Emotion Detection from Bangla Text Using Seven Emotion Classes

By

Md Toufiqur Rahman Plabon
Student ID: 211-15-14579

FINAL YEAR DESIGN PROJECT REPORT

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

Supervised By

Mr. Md. Sazzadur Ahamed

Assistant Professor

Department of Computer Science & Engineering

Daffodil International University

Co-Supervised By

Ms. Umme Ayman

Lecturer

Department of Computer Science & Engineering

Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

Dhaka, Bangladesh

January 12, 2025

APPROVAL

This Project titled **"Emotion Detection from Bangla Text Using Seven Emotion Classes"**, submitted by **Md. Toufiqur Rahman Plabon, ID No: 211-15-14579** 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 12 January, 2025.

BOARD OF EXAMINERS

Dr. Md. Fokhray Hossain — **Chairman**
Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Mr. Shah Md. Tanvir Siddiquee — **Internal Examiner**
Assistant Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Mr. Md. Umaid Hasan — **Internal Examiner**
Lecturer
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Nazibur Rahman — **External Examiner**
Technical Lead – Database Administrator
Telenor – Grameen Phone Account

DECLARATION

We hereby declare that this project has been done by us under the supervision of Mr. Md. Sazzadur Ahamed, Assistant Professor, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

Supervised by:

Mr. Md. Sazzadur Ahamed
Assistant Professor
Department of Computer Science and Engineering
Daffodil International University

Co-Supervised by:

Ms. Umme Ayman
Lecturer
Department of Computer Science and Engineering
Daffodil International University

Submitted by:

Md. Toufiqur Rahman Plabon
Student ID: 211-15-14579
Department of Computer Science and Engineering
Daffodil International University

ACKNOWLEDGEMENTS

This work would not have been possible without the support and contributions of many individuals over the past two semesters. We are deeply grateful to everyone who has assisted us in one way or another.

First, we express our heartfelt thanks and gratefulness to the almighty for His divine blessing making it possible for us to complete the Final Year Design Project (FYDP) successfully.

We are grateful and wish our profound indebtedness to **Mr. Md. Sazzadur Ahamed**, Assistant Professor, Department of Computer Science and Engineering, Daffodil International University, Dhaka, Bangladesh. Deep knowledge and keen interest of our supervisor in the field of Deep learning to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting them at all stages have made it possible to complete this project.

We would like to express our heartfelt gratitude to the **Dr. Sheak Rashed Haider Noori** Head of the Department of Computer Science and Engineering, for his kind help in finishing our project and also to other faculty members and the staff of the Department of Computer Science and Engineering, Daffodil International University.

We would like to thank our entire course-mates at Daffodil International University, who took part in this discussion while completing the coursework.

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

ABSTRACT

The focus of this thesis is the categorization of seven emotional states: anger, happiness, surprise, fear, sadness, confusion, and disgust. Additionally, a emotion detection study was carried out in Bangla text. This capability of automatically detecting emotions in text has grown in value with the expansion of digital communication. It can be used in social media analysis, consumer feedback, and mental health assistance. However, the complexity in Bangla morphologically and syntactically rich language are often missed by the existing emotion recognition methods that are mostly built over high resource languages like English. The aim of the study is to develop a classification model that will identify emotion from a single Bangla text sample with high accuracy in overcoming these limitations. A dataset was designed and annotated for the study, and then pre-processing techniques like tokenization, normalization, stemming applied specifically for Bangla. Efficiency in handling classification was tested by several machine learning and deep learning models. Model performance for each category of emotion has been presented with the help of key evaluation measures: precision, recall, F1-score. Confusion matrix is also shown in this paper.

Keywords: Emotion, Bangla Text, Social Media, Machine Learning, Deep Learning, Accuracy

Table of Contents

LIST OF FIGURES

LIST OF TABLES

Chapter 1
Introduction

We have discussed motivations, objectives, briefly methodology, expected outcomes of the project.

1.1 Introduction

Psychologists are studying in “Human Emotion” from the very beginning. It has been an intriguing topic to explore and analyze. Emotion refers to “Subjective Experience, Psychological Response, Behavioral Response.” “Behavioral Response” indicates how the emotions are expressed. “Physiological arousal, expressive behaviors, and conscious experience” are involved with human emotion said by David G [1]. Human interacts with emotions each and every moment. They express emotions with a smile or facial expressions, verbal speech, hand sign or sign language and written text. By the advancement of “Technology” we have to come to this point that we interact with global world through a common platform that is called social media. People are expressing themselves simultaneously and spontaneously. They can express their feelings through video, audio or written text. Emotion detection is easy from video or audio more than written text. Since a written text can convey a wide range of emotions, including anger, sadness, fear, confusion, happiness, disgust, surprise, positivity or negativity. Texting one to one is confidential and it doesn’t have a broad impact. On the other hand, commenting on a post or reviewing on a product can have an influence over others. Millions of data are being generated every day and are guiding us in many ways. These data are being generated based on our emotions. Detecting the right emotion from the data is a significant subject in this era. There has been extensive research conducted on detecting emotions from English corpus. But detecting emotion from Bangla is very few and the accuracy is not satisfactory. But Bengali is the Seventh most spoken native language and seventh most spoken language by the total number of speakers of the world. Millions of people are expressing their emotion though Bengali frequently in their daily life. It is a matter of concern whether their emotion is conveyed to others correctly or not.

This paper aim is to detect “happy, sad, angry, confused, fear, surprise, disgust. Data has been collected from comments on social media, reviews from e-commerce sites. Data has been annotated carefully. Then data has been preprocessed. After that we trained the established model and then tested it. The 1.1 figure describes the activation and deactivation parts of our emotions

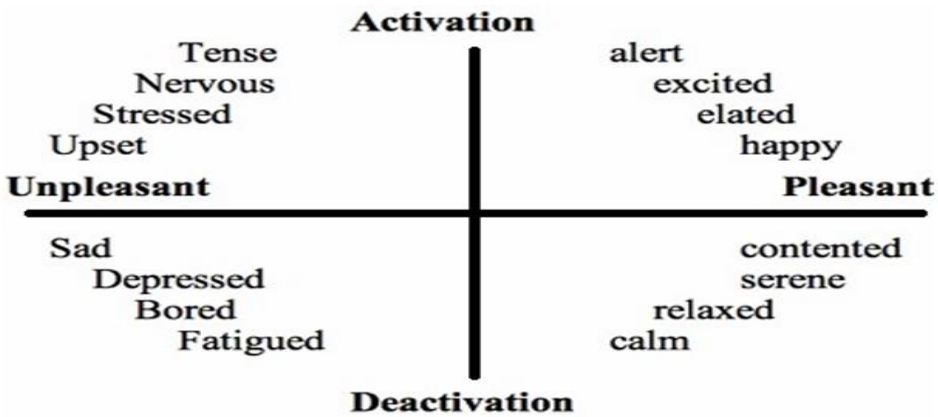


Figure 1.1 The 2D valence arousal model [2]

One of the most important tasks in natural language processing (NLP) is identifying emotions in textual data. This allows for applications in sentiment analysis, customer feedback analysis, mental health monitoring, and more. Emotion recognition for high-resource languages like English has advanced significantly, but because of its particular linguistic and resource limitations, emotion detection for Bangla text confronts a number of difficulties. This study is covering the issues that are mentioned below:

Is dataset collection and annotation done correctly?

