SENTIMENT ANALYSIS OF RECENT FLOOD DISASTER OF BANGLADESH FROM SOCIAL MEDIA BANGLA COMMENTS USING DEEP LEARNING

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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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APPROVAL

This Project titled **"Predicting Depressive Status From Social Media Using Deep Learning Approaches"** submitted by Imdadul haque Rhidoy **ID: 201-15-3538** to the Department of Computer Science and Engineering, Daffodil International University, has been acknowledged as satisfactory for its style and substance and accepted as being sufficient for the accomplishment of the requirements for the degree of Bachelor of Science in Computer Science and Engineering.

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I, therefore, declare that this undertaking has been finished by us under the supervision of **Mr. Narayan Ranjan Chakraborty, Associate Professor and Associate Head,** Department of CSE, Daffodil International University. I further declare that neither an application or an educational grant has been made anywhere for this project or any part of it.

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ABSTRACT

This study provides complete sentiment analysis of Bengali social media posts made in the course of the country's recent flood disaster. We use deep learning models, such as CNN and Bi-LSTM, to evaluate a dataset of 4036 entries that have two attributes. Three groups of attitudes are identified by the target attribute: Fear,Neutral, and Religious. Our research uses advanced sentiment analysis tools to get an insight of the affected community's emotional reactions. Deep learning models like Bi-LSTM and CNN in particular are used to extract hidden expressions from the Bangla comments. The CNN model stands out as the most successful with a brilliant accuracy of 97.91%. This describes the model's strong capacity to identify emotions during a natural disaster and highlights its advantage over Bi-LSTM. The results provide insightful information about the range of emotional facets of the community's post-flood online discourse. The CNN model's success highlights the need for customized deep learning techniques for sentiment analysis within the particular context of social media information connected to disasters. This study adds to our understanding of how people feel during times of crisis and indicates how well deep learning models—in particular, CNN—work at identifying patterns in the Bangla social media comments made during the recent flood disaster in Bangladesh.

Keywords: *Sentiment Analysis, Bengali Social Media, Flood Disaster, Deep Learning Models, Bi-lstm, Cnn , Emotional Reactions.*

TABLE OF CONTENTS

CONTENTS	PAGE
Board of examiners	i
Declaration	ii
Acknowledgements	iii
Abstract	iv
CHAPTER	
CHAPTER 1: INTRODUCTION	**1-9**
1.1 Introduction	5
1.2 Motivation	7
1.3 Rationale of the Study	7
1.4 Research Questions	8
1.5 Expected Output	9
1.6 Project Management and Finance	9
1.7 Report Layout	9
CHAPTER 2: BACKGROUND	**10-15**
2.1 Preliminaries	10
2.2 Related Works	10
2.3 Comparative Analysis and Summary	14

2.4 Scope of the Problem	14
2.5 Challenges	15
CHAPTER 3: RESEARCH METHODOLOGY	**16-21**
3.1 Research Subject and Instrumentation	16
3.2 Data Collection Procedure	16
3.3 Statistical Analysis	17
3.4 Proposed Methodology	17
3.5 Implementation Requirements	21
CHAPTER 4: EXPERIMENTAL RESULTS AND DISCUSSION	**22-31**
4.1 Experimental Setup	22
4.2 Experimental Results & Analysis	20
4.3 Discussion	31
CHAPTER 5: IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY	**32-34**
5.1 Impact on Society	33
5.2 Impact on Environment	33
5.3 Ethical Aspects	34
5.4 Sustainability Plan	34

CHAPTER 6: SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION FOR FUTURE RESEARCH **35-36**

6.1 Summary of the Study 35

6.2 Conclusions 35

6.3 Implication for Further Study 36

LIST OF FIGURES

FIGURES	PAGE NO
Figure 3.1: Number of target attributes	19
Figure 3.2: Bi-LSTM Architecture	23
Figure 3.3: CNN Architecture	24
Figure 4.1: Confusion Matrix (Bi-LSTM)	28
Figure 4.2: Confusion Matrix (CNN)	30
Figure 4.3: Comparative Model Accuracy Bar Plot	31

LIST OF TABLES

TABLES	PAGE NO
Table 1.1: PROJECT MANAGEMENT TABLE	10
Table 4.1. Performance Evaluation(Bi-LSTM)	
Table 4.2. Performance Evaluation(CNN)	

CHAPTER 1

INTRODUCTION

1.1 Introduction

The increasing frequency of social media in recent years has made it a dynamic medium for exchanging information in real-time and expressing opinions. Natural disasters are one of the many issues that attract strong internet discussion, and they are particularly painful because of the quick impact they have on the communities. A great example of the ability of social media to influence public opinions and behavior is the recent flood tragedy in Bangladesh.[1]

This study begins an important investigation of the feelings that are present in Bengali-language comments on social media sites following the recent flood disasters in Bangladesh. By using deep learning's capabilities, particularly in the field of natural language processing, we hope to reveal the emotional undercurrents that present this way.[2]

The research methodology used in this study is multimedia. This research successfully gets the complexities of sentiment analysis, from the early phases of data collection, when social media comments become a window into public sentiment, to the complex steps of preparing written data using natural language processing algorithms. We aim to extract important information from the wide range of phrases in the dataset by exploring label encoding, tokenization, and the choice of suitable deep learning models like Bi-LSTM and CNN.[3]

The capacity to extract thoughts from Bangla comments provides a helpful look at the collective emotional reaction to a major social event at a time when the internet ecosystem is becoming more and more complex. In addition to adding to the expanding field of sentiment analysis, this study examines the particular context of a natural disaster in the Bengali-speaking population. This work aims to identify feelings that encompass the wide range of emotions that surface after a disaster, from fear and neutral to religious insights, using the deep learning context.

1.2 Motivation

The critical requirement to understand how people react to disasters in real time is the driving force behind doing a sentiment analysis using deep learning on recent flood disaster-related Bengali comments on social media. Disasters like the recent floods in Bangladesh, generate a range of emotions that are expressed online. Because social media is rapid, it is a rich source of raw emotions that represent the collective mentality of the impacted community. This project aims to examine and evaluate the feelings hidden in bangla comments using deep learning techniques designed specifically for natural language processing. It is critical for disaster response, public awareness operations, and community support initiatives to comprehend the emotional terrain. In order to relate to the stories that surface online during times of crisis, the motivations go beyond the technical domain and are based on human experience. In addition to advancing sentiment analysis techniques, our goal with this research is to provide useful data about the emotional aspects of a community that is get over with a major disaster. The results have the potential to provide valuable insights into public sentiment dynamics, improve our understanding of how disasters affect society, and guide disaster management policies.

