapers.

Step 2: Store all data in Excel .xlsx file.

Step 3: Splitting datasets.

Step 4: Preprocessing dataset.

Step 5: Use word Embedding.

Step 6: Use LSTM and CNN model layers.

Step 7: Model train and test.

Step 8: Output or result check.

We completed our task by following these steps in order. In this models will help our sentiment classification of Editorial opinion and further experiment of others project.

6.2 Conclusion

We attempt to develop a method for detecting sentiment analysis of editorial news in this paper. The purpose of this paper is to work on the presentation of sentiment classification in English newspaper editorial news using two word embeddings: word2vec and glove. We begin by gathering raw data from various newspapers and cleaning it, as machines can more accurately interpret preprocessed data. We used three optimizers: Adam, RMSProp and Adamax. In this various optimizers, we got different result from models. Using two deep learning algorithms and combined it by layers wise and we got BiLSTM-CNN, CNN-

BiLSTM and BiLSTM-CNN-BiLSTM methods. Adam optimizer produces the best results out of these three optimizers. Our first proposed model BiLSTM-CNN with word2vec and Glove word embedding has an accuracy of 91.59% and 99.40%, respectively. The results of the CNN-BiLSTM methods are 92.60% and 94% and the final model BiLSTM-CNN-BiLSTM is 82.79% and 98.47%. The experimental results show how well the deep learning models work.

6.3 Implication for Further Work

We discovered some limitations in doing so, such as the fact that we had no deal with closed domains and that our dataset was insufficient. Any type of model is built for incoming improvement, as we all know. Because any kind of experimental research is a never-ending method that improves day by day. Following the completion of this study, we will need to expand the model. In this project, we only used three combined model with two word embedding. We plan to expand the dataset and test new models in the future. In the future, experiments with neural network-based models such as ANN, DNN, RNN, BERT and others may be conducted. we will try to use more classes and more data in the future. Future we will use Bangla datasets in our models for different projects. in This will help us figure out which model we should use for this task. After the research is completed, we want to work on how to apply it in our daily lives.

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