How to preprocess the dataset?

Is machine learning doing better or deep learning doing better?

Which model is detecting emotion more accurately?

1.2 Motivation

This rapid development of social media, online communication platforms, and the increased popularity of digital content development has dramatically changed the way in which people communicate their emotions by text. Human communication is saturated with emotions that form relationships, influence decisions, and encounters. Applications such as sentiment-based recommendation systems, mental health monitoring, and consumer feedback analysis now rely heavily on this understanding of emotions. However, while emotion recognition has significantly improved for global languages like English, low resource languages like Bangla lag far behind due to a lack of studies and datasets.

Bangla is the seventh most spoken language in the world and is extremely important on a social, cultural, and economic level. One of the major impediments toward exploiting the full potential of Bangla in various technical breakthroughs is the lack of reliable methods for emotion recognition in writing. Most Bangla sentiment and emotion analysis studies concentrate on binary or coarse-grained sentiment categorization and overlook the intricacy and richness of multiple emotions.

Since real-world text frequently conveys several emotions all at once, such as a mix of sadness and confusion or pleasure and surprise, emotion recognition is most important. This needfully complex understanding is called for in the development of systems that can better perceive human emotions. The motivation for this thesis was therefore to solve the challenges in the detection of emotion in Bangla text, a pressing need in this field. The research work will try to enhance NLP for Bangla and bridge the gap between technology and linguistic variation through proposing a comprehensive framework for the recognition and evaluation of emotions along several dimensions.

1.3 Objectives

The aim of this thesis is to develop a reliable and efficient model for emotion detection in Bangla text. The objective of the work is to identify from textual inputs reliably a number of co-occurring emotional states, which includes anger, happiness, surprise, fear, sadness, confusion, and disgust. This covers to the following:

Creating or selecting a collection of Bangla texts that have been annotated with these feelings.

Investigation and development of the latest natural language processing and machine learning techniques for appropriate classification.

Performance evaluation of the proposed model measuring using common measures such as accuracy, precision, recall, and F1-score to ensure dependability in identifying overlapping emotional categories.

1.4 Methodology

In the methodology section we have discussed how we collected the data and from where we collect the data. After that how we preprocessed the data. How we extract the feature from the data. Then, we applied the machine learning and deep learning techniques on the preprocessed data. We applied different types of models so that we can see the differences and the performance.

1.5 Project Outcome

The creation of an annotated dataset for the Bangla text, including several emotional classes such as fear, sadness, confusion, anger, happiness, surprise, and disgust, can be done. pertinent research papers, techniques, and technologies employed in the industry. The annotated dataset is preprocessed through multiple steps and cross validation is ensured. So, the words that have been preprocessed is in Bangla dictionary. Implying models that can detect emotion more accurately. Every model is applied cautiously. Thus, we can come up with the best model for detection emotion for this annotated dataset. The creation of detailed assessment criteria and standards for the identification of multilabel emotions in Bangla text. This assessment could help in future the researchers.

1.6 Organization of the Report

Our report is divided into six sections. Chapter 1 covered the following issues: study topics, research methodology, research potential, motivation, goal, expected results, and problem description. In chapter two, we discussed nomenclature, gaps in prior studies, and summaries. Chapter 3 included the overview, study methodology, dataset, gamma correction, split, deep learning, data preprocessing, and summary. Chapter Four was supported by Model Analysis, Visualization, Performance Analysis, Evaluation Technique, and Result Discussion. Chapter five presented discussions on the sustainability strategy, the effects on society and the environment, project management and financial analysis, and complicated technical problems. Chapter 6 was closed with discussions of Conclusion, Limitations, Future work.

Chapter 2
Background

In this section the related research background and their contribution and gaps have been discussed

2.1 Introduction

This part helps readers understand the current level of knowledge in the topic and approaches already in use for similar projects. By analyzing related literature, authors can highlight the study's novelty or uniqueness and place its findings within the broader research environment. Natural language processing is a part of Artificial Intelligence which deals with the interaction between computers and human language. We have used raw data. We have classified the data into seven classes. The classes are happy, sad, angry, confused, fear, surprise, disgust. There is no study have been found where these seven classes have been involved for detecting emotion. Deep learning, Machine learning approached have been taken to in this study to detect the emotion from the labeled data. Systems capable of self-improvement from experience, without explicit programming by a subset of artificial intelligence is referred as machine learning. A branch of machine learning that extracts intricate patterns from data by using multi-layered artificial neural networks is referred as deep learning. The background material sets the appropriate context for the data presented in the article. The background of the study arouses the viewer's interest in the issue raised by the findings and shows the importance of the issue.

2.2 Literature Review

Examining pertinent literature enables us to identify any gaps or topics that require more research. The limitations or shortcomings of previous studies may serve as a guidance when formulating research questions or objectives that aid in filling in these gaps. This helps us make sure that their research was worth it and also furthers the field. This subject was made known through numerous languages and forms. Here are a few relevant works that can help us in empowering the concept.

S. Azmin and K. Dhar [3] paper focuses on the use of a Multinomial Naïve Bayes classifier for classifying emotions such as happy, sad, and furious from Bangla text. The relatively unexplored field of emotion recognition in Bangla text is the focus of this work. It presents a machine learning-based method for classifying Bangla comments into three emotion categories by utilizing the Multinomial Naïve Bayes classifier in conjunction with a number of linguistic preprocessing

approaches. This dataset contains 4,200 Facebook post comments. It has been split into 3,780 training samples and 420 test samples. Emotions like happy, sad, and angry were taken into consideration. Part-of-Speech (POS) tagging using a tagger based on Hidden Markov Model. Word n-grams are uni-, bi-, and tri-grams. The best model performed using POS tagging, preprocessing, and bigram-based TF-IDF with an accuracy of 78.6%. The model performed poorly in the "sad" class but was good in the "happy" class due to an imbalanced data distribution.

Rowshan Rahman Rushan et al. [4] paper presents a systematic approach toward the development of a Bangla text emotion detector and associates those emotions with appropriate emojis. The study presents specific objectives, which are collecting a diverse dataset, data preprocessing, and applying multiple machine learning models. It also points out the novelty of the approach, including emoji incorporation and cultural sensitivity in Bangla language emotion recognition. The databases, containing encoded emojis, sentiment labels, and text descriptions, are documented in detail. The approaches to data preprocessing such as EDA, lemmatization, and tokenization are sufficiently explained. Only three emotions are studied in the paper: happiness, sadness, and anger. It would be more complete by including a wider range-for example, fear, surprise, and disgust. Since the majority of the datasets are originating from social media platforms, they may not reflect many situations where Bangla texts are being used. Using Bangla Bert they gain 85% accuracy.