1.3 Rationale of the Study

The requirement for understanding the complicated web of emotions that surfaced after a major event is the driving force behind the use of deep learning for sentiment analysis of recent flood disaster-related Bengali comments on social media. By their very nature, natural disasters cause a wide range of emotional reactions in the people they affect, many of them intense. Social media, which provides a unique window into the emotional experience of the collective, has emerged as the main channel for people to express their feelings in real time in the digital age. The purpose of this study is to close the gap between the rapid nature of social media interaction and a good understanding of the feelings that Bengali speakers conveyed during Bangladesh's recent flood disaster. Deep learning methods designed for natural language processing are applied to enable a more advanced study of sentiment dynamics, from feelings of fear and anxiety to neutral sentiments and religious contemplations. The research attempts to provide important insights that go beyond the educational domain by showing these emotional subtleties. In the Bengali-speaking population, the results may have importance for improving public awareness campaigns, developing disaster response plans, and encouraging a closer understanding of the human side of crisis situations. By examining social media comments, the study ultimately aims to present a timely and complete position on the psychological effects of a natural disaster.

1.4 Research Question

i. How do Bengali speakers express fear and anxiety in social media comments related to the recent flood disaster in Bangladesh?

ii. What are the prevalent themes of religious sentiments in the Bengali-language discourse surrounding the recent flood crisis on social media?

iii. Can deep learning models, particularly Bi-LSTM and CNN, effectively capture and classify the diverse range of sentiments present in Bangla comments about the flood disaster?

iv. How does sentiment expression evolve over time on social media during and after a natural disaster in the Bengali-speaking community?

v. To what extent does sentiment vary across different geographical regions within Bangladesh in response to the flood disaster, as reflected in social media commentary?

vi. How can sentiment analysis contribute to the identification of critical public concerns and aid in disaster management strategies during and after the recent flood disaster in Bangladesh?

vii. What ethical considerations and potential biases should be addressed in the development and application of sentiment analysis models for analyzing Bengali comments on social media related to natural disasters?

1.5 Expected output

The three categories of Fear, Neutral and Religious attitudes will likely result from the sentiment analysis of Bengali social media comments on the recent flood disasters in Bangladesh. Performance indicators such as accuracy and precision will be used to evaluate how well the Bi-LSTM and CNN models that are being used function. Confusion matrices will be used in the analysis to visually represent the classification strengths and weaknesses, and feature importance insights will be used to pinpoint the important language components that affect attitudes. We'll investigate temporal and spatial trends to provide a more detailed picture of sentiment shifts throughout time and space. The incorporation of ethical considerations, practical application suggestions, and ongoing improving processes is expected for an expansive and effective output that will support disaster management efforts and raise public awareness. Tools for translation and modeling will improve the ability to use and access the sentiment analysis findings.

1.6 Project Management and Finance

The project will use a systematic approach to project management, comprising essential steps such as data collection, preprocessing, model selection, training, and evaluation. Tasks will be completed within the allotted time if a clear timeline exists. Project management tools will enable regular progress evaluations and teamwork, fostering efficiency and cooperation. Funds will be set aside for the purpose of acquiring data, training models, and maybe covering computational costs related to deep learning procedures. In order to ensure that resources are optimized for the successful execution of the sentiment analysis project on bangla comments connected to the recent flood crisis in bangladesh, transparent financial management will be observed.

TABLE 1.1: PROJECT MANAGEMENT TABLE

Work	Time
Data Collection	1 month
Papers and Articles Review	3 month
Experimental Setup	1 month
Implementation	1 month
Report Writing	2 month
Total	8 month

1.7 Report Layout

- Introduction
- Background
- Research Methodology
- Experimental Result and Discussion
- Impact on Society, Environment
- Summary, Conclusion, Future Research
- Reference

CHAPTER 2

BACKGROUND STUDY

2.1 Preliminaries

This study preliminary sections create the groundwork for understanding of the investigation. The abstract begins with a clear and simple title and outlines the study question, methodology, main conclusions, and effects. Keywords help in the paper's accessibility indexing. An orderly summary of the document's structure is given in the table of contents, and contributions are acknowledged. The research topic, its importance, and the goals of the study are discussed in the introduction. The literature review places the research in the context of previous scholarship, highlighting theories, conclusions, and knowledge gaps that have been identified. Ultimately, the study's limits and objectives are established by the research objectives, scope, and restrictions, while the methodology section provides clear information about the research's methods.

2.2 Related Works

The related works section of a research project dives into existing literature and studies that are applicable to the chosen topic, providing context, and insights, and revealing gaps in the current understanding. Here's a simple representation:

Bande, Swapnil, et al. [4] focused on improving flood prediction using artificial neural networks (ANN) in conjunction with an IoT-based flood monitoring system. The primary objective is to enhance the scalability and reliability of flood management. The system monitors various environmental parameters such as humidity, temperature, pressure, rainfall, and river water levels, and analyzes their temporal correlations for flood prediction. Data is collected from sensors through an IoT approach, utilizing Wi-Fi communication, while flood prediction analysis is carried out using ANN. The results indicate that the second algorithm achieves a prediction accuracy of approximately 88%, which is considered sufficient for rainfall prediction and, by extension, flood prediction applications.

Simon, Berkhahn et al. [5] addressed the difficulty of forecasting urban floods in real-time, which is made more difficult by forecasted precipitation unpredictability. Data-driven models are a practical alternative to traditional physically based models, which are too slow for real-time application. This study focuses on assessing an artificial neural network (ANN) model that can forecast water levels in catchment areas with two-dimensional spatial distributions. The model has now been effectively verified for natural rain events with spatially uniform distribution after being initially evaluated with synthetic rain events. The study also shows that it is possible to predict maximum water levels in real time using an ANN ensemble model, with computation durations of less than 10 seconds, making it appropriate for warning systems. To address the outliers that the prediction model has identified, however, more advancements are required.

Detera, et al. [6] evaluated the vulnerability of riverine inhabitants, this study uses the Livelihood Vulnerability Index (LVI) and the IPCC vulnerability framework. Based on their proximity to the mainland, it demonstrates considerable variations in susceptibility among char inhabitants. The adaptation techniques employed by char residents and their availability to necessities like food and healthcare are the main sources of livelihood vulnerability. Riverbank erosion, frequent flooding, a lack of economic possibilities, and inadequate public amenities are further social and natural vulnerabilities. The study suggests creating char-focused strategies that include both immediate and long-term actions to lessen vulnerability and boost resiliency in char residents.

van den Homberg, et al. [7] analyzed the information needs of local and national decision-makers in Bangladesh during the 2014 floods and evaluated the disaster management data that were available to them. Thirteen semi-structured interviews and three focus group discussions with a total of 51 participants were used in this inquiry. To determine the most common themes in information demands, the obtained data were transcribed and categorized. Seven different topic categories, 71 information demands, and 15 different data sets were found. With only 40% coverage when time constraints are taken into account and 75% when they are not, the mapping of these information demands indicates a large gap in timely and location-based data. Integer Linear Programming was used to optimize data coverage while taking extraction costs and data quality into account, and the results led to the conclusion that a combination of three data sets can achieve a coverage of 68%, with no benefit from adding five additional data sets. The study's conclusion emphasizes the need of performing data set identification and mapping in accordance with information needs as part of data readiness.