Abdullah Al Jamil , Rifat Rahman[5] analyzes the task of emotion classification using various feature extraction methods and machine learning classifiers on Bangla and other multilingual text data. For emotion-specific multilingual text, the study used Bangla. The machine learning classifiers for identifying emotions like anger, fear, joy, and melancholy in multilingual text, including Bangla, were used. 7,103 samples from the WASSA-2017 dataset which was tagged for four different classes of emotions were used.They extended this to low-resource languages with the addition of a Bangla dataset of 600 manually collected samples. Feature extraction was done on textual data using the Count Vectorization and TF-IDF techniques. The approach they proposed had an accuracy of 74.3% on the Bangla dataset.

Amit Kumar Das et.el.[6] examines the use of deep learning algorithms in order to detect hate speech in Bangla social media texts. The authors have grouped the Bangla social media comments into seven categories, such as hate speech, aggressive comments, religious hatred, ethnic attack, religious comments, political comments, and suicidal comments. It would be performed using an encoder-decoder-based neural network model with an attention mechanism. The authors manually annotated 7,425 Facebook comments into seven categories, including special classes like "suicidal comments. The data was preprocessed using methods like stopword removal, tokenization, stemming, and a custom-designed Bangla Emot Module for emojis and emoticons. This paper utilized 1D Convolutional Neural Networks (CNNs) as encoders to record the text's temporal and spatial relationships investigated three decoder architectures: an attention-based RNN, GRU, and LSTM. The most accurate RNN, attention-based, was 77%.

Shahidul Islam Khan et. el.[7] proposes a traditional statistical approach to ranking terms in a document based on rarity and frequency. A methodology to record the frequency of words present within a document. The models are used in this paper are Random Forest, Linear Support Vector Machines, Naïve Bayes, and Logistic Regression. The data has been labeled into four classes and they are sadness, joy, fear, and anger. The authors have collected 600 samples manually to detect emotions in the Bangla language. The accuracy of the proposed model is 74.3%.

Moshiur Rahman Faisal et el. [8] addresses the challenges of emotion detection in Bengali and Banglish with regard to the complexity of multilingualism and limited language resources. This dataset is an important resource for low-resource NLP, as it contains 80,098 items for each of the six emotions: disgust, fear, joy, sadness, surprise, and anger, in both Bengali and Banglish. Comparison with transformer, DL, and classical ML models set the baseline for further study. BanglaBERT performed best with a weighted F1 score of 71.30% for Bengali and 64.59% for Banglish. The linguistic and cultural variety cannot be represented by data acquired from only YouTube and Twitter. The focus on BanglaBERT and related designs may limit the exploration of other promising approaches.

Md Ataur Rahman, Md Hanif Seddiqui [9] investigates fine-grained emotion classification in Bangla, a low-resource language, focusing on six emotions: sadness, happiness, disgust, surprise, fear, and anger. The corpus contains 6,314 manually annotated Facebook group remarks with a sociopolitical focus. Five methods are explored in depth: K-Means Clustering, Naïve Bayes (NB), Decision Tree (DT), Support Vector Machine (SVM), and k-Nearest Neighbor (k-NN). The best performance was given from the nonlinear SVM (RBF kernel) with a performance of 52.98% accuracy, F1-macro: 0.3324. performance benchmarks were set. Therefore, different preprocessing methods including TF-IDF representation, feature vectors, unigram and n-gram, were tried and tested. Feature extraction included POS tagging, considering tags important for emotions, such as nouns and adjectives. The best model has shown potential for improvement by having a low F1-macro of 0.3324 and modest accuracy of 52.98%, considering the modifications made.

Tahmina Akter et. el. [10] this paper includes some of the ML and DL models for emotion recognition. They are k-NN, Decision Tree (DT), Random Forest (RF), SVM, CNN, and LSTM. Maximum accuracy was obtained by CNN and LSTM with 86% and 85%, respectively, proving to be effective in Bangla text emotion detection. They collected 36,000 Facebook comments in Bangla related to the following six emotional states: joy, sorrow, rage, contempt, surprise, and terror. Indeed, it took a lot of preparation over the quality of the dataset, with tokenization and the removal of noisy information. The features were extracted using word embedding and TF-IDF, gathering statistical and semantic elements from the text. Data was drawn from a single source, Facebook, which may create biases and limited generalizability across Bangla text genres or domains. Though the preprocessing is reliable, feature representation can be further improved by using more sophisticated approaches in languages, such as stemming or domain-specific vocabulary.

Sadia Afrin Purba et el. [11] paper proposes a scheme for document-level emotion detection- "happy", "sad", and "angry " in Bangla text. In this paper, the authors evaluate a new dataset of 995 hand-annotated Bangla documents using ML and DL models: 995 Bangla texts in total divided into 249 for testing and 746 for training. The pre-processing steps include symbol removal, stemming, and stopword removal. For feature extraction, TF-IDF, word embeddings, and count occurrences were used. Some utilised models are CNN, ANN, Multinomial Naïve Bayes, and LR. Among them, Multinomial Naïve Bayes performed best with 68.27% accuracy.

A machine learning technique based approach for sentiment detection is proposed in [12], in this paper they have also analyzed some features but did not actually use them in their research. They performed a binary classification using tf-idf classifier to find out the most informative words and got 83% accuracy using this approach.

A Bangla tweet sentiment polarity detection using word and character n-grams along with Naïve Bayes has been proposed in [13]. Authors also looked at the Sent WordNet feature, which is a lexical resource of sentiment polarity analysis. They classified the tweets using Multinomial NB. Using 1000 training and 500 test data, they achieved 48.5% accuracy.

In another paper [14], a lexicon-based backtracking approach has been used over 301 test sentences for binary emotion classification. In this paper, they first classified the sentiment of the data and then the emotion. The dataset was mainly collected from Facebook status, news headlines, textbook, and direct speech. They claimed an accuracy of 77.16% using this approach.

A good study on emotion tagging has been done on paper [15]. In this paper, authors aimed at doing the manual annotations of sentence-level text from web-based Bengali blog corpus and observed the classification results on the corpus they annotated. With 1200 training instances, The Conditional Random Fields (CRF) classifier gave them an average accuracy score of 58.7% and Support Vector Machine (SVM) managed to get them to 70.4%.

In paper [16] proposes a machine learning-based approach for Bangla text emotion identification. The present study focuses on the much less explored area of emotion recognition for Bengali literature. It outlines a framework for classifying the six primary emotions of fear, surprise, anger, sadness, happiness, and disgust. addressed the dearth of resources in Bangla language processing by creating a special corpus with 1200 tagged samples of Bangla emotions. Techniques for preparing data, including feature extraction and tokenization, are well explained. makes use of feature extraction techniques that are appropriate for the task, such as Bag-of-Words and CountVectorizer. When compared to the Naive Bayes classifiers, SVM outperforms them with an accuracy of 73%.The dataset size is too short, which makes the model not robust and less generalizable (1200 text samples).The system only handles pre-labeled test samples. There is no mention of applying the method to the real world.

The summary of literature review is detailed in Table 2.2.1 below, which we utilized to guide our next steps.

TABLE 2.2.1 SUMMARY OF LITERATURE REVIEW

References	**Year**	**Problem Dealt with**	**Size of image Data Set**	**No. of Classes**	**Algorithm**	**Findings**
This work	Null	Emotion Detection from Bangla Text using seven classes	4102	7	Logistic Regression, RNN, DNN, Multinomial Naive Bayes, Gradient Boosting Classifier, CNN, Bangla Bert	Best Algorithm Model: CNN Accuracy : 88.64%
S. Azmin and K. Dhar [3]	2019	Classify the text into three different classes Happy, Sad, Angry	420	3	Multinomial Naïve Bayes	Best Algorithm Model: Accuracy: 78.6%

Rowshan Rahman Rushan et al. [4]	2024	structured approach to developing a system for detecting emotions in Bangla text and associating them with emojis	9940	3	Random Forest, SVM, Naive Bayes, SGD Classifier, BERT-based Deep Learning	Best Algorithm Model: Bert Based Deep Learning Accuracy: 85%
Abdullah Al Jamil ,Rifat Rahman[5]	2021	Sentiment positive , negative and None, Disgust/Anger, Surprise/Fear	7732	5	BiLSTM, BiGRU, CNN, NB, SVM, RF, DT	Best Algorithm Model: CNN CNN Model Accuracy: 83%
Amit Kumar Das et.el. [6]	2020	Hate Speech Detection	7425	7	CNN, LSTM, GRU	Best Algorithm Model: CNN+ Attention model Accuracy : 77%

Shahidul Islam Khan et. el.[7]	2022	Detecting Anger, Fear, Joy, Sadness	600	4	Logistic Regression, Naive Bayes, LSVM, Random Forest	Best Algorithm Model: LSVM Model Accuracy : 74.3%
Moshiur Rahman Faisal et el. [8]	2024	Detecting emotion from Bangla and Banglish Text	80098	6	Random Forest, Naïve Bayes, CNN, BiLSTM, BanglaBert , XML Roberta	Best Algorithm Model: Bangla Bert Model Accuracy : 71.3%
Md Ataur Rahman , Md Hanif Seddiqui[9]	2019	Comparison of classical machine learning approaches on Bangla texual emotion analysis	6314	6	KNN, Naïve Bayes, Decision Tree, Support Vector Machine, K-means clustering	Best Algorithm Model: SVM Model Accuracy : 52.98%

Tahmina Akter et. el. [10]	2024	Evaluating Machine Learning methods for Bangla text analysis	36000	6	KNN, Decision Tree, Random Forest, SVM, CNN, LSTM	Best Algorithm Model: CNN Model Accuracy : 86%
Sadia Afrin Purba et el. [11]	2021	Document Level Emotion Detection from Bangla Text Using Machine Learning Techniques	995	3	Logistic Regression, Multinomial naive bayes, Artificial Neural Netwrok, Convolutional Neural Network	Best Algorithm Model: Multinomial Naïve Bayes Accuracy : 68.27%

2.3 Gap Analysis

As we can see that there is no study found that has worked on seven classes. Work on sentiment analysis has been done on a vast amount but emotion detection hasn't been done that much. Additionally, the data collection was from single source either YouTube or Facebook or Twitter. But the users are different from every site. So, this is also a gap since age and environment and platform varies a lot and the expression of emotion is also very different.

2.4 Summary

Most of the recent studies on textual emotion recognition implement various machine learning and deep learning-based techniques. While a lot of research is going on in different parts of the world, nothing was known about identification in Bangla texts. The challenge arises with linguistic difficulties, the unavailability of enough annotated datasets, and contextual ambiguity. Recent development with the transformer model and word embedding increased accuracy even for low-resource languages.

CHAPTER 3

Research Methodology

This chapter highlights the research design, methods of data collection, and experimental method adopted for the study. It outlines the methodology and instruments used to achieve accurate identification

3.1 Methodology

It articulates the structured approach for research, involving preparation strategies, model selection, training, and assessment. The section provides a systematic record of methodologies adopted to identify breeds of nuts accurately.

3.1.1 Overview

The methodological section of our study tries to present to the readers in detail all the methods and techniques that have been followed in carrying out the inquiry. In this part of our study, we go into detailed descriptions of the methods that were employed to generate, preprocess, and refine the data that we have in hand. We also provide illustrations of the gathered data and associated procedures. We also discuss the classification problem we want to solve with our proposed model, the specific classification models used, the different levels and their components in these models, and the data set assembled to achieve the best accuracy and minimize the loss. This section presents a detailed and profound analysis of the methods used for information production, preliminary processing, enhancement, graphical representation, and choice and building of categorization frameworks. In such a way, it is possible to solve the current research problem by creating a valid and relevant approach. It was really significant for us to follow the data gathering and data cleansing steps because the process depended on them. In training the classification model, we also faced some challenges as the best strategy for training was tricky to choose.

3.1.2 Proposed Methodology

This is the Methodology we have come up with:

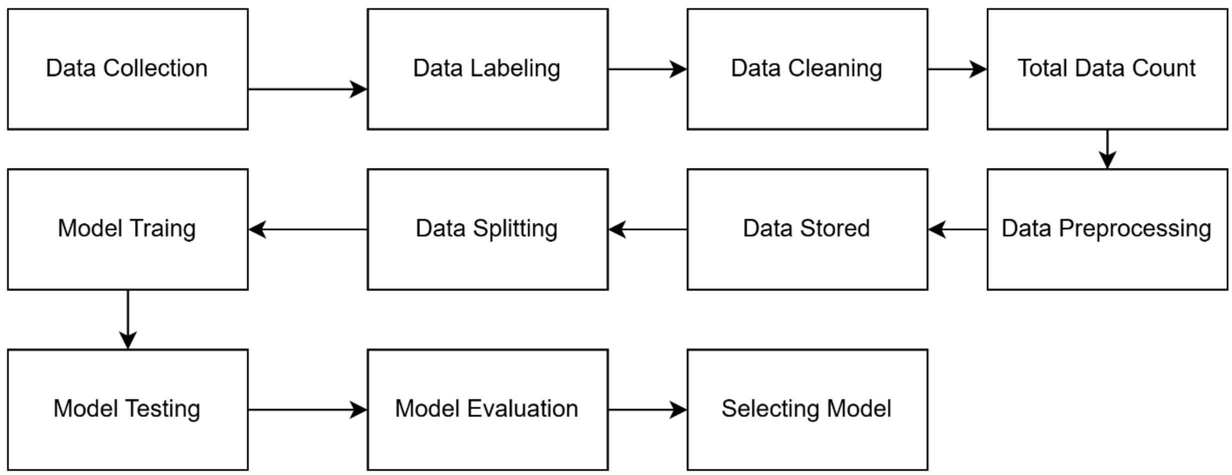


Figure 3.1.2.1 Methodology Process

3.2 Detailed Methodology and Design

3.2.1 Data collection procedure

The dataset collection process for the Bangla text was, therefore, not an end in itself but a means to ensure that the proposed system was robust and reliable. This section describes the step-by-step process adopted to collect, select, and annotate the data required for the research into multilabel emotion recognition in Bangla text.

The text data in Bangla was collected from a wide range of publically accessible sites to ensure that different varieties of language styles, emotional expressions, and settings are covered. Some of the primary sources were:

Social Media: Now a days people convey their emotion more in social media.