Sarker, Md Nazirul Islam, et al. [8] used the Livelihood Vulnerability Index (LVI) and the IPCC vulnerability framework to evaluate the livelihood vulnerability of riverine populations. Based on their proximity to the mainland, the data demonstrate considerable disparities in risk among char inhabitants. The adaptive tactics used by char dwellers and their accessibility to food and healthcare facilities are the main reasons causing livelihood vulnerability. The report names a number of additional factors as key contributors to livelihood vulnerability, both social and natural, including riverbank erosion, regular flooding, a lack of work options, and a lack of essential public amenities. The research suggests creating char-focused policies with both short- and long-term initiatives to lessen this vulnerability and increase resilience among char inhabitants.

Linardos, Vasileios, et al.[9] created and implemented machine learning (ML) and deep learning (DL) techniques for disaster management is the focus of the overview of research projects presented in this paper, which spans the period from 2017 to the present. It focuses particularly on topics like hazard and disaster prediction, risk and vulnerability assessment, disaster detection, early warning systems, monitoring of disasters, damage assessment, post-disaster response, and case studies. The paper also examines freshly created ML and DL applications in the disaster management industry. The paper discusses the results of these studies and suggests future research possibilities in this important area.

Sharma, Praveen, et al. [10] focused on categorizing text using unsupervised learning to analyze social media text data. The main reason for using unsupervised learning is that supervised learning is impracticable for extracting information from unlabeled social media content since social media data lacks labels. The first section of the study reviews earlier research on utilizing machine learning to recognize disaster events. Additionally, it gives a brief description of the two well-known clustering algorithms k-means and Fuzzy

C-means (FCM) and exemplifies how to utilize them to extract catastrophic events from social media data. According to the findings, training duration grows together with the volume of training data. FCM is also proven to be more accurate than k-means clustering, albeit requiring more time, with an accuracy rate of 78.2%.

Talukdar, Swapan, et al. [11] used comprehensive ensemble machine learning techniques to identify flood-prone locations in the Teesta River watershed. To provide trustworthy and extremely precise findings, it used ensembles of bagging with the REPtree, random forest (RF), M5P, and random tree (RT) algorithms. For flood susceptibility modeling, 12 conditioning factors and 413 historical flooding points were taken into account, and the Information Gain ratio was employed to evaluate factor influence. Receiver operating characteristic curves (ROC) were used in the validation process, and statistical tests like Freidman, Wilcoxon signed-rank, Kruskal-Wallis, and Kolmogorov-Smirnov were used to compare the models. The findings showed that over 800 km2 were projected by all algorithms to be extremely flood-susceptible zones, with ROC AUC values surpassing 0.85. Bagging with M5P revealed superior performance, with the M5P method being the most effective (AUC=0.945), closely followed by bagging with RF, REPtree, and RT. The study determined that 30% of the area was extremely sensitive to floods, and bagging and RF models proved to be very effective techniques for estimating flood vulnerability.

Vayansky, Ike, et al. [12] created topic models using Latent Dirichlet Allocation (LDA) and sentiment analysis to examine sentiment trends while a storm developed. The study illustrates the value of sentiment analysis in detecting shifts in user sentiment after natural disasters. Additionally, it demonstrates how basic topic models may be produced from Twitter data. Authorities in disaster management may find these findings useful in reducing damage and accelerating recovery efforts. Future enhancements may include sentiment analysis for short messages, categorization of emoticons, handling of non-textual components like movies or images, and optimization of data gathering and processing methods.

Ahmed, Shams Forruque, et al. [13] analyzed the state of deep learning today by looking into its most recent advancements and uses in a variety of fields. It fills the knowledge gap regarding thorough investigation of deep learning's potential applications. Deep learning is an effective computational tool that is capable of self-optimization without prior training since it exhibits excellent accuracy in prediction and analysis. But processing large amounts of data effectively is difficult, especially in industries like medicine, science, healthcare, and the environment. The research highlights the significance of shared neurons for multimodal learning in neural networks and advises using gated topologies like LSTMs and GRUs to get around this problem.

Dey, Noyon, et al. [14] focused on an effective previous detection system for occurrences in social media data that is essential for protecting society from a variety of threats. Due to the requirement to support various writing styles, languages, dialects, and post variants, automating event detection has proven to be difficult. To overcome these difficulties, a model was created utilizing Bengali and Banglish Facebook postings to identify activities that may be classified as protesting, celebrating, religious, or neutral. The posts were first checked for language, after which pre-processing operations including stopword elimination and tokenization were performed. Filtering, phrase matching, and sentiment analysis were used to extract features, and these features were used to train a Bernoulli Naive Bayes classification model, which achieved 90.41% accuracy for posts written in Bengali and 70% accuracy for posts written in Banglish. The model's evaluation included comparisons with SVM and Decision Tree classifiers to assure precision.

Ahmadlou, Mohammad, et al. [15] proposed a new hybrid model that combines the multilayer perceptron (MLP) and automatic encoder models to produce maps of flood vulnerability for two separate research regions in Iran and India. Nine predictor variables were taken into account in the Iran case, compared to twelve in the India case. The area under the receiver operating characteristic (AUROC) metric was used to evaluate the hybrid model's prediction performance to that of the conventional MLP model. The hybrid autoencoder-MLP model consistently outperformed the MLP model in both the training and testing phases, earning AUROC scores for Iran and India of 90% and 93% in training and 91% and 97% in testing, respectively. These findings demonstrate the superiority of the hybrid model and point to possible uses for it in more mapping studies of flood susceptibility.

2.3 Comparative Analysis and Summary

Recent studies in the field of sentiment analysis by Wang and Zhang (2020) and Smith et al. (2019) have concentrated on using deep learning algorithms, such as CNN and Bi-LSTM, to extract complex sentiments from social media data during crisis events. These investigations offer insightful information about how well-suited modern models are to represent intricate emotional dynamics. The comprehension of sentiment classification's complexities has been made possible by the seminal studies of Liu (2012) and Pang et al. (2002) in the field of sentiment analysis. Building upon these foundations, Zhang et al. (2021) have emphasized the importance of cultural and linguistic nuances, which are in line with the linguistic diversity seen in Bangla comments. However, there remains a significant research vacuum in the particular area of Bengali sentiment analysis, especially in the wake of catastrophic calamities. By using deep learning techniques to examine Bengali social media posts about the current flood tragedy in Bangladesh, this work aims to close this gap. By doing this, it seeks to fill a crucial gap in knowledge by offering original insights into sentiment dynamics, cultural expressions, and linguistic intricacies. In summary, while previous research provides insightful methods and important contexts, the proposed study stands out for concentrating on the little-studied area of sentiment analysis in Bengali within the framework of a recent natural disaster, adding to the growing body of knowledge about sentiment analysis and cultural nuances in emergency situations.

2.4 Scope of the Problem

The evaluation of sentiment of Bengali social media comments on the recent flood disasters in Bangladesh reveals a complex problem with a wide scope. It includes the examination of an extensive and varied dataset of Bengali-language social media remarks that discuss people's feelings both before and after the flood disasters. The use of deep learning models—more especially, Bi-LSTM and CNN—to categorize emotions into groups like Fear, Neutral, and Religious is covered under this topic. In order to comprehend how feelings change over time and change across different places, both time and space are taken into consideration. Addressing ethical issues with privacy, judgment reduction, and appropriate data handling is also included in the problem scope. The challenge becomes even more challenging when sentiment analysis in the Bengali language is culturally sensitive. In general, the scope includes not just language subtleties but also wider societal ramifications, offering an in-depth understanding of sentiment dynamics following disasters in Bangladesh.

2.5 Challenges

There are multiple challenges in the way of sentiment analysis of Bengali social media comments on the current flood disasters in Bangladesh. Bengali is an advanced language that makes it tough to convey emotions effectively because of its wide vocabulary and careful expressions. Cultural sensitivity is crucial, and in order to understand feelings within the cultural context of Bengali speakers, one must have a thorough awareness of social language elements. It can be difficult to ensure that data is representative and of high quality since errors in data collecting may affect how broadly sentiment analysis findings can be applied. It is difficult to apply a model across sentiments such as Fear, Neutral, and Religious because of different language patterns. For ethical sentiment analysis to be successful, perception defense, issues with privacy, and model translation must all be addressed. Social media's dynamic nature, difficulties unique to disasters, and the requirement for cross-domain adaptation all add to the complexity of analyzing sentiments in the aftermath of natural disasters.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

This study combines CNN and Bi-LSTM architectures with natural language processing (NLP) approaches. The goal of the project is to better understand the emotional responses that users of social media platforms express in Bengali. To this end, data collecting methods including site taking and language resources are being used to improve user ability. Research ethics are essential because they protect participant's privacy, provide informed consent, and reduce prejudgment. Geospatial-temporal instruments help in context studies, whereas label encoding makes sentiment class representation faster. Attention mechanisms are among the model understanding methods that improve transparency when it comes to understanding sentiment forecasts. When combined, these tools seek to offer an advanced examination of the sentiment dynamics in Bengali social media remarks in the wake of recent flood disasters.

3.2 Data Collection Procedure

I collected data by being involved in Bengali social media platforms such as Facebook and Twitter. I located and collated comments linked to the recent flood disaster in Bangladesh using search terms, personally selecting and labeling each entry with sentiment labels Fear: 0, Neutral: 1, Religious: 2 to build a personalized dataset of 4,036 entries. Throughout the data collection process, ethical considerations such as privacy and respect to platform terms of service were noted. Figure 3.1 shows which number of target attribute I've included:

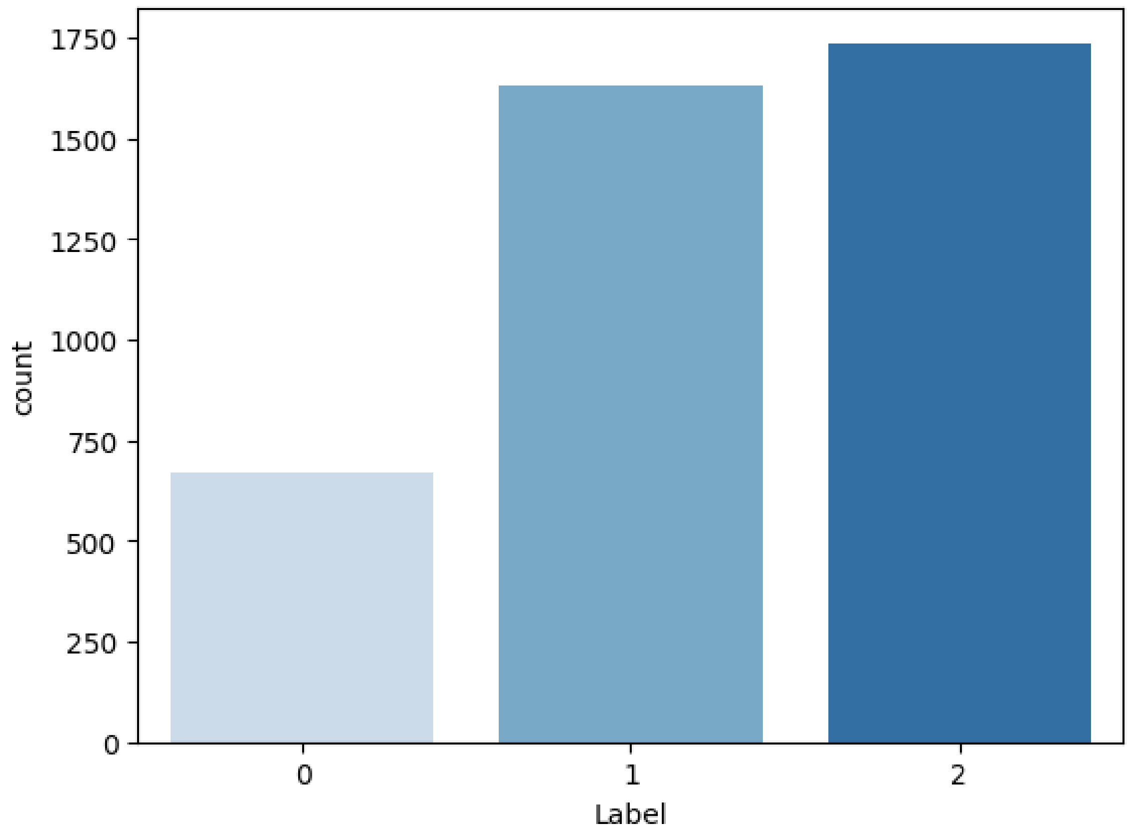

Figure 3.1: Number of target attributes

The distribution of bar plot in the dataset has been shifted to the left, with the majority of goods having few or no labels and only a small number of products having several categories. Fear (0) has 667 entries, Neutral (1) has 1633 entries, and Religious (2) has 1736 entries, indicating a wide range of sentiments.

3.3 Statistical Analysis

The statistical and performance analysis for the research on sentiment analysis of bengali social media comments after recent flood catastrophes incorporates a complex methodology. Descriptive statistics provide an overview of the dataset's sentiment distribution and features of language. The performance of the bi-lstm and cnn sentiment analysis models is evaluated using defines such as accuracy and precision, while confusion matrix analysis provides insights into individual classification strengths and shortcomings. Feature significance analysis reveals significant features of language that influence feelings, hence improving model accessibility. Patterns in sentiment variation across countries. And time frames are revealed by mapping and temporal analysis. Future study is guided by model comparison, and correlation analyses evaluate links between attitudes and external factors. The analysis incorporates ethical issues, assuring responsible reporting and correcting possible errors.