Data was collected from Facebook, YouTube.

E-commerce website: Data was collected from customer review given on the products they purchased and used. Daraz, Shajgoj, Chardike.

TABLE 3.2.1.1 SAMPLE COLLECTED DATASET

Sentence	Label
নববধূর জন্য এর চেয়ে সেরা উপহার একজন ক্রিকেটার স্বামীর জন্য আর কি হতে পারে😌😌😌	Happiness
বুদ্ধি জ্ঞান একেবারে শুন্যের কোঠায়	Sadness
ওদেরও বিষ খাওয়ে মার	Angry
এগুলার দরকার কি ?	Confused
রাস্তা দিয়ে হেঁটে যাওয়ার সময় হঠাৎ কুকুর দেখে পিছিয়ে পড়লাম।	Fear
এটা ভাবলেই গা ঘিনঘিন করছে।	Disgust
বিশ্বাসই করতে পারছি না, এটাই সত্যি!	Surprise

3.2.2 Dataset Cleaning

First, we imported the dataset into the 'Google Colab'. Then we extracted some information like how many unique data, how many null values are there. Then it was checked if there is any spelling mistake. After that, we dropped the null value, and spelling mistakes were corrected. After that, we drew a graph.

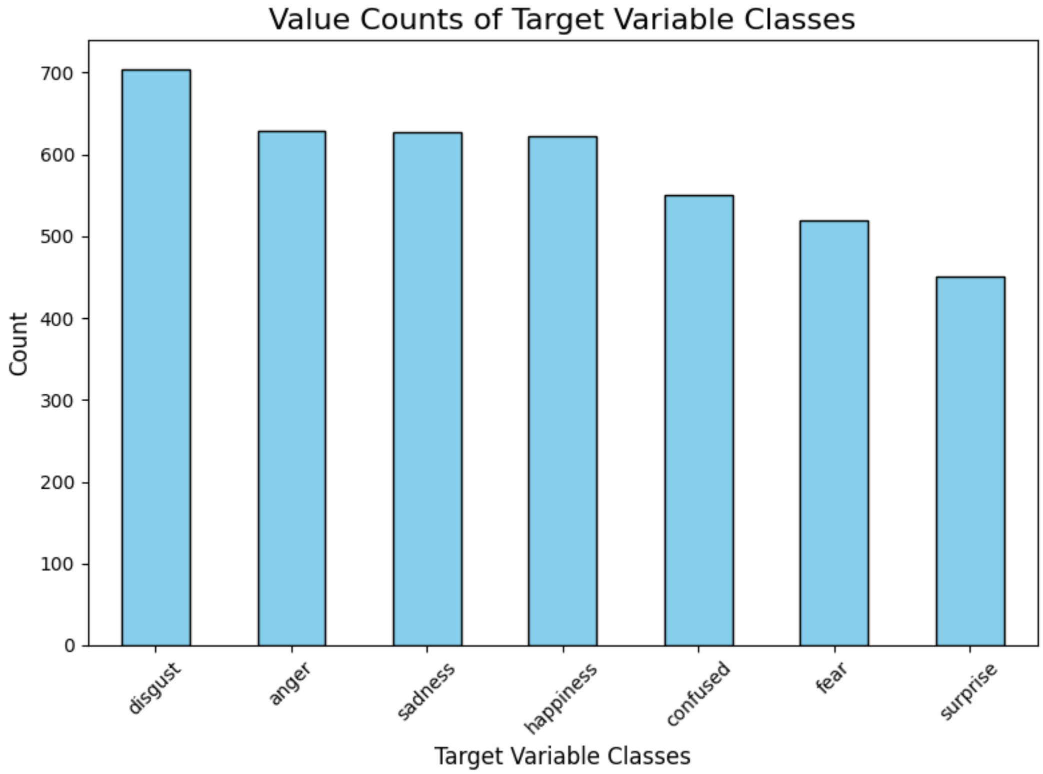


FIGURE 3.2..2.1 DATA COUNT OF SEVEN CLASSES

Table 3.2.2.1 The Final Dataset Table

EMOTION	COUNT
DISGUST	704
ANGER	629
SADNESS	627
HAPPINESS	622
CONFUSED	550
FEAR	520
SURPRISE	450

3.2.3 Dataset Preprocessing

Data preparation is an important phase of the data assessment segment. It involves cleaning, converting, and arranging raw data in a manner to make it ready for evaluation and training models. In Natural Language Processing, the most important part is data cleaning, as the data is not in a shape from which it can be used to train. There is a long process to follow for the data preprocessing step.

Removing Emoji: Pattern recognition was used to remove the emoji at the very first. But after applying Pattern Recognition there were a few emoji left. Then emoji library was used to remove remaining emoji. That's how all the emoji was removed from the cleaned dataset.

Table 3..2.3.1 Cleaned Dataset Table

Sentence	emotion	n_emotion	Cleaned sentence
অনেক হইছে ভাই।এইবার শাটার নামান। 😬	anger	1.0	অনেক হইছে ভাই।এইবার শাটার নামান।
অনেক মজা পাইসি ভাই😂	Happiness	2.0	অনেক মজা পাইসি ভাই
ওই লোকটা মারা গেসে 😢	Sadness	5.0	ওই লোকটা মারা গেসে

Tokenization: Tokenization is the process of breaking down text into smaller units called tokens. These tokens can be words, characters, or even subword units. This process is a basic step for many NLP tasks, such as sentiment analysis, machine translation, and text summarization. From bnlp we used Basic Tokenizer to tokenize. Some of the sentences were not tokenized. Then dataset was tokenized again using NLKT.

Table 3.2.3.2 Tokenized Dataset Table

Cleaned Sentence	Tokenized
হায় হায়, এটা কী হলো!	[হায়, হায়, ,, এটা, কী, হলো, !]
ওরে মা, এমন কিছু আগে কখনো শুনিনি!	[ওরে, মা, ,, এমন, কিছু, আগে, কখনো, শুনিনি, !]
পায়ের উপর পা দিয়ে বসাটা কি ভদ্রতা?	[পায়ের, উপর, পা, দিয়ে, বসাটা, কি, ভদ্রতা, ?]

Stop word, Punctuation, Vowel, Digits, Single Letter removing:

corpus.stopwords: A collection of frequently used Bengali stopwords , such as 'অতএব', 'অথচ', 'অথবা', 'অনুযায়ী', 'অনেক', 'অনেকে', 'অনেকেই', 'অন্তত' and so forth, that are typically omitted from text processing tasks.

Corpus Punctuations: A list of Bengali punctuation symbols. !"#$%&'()*+,-./:;<=>?@[\]^_`{|}~।ঃ

Bengali letters: All Bengali letters are listed in corpus letters. অআইঈউঊঋএঐওঔকখগঘঙচছজঝঞটঠডঢণতথদধনপফবভমযরলশষসহড়ঢ়য়ৎংঃঁ

Bengali Digits: A list of Bengali digits is called corpus digits. ০১২৩৪৫৬৭৮৯

Corpus vowels: A list of vowel characters in Bengali. া ি ী ু ূ ে ৈ ো ৌ

English letter, punctuation, digits remove: After removing Bengali digits, punctuations, vowel, English letters, digits were removed.