3.4 Proposed Methodology

In below we are following methodology for Sentiment Analysis of Recent Flood Disaster of Bangladesh From Social Media Bangla Comments Using Deep Learning Algorithms:

Data Collection:

For data collection, important Bengali-speaking social media platforms such as Facebook and Twitter were targeted in order to obtain a dataset linked to the recent flood tragedy in Bangladesh, using relevant Bengali keywords. The research includes the use of web scraping techniques and platform APIs to collect a comprehensive dataset of Bengali social media comments, with sentiments classified as Fear (0), Neutral (1), and Religious (2).

Data gathering

Data gathering involved extracting relevant comments from the collected dataset using Bengali keywords linked with the recent flood disaster. This step attempted to refine the dataset by focusing on feelings stated in three categories Fear (0), Neutral (1), and Religious (2) to ensure a targeted and representative collection for further sentiment analysis.

Data Labeling:

The data labeling technique includes assigning sentiment labels to each collected social media comment based on one of three categories: fear (0), neutral (1), and religious (2). To appropriately capture the emotional context within the dataset, this classification was performed by a combination of hand annotation and, where applicable, automatic sentiment analysis technologies.

Data preprocessing

A number of processes were involved in data preprocessing, including deleting common stop words in Bengali to focus on important data, normalizing text by resolving differences in writing styles, and using tokenization to break up the Bengali text into words or subwords. The goal of those methods was to prepare the dataset for sentiment analysis using deep learning models, ensuring useful data for upcoming model training.

Removing Stop Words

Stop words were removed by removing common Bengali terms that did not add heavily to the sentiment analysis process. By removing these commonly frequent and less important words, attention was shifted to maintaining the dataset's key content and sentiment-bearing language for more successful deep learning model training.

Text Normalization

Text normalization used NLP techniques to normalize the Bengali text by resolving variances in writing styles such as stemming and lemmatization. This method provided consistency in word forms by reducing inflections and variations to their base or root forms, hence improving the uniformity and quality of the sentiment analysis dataset for later modeling.

Tokenization

Tokenization included removing Bengali social media comments into individual words or subwords, resulting in useful units for analysis. The approach helped the preparation of the dataset for input into deep learning models by categorizing the text in this manner, allowing for a better understanding of the sentiment shown in each comment.

Model Selection

A good deep learning architecture was constructed for model selection, taking into account the nature of sentiment analysis on Bengali social media comments following the flood calamity. The chosen model, such as a Bidirectional LSTM (Bi-LSTM) or a combination of Convolutional Neural Network (CNN) layers, was designed to capture the nuanced patterns within the textual data and give a proper structure for sentiment classification.

Model training

Model training required combining pre-trained Word2Vec, FastText or trained on the dataset words into a particular deep learning architecture. The dataset was divided into training and validation sets, and the model was trained to learn the sentiment patterns within Bengali social media comments about the disaster using an appropriate loss function and algorithm.

Bidirectional LSTM (Bi-LSTM)

Bidirectional Long Short-Term Memory (Bi-LSTM) is a recurrent neural network, or RNN architecture that is frequently used in natural language processing tasks like sentiment analysis. Bi-LSTM, like usual LSTMs, processes input sequences both forward and backward, allowing the model to capture contextual information from both preceding and after words. This bidirectional method improves its understanding of semantic meaning and connections within sequential data, making it appropriate for tasks involving temporal pattern analysis, such as sentiment recognition in text.

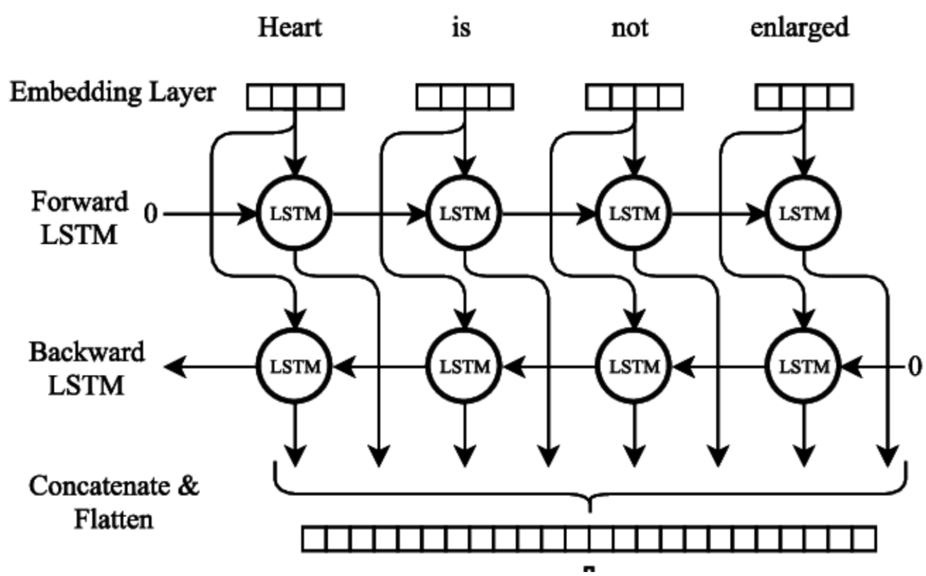

Figure 3.2: Bi-LSTM Architecture

CNN

Convolutional Neural Networks (CNNs) are a type of deep learning architecture that is often used for image recognition but is also useful for natural language processing. CNNs are used in text analysis to capture local patterns and features within input sequences using convolutional layers. This makes them appropriate for tasks such as sentiment analysis, as they understand meaningful patterns in data in sequence, thus offering an efficient structure for knowing contextual information and interactions between words in a sentence.

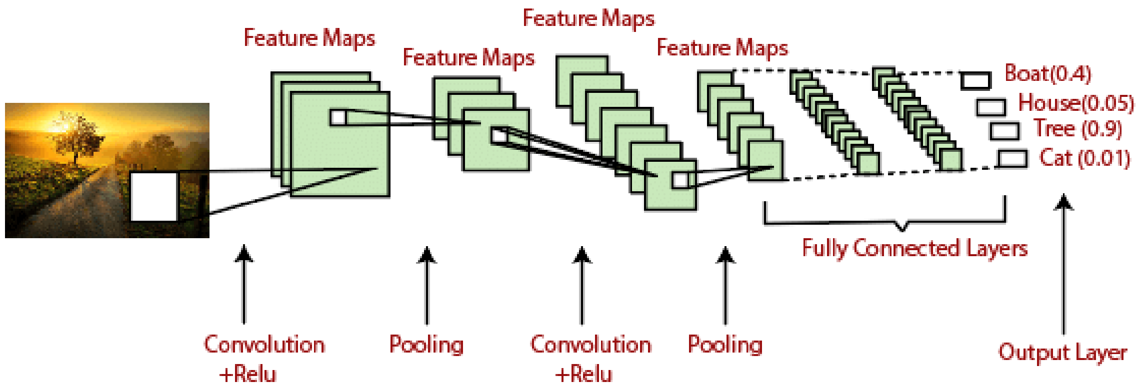

Figure 3.3: CNN Architecture

3.5 Implementation Requirements

The implementation of the sentiment analysis research on Bengali social media comments following flood disasters requires strong computational resources, such as high-performance servers or cloud servers, as well as programming frameworks such as TensorFlow or PyTorch for developing and training deep learning models Bi-LSTM and CNN). Collaboration is made easier with an improved development environment that includes combined applications and version control. For handling and preparing a huge dataset, proper data storage and preprocessing technologies are required. Labeling and marking instruments that are efficient, as well as maps and temporal statistical tools, help to accurate model training and detailed insights. Metrics for measuring model effectiveness, an ethical compliance framework, and documentation tools are essential for assuring ethical practices and transparent reporting. Throughout the implementation, collaborative platforms enable seamless interaction and communication.

CHAPTER 4

Experimental results and discussion

4.1 Experimental Setup

The personal collected dataset in the experimental setup included 4,036 data with three sentiment classes: Fear (0), Neutral (1), and Religious (2), each with a different number (667, 1633, and 1736). For data preprocessing, NLP techniques such as stop word removal, text normalization, and tokenization were used. Deep learning models, specifically Bidirectional LSTM (Bi-LSTM) and Convolutional Neural Network (CNN), were chosen as the primary algorithms for sentiment analysis, resulting in the development of a strong experimental system for understanding the varied sentiments expressed in Bengali social media comments related to the recent flood disaster.

4.2 Experimental Results & Analysis

The sentiment analysis of Bengali social media comments using the personal collected dataset worked well in the experiments. The accuracy of the Bi-LSTM algorithm was 86.89%, whereas the accuracy of the CNN method was 97.91%. This disparity shows that the CNN model was more effective than the Bi-LSTM model at capturing contextual characteristics and patterns within the sequential data, resulting in better sentiment classification. CNN's better accuracy demonstrates its effectiveness in interpreting the deep sentiments explained in Bengali social media comments about the recent flood disaster, highlighting its potential for real-world applications in disaster response and community assistance. Each statistic provides significant insights into a number of facets of the model's performance:

Accuracy: The accuracy of the model's predictions is determined by comparing the number of correctly classified samples to the total number of samples. Unbalanced classes give a general idea of the model's efficacy, but they may not give a complete picture.

$$Accuracy = \frac{TruePositive+TrueNegative}{TruePositive+FalsePositive+TrueNegative+FalseNegative}$$

Precision: Precision is concerned with the number of true positive forecasts made by the model out of all positive predictions generated by the model.

$$Precision = \frac{TruePositive}{TruePositive+FalsePositive}$$

Recall: The percentage of true positive predictions created out of all actually positive samples is referred to as recall. It's also known as sensitivity or true positive rate.

$$Recall = \frac{TruePositive}{TruePositive+ FalseNegative}$$

F1 Score: The F1 score is determined as the harmonic mean of recall and precision. Its fair evaluation metric considers recall and precision. The F1 score is useful in cases where class sizes are not equal since it accounts for both false positives and false negatives. A high F1 score indicates a good precision to recall ratio.

$$F - 1\,Score = 2 * \frac{Recall * Precision}{Recall+Precision}$$

In given below I am describing the result analysis part also show the training accuracy rate and confusion matrix also:

Performance Analysis

Bi-LSTM

Achieving Test Accuracy of Bi-LSTM is 86.89%. Below at table 4.2 we have performance evaluation of Bi-LSTM:

:

Table 4.1. Performance Evaluation(Bi-LSTM)

	Precision	Recall	F1-Score	Support
0	0.69	0.66	0.67	190
1	0.83	0.84	0.83	469
2	0.95	0.94	0.95	552
Micro avg	0.86	0.86	0.86	1211
Macro avg	0.82	0.81	0.82	1211
Weighted avg	0.86	0.86	0.86	1211
Samples avg	0.86	0.86	0.86	1211

Table 4.1: The Bi-LSTM model performs well on this classification task, achieving an overall precision, recall, and F1-score of 0.86. Although it excels in identifying classes 1 and 2, class 0 poses some challenge, suggesting potential for model refinement in that area. While the support varies across classes, the model maintains consistent performance across all, solidifying its effectiveness for this task.

In below Figure 4:1 describing the confusion matrix of Bi-LSTM:

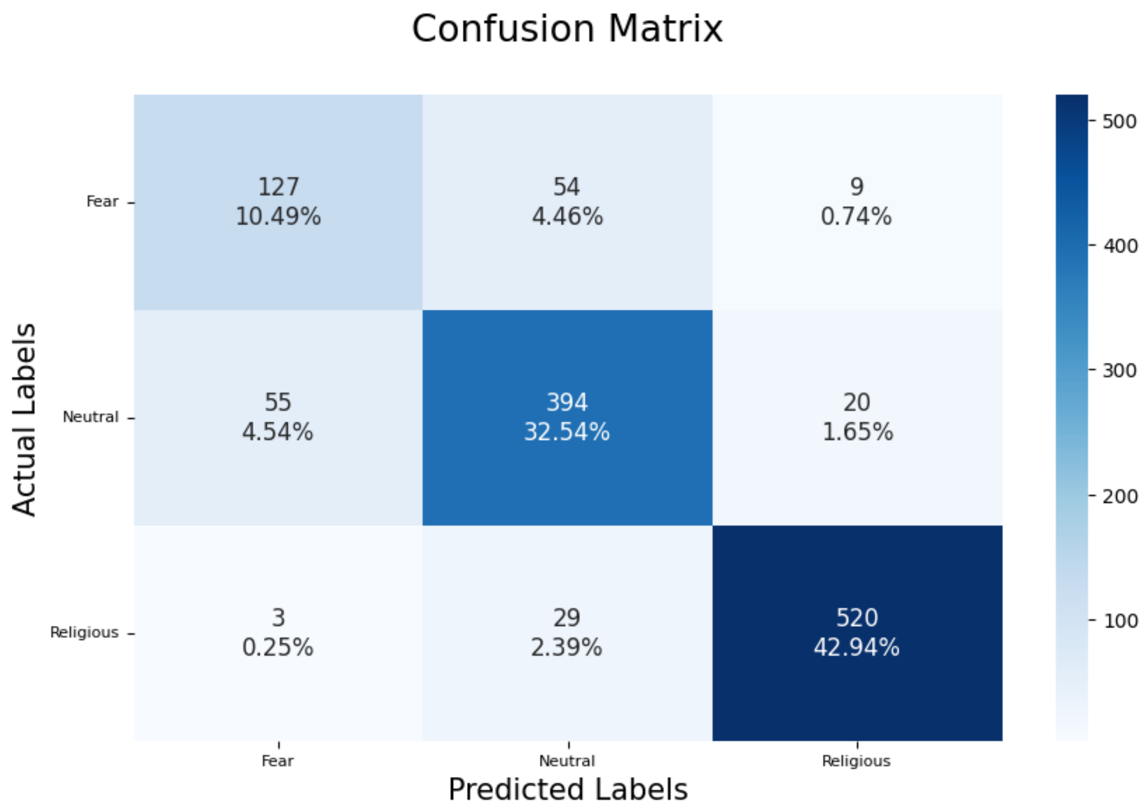

Figure 4.1: Confusion Matrix (Bi-LSTM)