Dropping null value: After taking these steps, some null value has been found. Then these null values have been removed.

Cross word validation: The validation of the words is needed since a lot of preprocessing has been done on the dataset. To check if the words are in the Bangla dictionary or not. https://github.com/tahmid02016/bangla-wordlist?tab=readme-ov-file#basic-tokenizer from this link we have validated the preprocessed words. Currently it contains 454650 words and it is sorted. Till now preprocessed words are checked and validation was ensured.

Lemmatization: After doing lemmatization, a few words were found that are not in the dictionary. "লাগে" is a Bangla word. After lemmatizing this word, it becomes "লা." But there is no "লা" in that word list. So, we didn't change it. "বৎসরে" and "বঞ্চিত" couldn't be lemmatized. So, it remained the same.

Stemming: After lemmatization we used Bangla stemmer for stemming. Then the word "লাগে" was turned into "লাগ" . We dropped tha null values after the stemming step.

Feature Extraction: One of the efficient and popular ways for feature extraction in applications regarding emotion detection is TF-IDF vectorization. It means converting unstructured text into structured numerical data, which will be good to go for the machine learning algorithms.

Term Frequency

The frequency of a word within a document is the number of times it occurs. It gives an idea of the meaning of the word in a local sense in a given document.

$$TF(t) = \frac{Total\ number\ of\ terms\ in\ a\ document}{\text{Numbers of times term t appears in a document}}$$

This makes it easier to find terms that appear frequently in a document and gives an indication of how relevant they are to that particular context.

IDF is the frequency of inverse documents:

Considering the word frequency across the entire set of documents of the corpus, the inverse document frequency calculates how much information a word conveys.
Common stopwords and other words frequent in many papers are given lower IDF, while words occurring seldom in many documents are given higher IDF, signifying the higher importance or distinctiveness in the document.

$$IDF(t) = \log(\frac{Total\ number\ documents}{Number\ of\ documents\ containing\ term\ t})$$

Formula :

$$TF\text{-}IDF(t,d) = TF(t,d) * IDF(t)$$

t is the term

d is the document

Data splitting for training and testing: We split the data into two parts for machine learning. They are training and testing. Eighty percent data is used for training and twenty percent data is used for testing. For Deep learning twenty percent data is used for

3.2.4 Logistic Regression

Logistic regression is one of the most popular statistical and machine learning approaches for classification tasks. Despite its name, it is actually a method for binary or multiclass classification rather than a regression method. It predicts the probability that a data point belongs to a certain class by using a logistic (sigmoid) function to model the relationship between the input attributes and the target class.

Logistic Regression model is initiated with a fixed random state and a maximum of 1000 iterations.

Then, the fit() method is used to train it on X_train and y_train.

The predictions are then stored in y_pred_log_reg after the model uses the predict() method to generate predictions for test data that has not been seen, X_test.

If p is the probability that a binary response variable Y = 1 when input variable X= x, then the logistic response function is modeled as:

$$p = P(Y = 1|X = x) = \frac{e^{\beta_1 + \beta_0 x}}{1 + e^{\beta_1 + \beta_0 x}}$$

This function non-linear and a s shaped curved [17] In this training we have set hundred iterations and ranom state is fourty two.

A logistic regression architecture figure is given here.

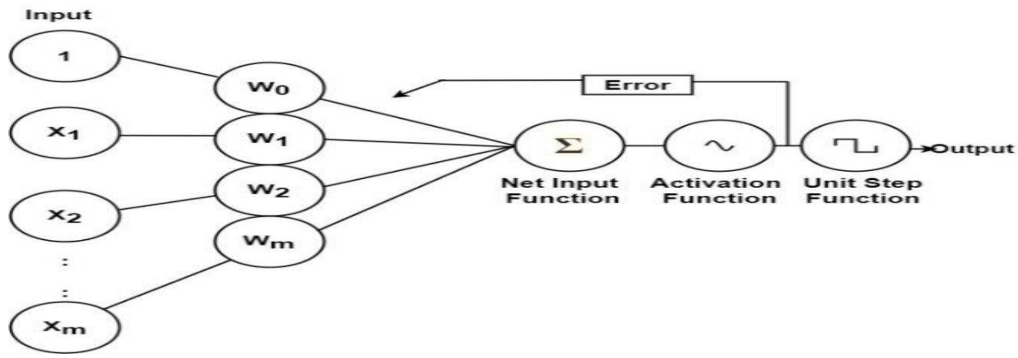


Figure 3.2.4.1 Logistic Regression Architecture

3.2.5 Random Forest Classifier

The Random Forest Classifier is a robust and flexible machine learning algorithm that belongs to the family of ensemble learning techniques. It works particularly well on applications involving both regression and classification. During training, the Random Forest algorithm constructs multiple decision trees and returns a class that is the mean prediction (regression) or the mode of the classes (classification) of the individual trees.

N estimators=100 is the parameter informing about the number of Decision Trees to be constructed in the forest. It is set to 100 in this example, although the larger the value the better the model's accuracy, and it is at the cost of the computing time and other resources.

Random state=42: This ensures reproducibility in the results. By setting a random seed, we ensure that the same split and the same random model selections are returned every time we run the code.
A Random Forest Classifier architecture figure is given here.

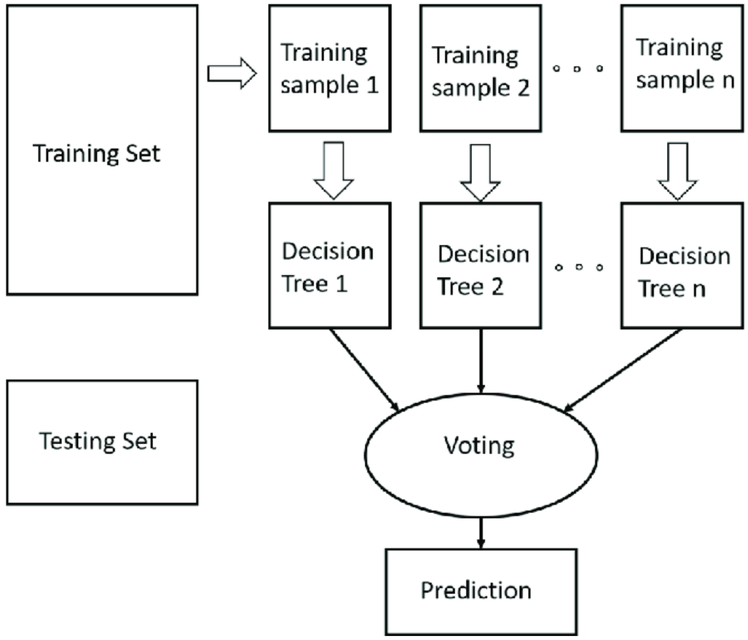


Figure 3.2.5.1 Random Forest Classifier Architecture

3.2.6 Multinomial Naive Bayes Classifier Model

Naïve Bayes is a simple and efficient probabilistic machine learning technique based on Bayes Theorem. It is generally used for classification problems and is particularly popular in NLP for tasks like text classification, sentiment analysis, and spam detection.