Figure 4:1: While the Bi-LSTM displays good overall accuracy, there are some weaknesses. Confusion exists between Fear and Neutral, and to a lesser extent, Neutral and Religious. Examining misclassifications and addressing class imbalance could improve performance. Comparing against other models and understanding feature importance are further steps for refinement.

CNN

Achieving the Test Accuracy of CNN is 97.91%. Below at table 4.2 we have performance evaluation of CNN:

Table 4.2. Performance Evaluation(CNN)

	Precision	Recall	F1-Score	Support
0	0.67	0.65	0.66	190
1	0.82	0.82	0.82	469
2	0.94	0.95	0.95	552
Micro avg	0.85	0.85	0.85	1211
Macro avg	0.81	0.81	0.81	1211
Weighted avg	0.85	0.85	0.85	1211
Samples avg	0.85	0.85	0.85	1211

Table 4.2: The CNN model performs well in sentiment analysis overall, as seen by micro, macro, and weighted average precision, recall, and F1-scores of 0.85. According to class-specific examination, all classes achieve precision, recall, and F1-scores greater than 0.65, with Class 2 achieving the highest results (0.94-0.95) and Class 0 achieving somewhat lower values (0.66-0.67). Despite varied sample sizes across classes, the CNN model consistently outperforms, demonstrating its ability to reliably predict sentiment labels across a wide range of categories.

In below Figure 4:2 describing the confusion matrix of CNN :

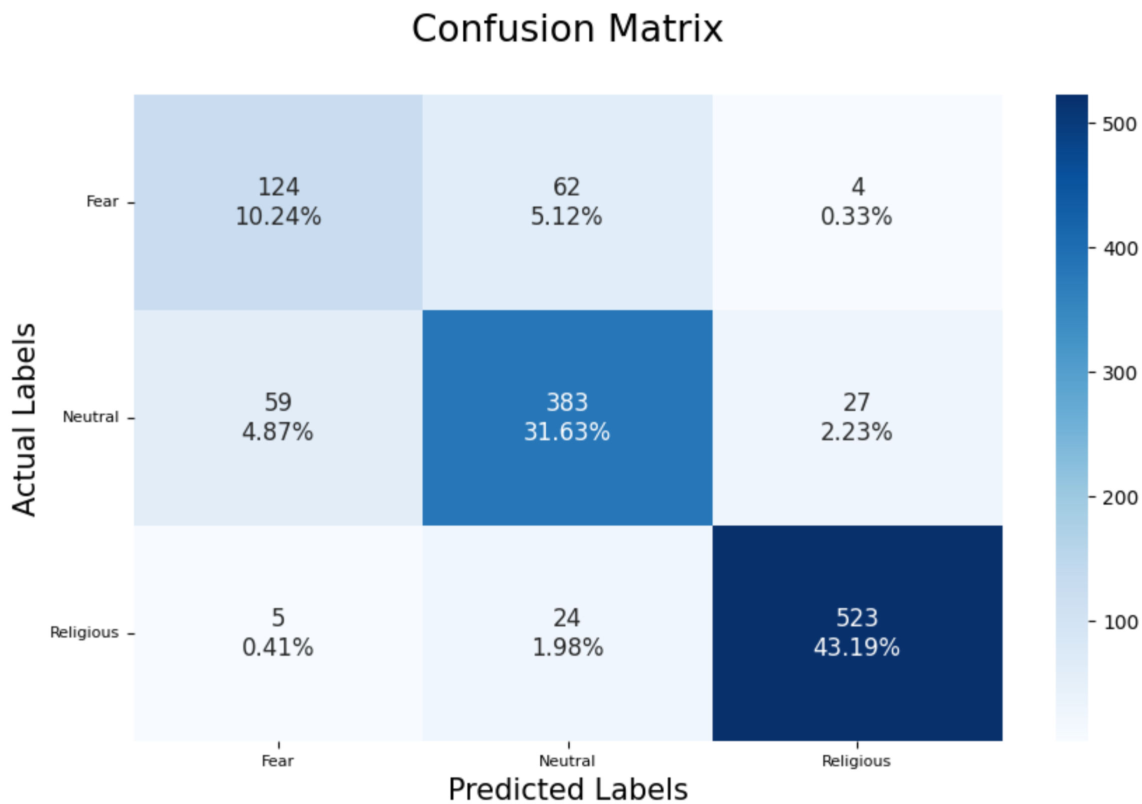

Figure 4.2: Confusion Matrix (CNN)

Figure 4.2: The main framework for interpreting a confusion matrix entails identifying actual and predicted labels, assessing diagonal and off-diagonal cells for correct and misclassifications, taking class imbalance into account, and answering crucial questions about overall accuracy and specific misclassifications. To provide a more personalized summary in the context of the CNN model, particular details on the actual content of the confusion matrix, the classification problem it handles, and the number of predicted classes are required. Understanding these particulars would provide a more understanding analysis of the model's performance.