X_train: Feature matrix of training data, generally preprocessed text data, for instance word frequency counts or TF-IDF.

y_train: Target labels that match the training data.

The algorithm now calculates the prior probability of each class.

$$P(Y = c) = \frac{\text{Number of samples in class } c}{\text{Total number of samples}}$$

For a particular class, it then determines a feature's probability:

$$P(x_i|Y = c) = \frac{\text{Count of feature } x_i \text{ in class } c + \alpha}{\text{Total count of all features in class } c + \alpha n}$$

The Laplace smoothing parameter prevents zero probabilities to unseen features.

3.2.7 Support Vector Machine

The Support Vector Machine is a popular supervising machine learning approach for classification and regression problems. It performs very well in applications related to image recognition, sentiment analysis, and text classification, especially in high-dimensional areas. SVC: This is the Scikit-learn implementation of the Support Vector Classifier for classification problems. kernel='linear': This suggests that a linear kernel is used by the SVM. The type of decision boundary is determined by a kernel function. random_state = 42. This sets the seed to ensure that any random processes in the model (if any) are reproducible. X_train: Feature matrix of the training set. y_train: Target labels of the training set. The algorithm SVM determines the best hyperplane dividing the data points of various classes with the maximum margin at train time.

3.2.8 Gradient Boosting Classifier

The Gradient Boosting Classifier is an ensemble learning algorithm useful in classification problems. This class of methods leverages multiple weak learners, typically decision trees, to produce a strong predictive model by combining them sequentially. The approach uses gradient descent in a step-by-step minimization of the prediction error to optimize for accuracy.

In classification problems, Gradient Boosting Classifier initiates a Gradient Boosting model. This is an ensemble method in which several decision trees are sequentially added to improve the performance. random_state=42: The random seed is fixed for reproducibility. This ensures that running the same code multiple times will have the same result.

fit(X_train, y_train): Fit the Gradient Boosting Classifier according to the training data.

X_train: The training input feature matrix.

y_train: Target labels for training data.

predict(X_test): Predicting the class labels for test dataset using the trained model of Gradient Boosting, where X_test is called the input feature matrix for invisible data.

3.2.9 CNN

One variant of deep learning, the Convolutional Neural Network or CNN, is designed primarily to analyze data that comes in a structured grid format such as time-series data, images, etc. They are particularly suited to tasks like speech recognition, object detection, picture classification, and natural language processing.

In NLP tasks, the length of the text sequences is often different. Longer sequences are cut down to a certain size, and shorter ones are padded with zeros since neural networks require input sequences of the same size.

Pad sequences: Pads a sequence to a maximum length (maxlen) that is supplied. We have taken the maxlen=100. Ensures that each sequence exactly has 100 tokens. We have taken 128 layers in each convolutional layer. We have taken embedding vector size as 100. To introduce non reality we have used Relu activation. To prevent overfitting we have randomly dropped fifty percent of the Neorons.

A CNN architecture figure is given here.

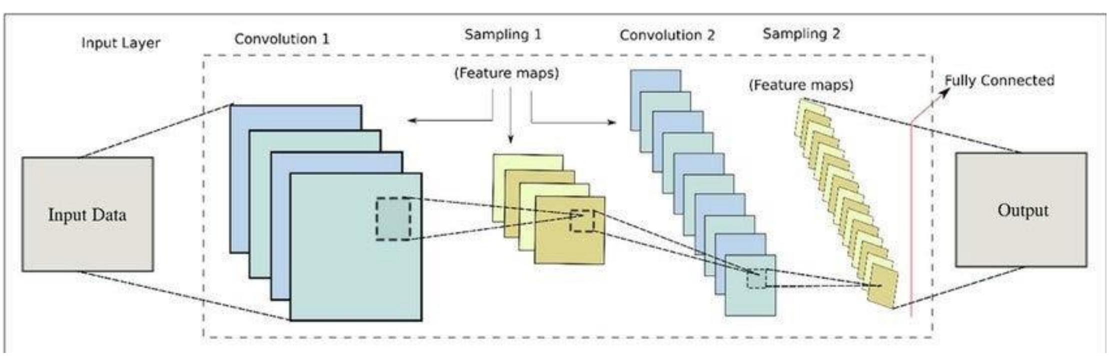


Figure 3.2.9.1 CNN Architecture

3.2.10 Bangla Bert

Bangla BERT is a transformer-based language model that has been specially pre-trained on Bengali (Bangla). Based on the popular BERT concept-which was first presented by Google-Bidirectional Encoder Representations from Transformers, it is built to handle the linguistic subtlety, vocabulary, and syntax of Bangla.

Exchanges Bangla text in the custom dataset Bangla Dataset using the Bangla BERT tokenizer (sagorsarker/bangla-bert-base). Sequences will then be padded or truncated up to a specified length before transformation into PyTorch tensor blocks (max_len= 128). PyTorch DataLoader has been used for batching with shuffling for training and validation datasets. Instantiating and setting up a pre-trained Bangla BERT model for the purposes of sequence classification with seven labels.

The training loop keeps track of progress using tqdm and adjusts weights using the AdamW optimizer. Pre-trained weights are adjusted to fit the particular dataset as the model is fine-tuned over five epochs. A Bangla Bert model architecture figure is given below.

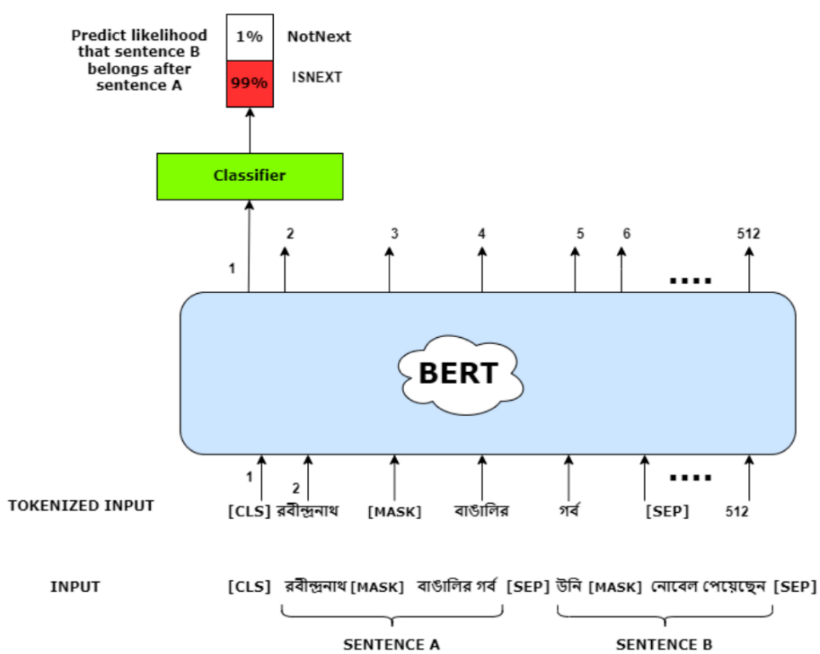


Figure 3.2.10.1 Bangla Bert model Architecture

3.2.11 RNN

One kind of artificial neural network made for sequential data, including time series, text, audio, or video, is called a recurrent neural network (RNN). By preserving a hidden state that records details about prior inputs, RNNs are able to process sequences of different lengths, in contrast to conventional feedforward neural networks.