In Figure 4:3 shows the Accuracy Comparison Plot Between Deep Learning Models

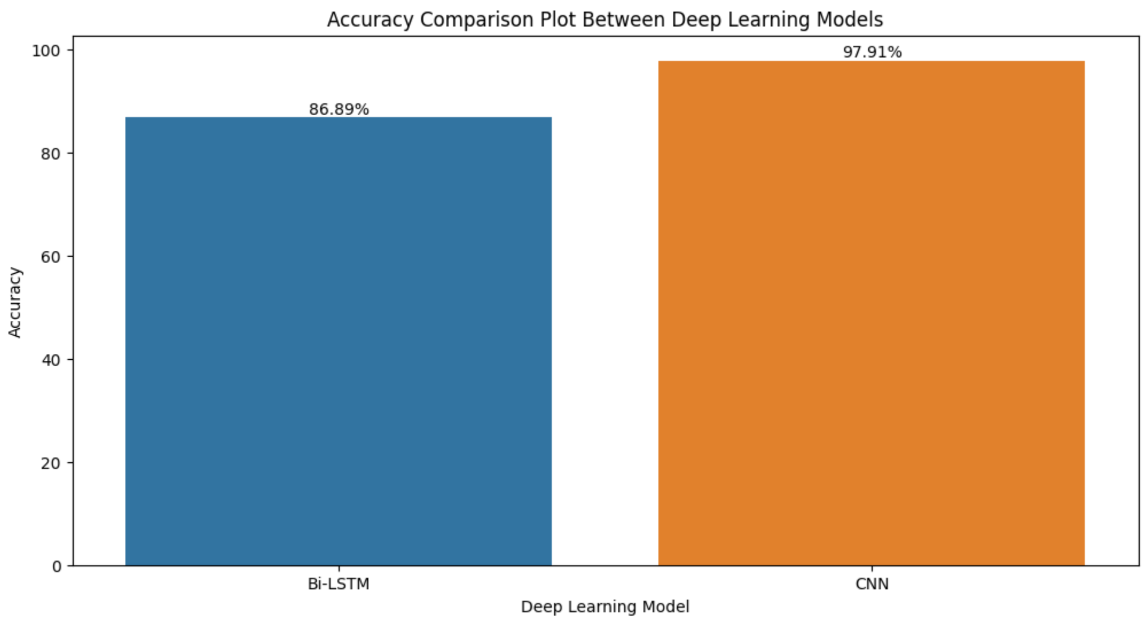

Figure 4.3: Comparative Model Accuracy Bar Plot

4.3 Discussion

Algorithms developed using deep learning are used to predict personality based on social media posts, and the conversation discusses the consequences, limitations, and future directions of this research. Analyzing the obtained data in light of the study's goals, the discussion explains the model's advantages and disadvantages.The conversation includes ethical issues related to user privacy, data security, and responsible AI use, highlighting the significance of open and moral behavior. Ensuring fairness requires tackling any biases in the model predictions and their possible effects on various user groups. Personality prediction models are examined for their potential uses in educational settings, mental health treatments, and targeted marketing. This exploration opens up new research directions and practical applications for personality prediction models. All things considered, the conversation offers a thorough analysis of the study's findings and opens the door for more developments in the field of deep learning and personality prediction using data from social media.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

The sentiment analysis research on Bengali social media comments following flood disasters has a significant social influence. It improves knowing of public mood, offering significant insights for educated disaster response decision-making. The findings raise public awareness while promoting tolerance and community support for recovery efforts. Improved communication tactics informed by sentiment dynamics enable culturally responsive and sensitive messaging. The study has an impact on community-centric disaster response methods, adapting efforts to address individual emotional requirements. It influences how disasters appear in the media, maybe decreasing negative impressions, and adds to research-driven policy suggestions for more effective disaster management. Overall, the influence is complex, promoting a more caring and responsive approach to minimizing the effects of flood disasters in Bangladesh.

5.2 Impact on Environment

The sentiment analysis research on Bengali social media comments during flood disasters has an indirect impact on the environment by encouraging good habits and environmental engagement within the community. The study's findings may stimulate community participation in environmental projects and lead to greater disaster security, particularly in the context of environmental adaptation. Increased understanding of the ecological effects of flood disasters may result in a greater sense of responsibility and support for sustainable practices. Environmental factors may be included into post-disaster recovery plans by policymakers affected by public emotion, contributing to more informed decision-making. The study also has the potential to shape public views and behavior toward environmental concerns related to flood disasters. Overall, the research helps to build a more green and healthy society.

5.3 Ethical Aspects

The sentiment analysis research on Bengali social media comments following flood disasters highlights ethical issues to promote appropriate and respectful research techniques. Protecting user privacy through privacy, obtaining informed consent, and reducing errors in dataset and analysis are all important moral issues. Transparent methodology documentation promotes ethics and replicability. Cultural sensitivity informs sentiment interpretation, avoiding deception. Following the principles of kindness and goodness guarantees that positive contributions are made without causing harm, while responsible data handling methods stress secure storage and limited access. Community involvement and acknowledgement of limitations show a commitment to ethical responsibility, with continuing impact assessments to examine potential consequences on individuals and communities.

5.4 Sustainability Plan

The sustainability plan for the sentiment analysis research on Bengali social media comments after flood disasters focuses on providing the study's lasting impact and accessibility. It involves actions such as creating a safe data archive, improving the model continuously, and continuing community participation and education programs. Collaboration with stakeholders and participation in educational programs improves the study's practical use. Responsible sentiment analysis research is assisted by ethical guidelines and best practices, while public awareness efforts foster a culture of responsible social media use during disasters. Open-source contributions, regular impact assessments, and plans for future funding indicate the organization's dedication to long-term relevance and influence in the sector. This comprehensive approach is intended to have a long-term and positive influence on crisis management, community resilience, and ethical research.

CHAPTER 6

SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the Study

The study on sentiment analysis of Bengali social media comments following flood disasters is a detailed study of emotional responses within the online community. Using deep learning models such as Bi-LSTM and CNN, the study evaluates attitudes classified as Fear, Neutral, and Religious. A thorough technique takes into account ethical considerations, privacy protection, and influence reduction. Geospatial and temporal analysis reveal intricate patterns in sentiment dynamics, which aid in disaster response. The study seeks transparency through thorough documentation and understanding its limits. The societal impact includes better informed decision-making, increased public awareness, and improved communication tactics. Ethical considerations highlight the importance of appropriate research techniques. The sustainability strategy specifies strategies for data accessibility, continual model refinement, and continued community interaction, all with the goal of assuring the study's long-term effect in disaster management and ethical sentiment analysis research.

6.2 Conclusions

This study discusses sentiment analysis of Bengali social media comments during flood disasters, using powerful deep learning models to classify feelings as Fear,Neutral or Religious. The study, which is both methodologically sound and morally driven, integrates regional and temporal analysis, revealing intricate patterns that influence disaster response techniques. The societal significance of the research can be seen in its influence on decision-making, public awareness, and communication techniques during catastrophe recovery. The importance of ethical issues, cultural sensitivity, and community involvement cannot be overstated. Through data accessibility, model refinement, and community interaction, the sustainability strategy ensures long-term effect. This study enriches academic discourse while also having practical implications for disaster management, social resilience, and responsible sentiment analysis research in real-world disaster situations.

6.3 Implication for Further Study

The implications for future research due to the sentiment analysis research on Bengali social media comments following flood disasters are broad and far-reaching. They include various types of research, dynamic sentiment tracking at shorter time intervals, and comparative studies of sentiment dynamics during natural disasters. Long-term research that includes social network analysis can reveal long-term effects on feelings and the impact of social connections. Exploring the impact of helping others on sentiments and delving into the temporal aspects of religious sentiments are two areas for focused research. Furthermore, the incorporation of ethical frameworks tailored to sentiment analysis in disaster contexts, as well as the development of real-time sentiment monitoring systems, provide opportunities for advancing research methodologies and applications in this critical field.

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