We used Tokenizer to convert the preprocessed Bangla text data into sequences of numbers. For homogeneity, pads sequences to a pre-specified length: max sequence length=100. We used LabelEncoder to encode categorical target labels (like emotion) into numerical representation. It captures meaningful links by mapping words to dense vectors (embedding_dim=100). A RNN architecture figure is given below.

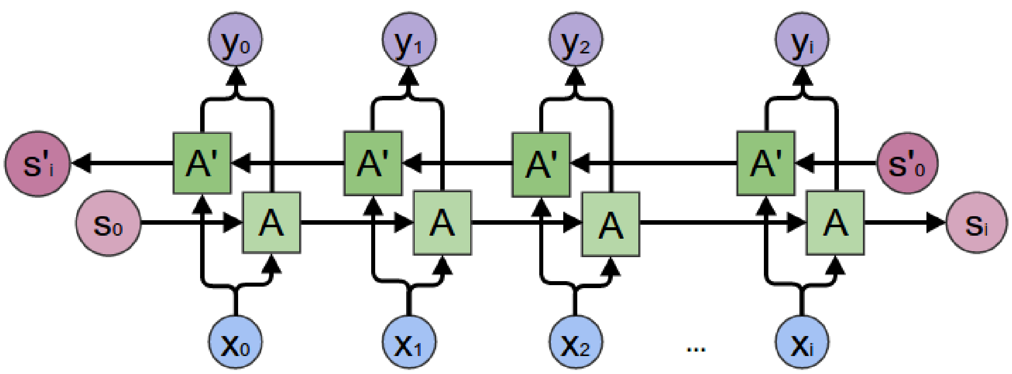


Figure 3.2.11.1 RNN architecture

3.2.12 DNN

A deep neural network (DNN) is a type of ANN that contains more than one layer between the input and output layers. Having a large number of hidden layers enables the network to learn hierarchical patterns from input, thus the name "deep" in this context. DNNs are widely used nowadays in such areas as computer vision, natural language processing, speech recognition, and many more. They form the basis for many complex machine learning tasks.

We used a tokenizer to convert the Bangla language into number sequences. Pad_sequences ensures that the input will have a fixed length, here max_sequence_length=100. We used Label Encoder to convert categorical labels (emotion) into numeric representation. We split the dataset into 20% test sets and 80% training sets. In semantic representation, the word indices are changed into dense word embeddings with size embedding dim=100. ReLU activated dense layers to learn and extract features. Dropout Layers go ahead and randomly turn off neurons while training to avoid overfitting. trains the model, with a batch size of 128, in 10 epochs, monitoring loss and validation accuracy.

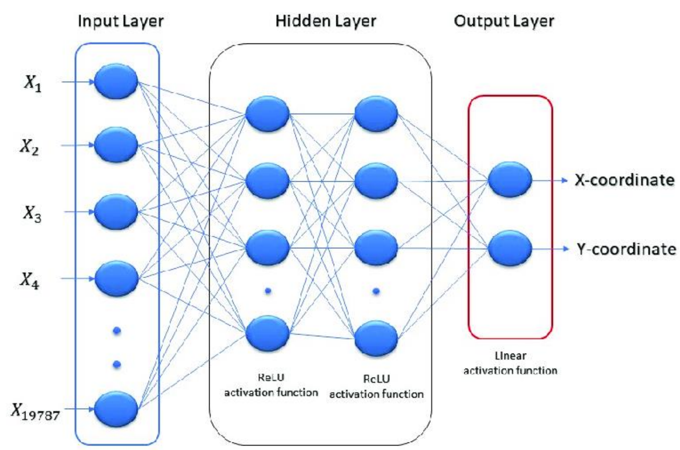


Figure 3.2.12.1 DNN model architecture

3.3 Project Plan

The project plan delineates the organized timetable, resources, and milestones necessary for the effective implementation of this research on nut breed recognitionwith deep learning. It offers a framework to guarantee the methodical advancement of the research while conforming to established objectives and timelines.

Table 3.3.1 Project Plan

Phase	Activities	Duration	Outcome
Phase 1: Problem Identification and Literature Review	What's the problem and how should I solve this. The previous work or paper had been searched or read.	2 weeks	I gained knowledge about the previous paper and had an idea how to proceed in future
Phase:2 Data Collection and Preprocessing	Collecting the data from Social Media, E-Commerce sites and annotation them	4 weeks	A diverse dataset was created
Phase 3: Model Development	We developed nine models	4 weeks	Optimized models for detecting emotion from Bangla Text
Phase 4: Model Evaluation and Analysis	We have evaluate the model And was testing	2 weeks	The performance done by the models
Phase 5: Result Visualization and Documentation	Models result visualization	1 week	Confusion matrix, Training and Validation accuracy and training and validation loss

Phase 6: Finalization and Submission	Revise the paper again and try to find out any mistake	1 week	Submitted the paper to our supervisor

The 3.3.1 project plan table gives us an idea about the time schedule and step by step proceeding towards the goal

3.4 Task Allocation

The thesis had been done only by me. So, I had to all the task all by myself.

3.5 Summary

In this thesis, several machine learning and deep learning techniques were employed for emotion categorization in the Bangla language. It uses some conventional models like Random Forest, Support Vector Machine, Logistic Regression, Gradient Boosting Classifier, and Multinomial Naive Bayes for a baseline comparison. The complex patterns of text were captured using the sophisticated design of CNN, RNN, and DNN. A pre-trained transformer-based model, Bangla BERT, was fine-tuned to enhance the contextual understanding of the Bangla language.

CHAPTER 4

Implementation and Results

In this section we have discussed environment setup , performance, results.

4.1 Environment Setup

Programming Language and Frameworks:

Python : Selected due to the availability of a rich library and framework for machine learning and natural language processing.

Key libraries:

Scikit-learn: Traditional machine learning models such as SVM, Random Forest, Logistic Regression, and Naive Bayes.

TensorFlow/Keras and PyTorch: Deep learning models such as CNN, RNN, DNN, and Bangla BERT.

Jupyter Notebook or Google Colab: For the development and interactive experimentation with the model.

Integrated Development Environment (IDE): Used Visual Studio Code for maintaining project files and debugging.

Hardware

RAM:

At least 16GB is recommended to handle the dataset and model training.

Libraries for NLP:

NLTK, spaCy, and Bangla FastText for preprocessing and embeddings.

Data handling:

Pandas and NumPy for efficient data manipulation and analysis.

Visualization:

Matplotlib and Seaborn for plotting performance metrics analysis results.

Dataset Storage:

The dataset was stored in CSV format, and tools like Google Drive or local disk were used for storage during experimentation. This ensured a well-configured environment in which the implementation of machine learning and deep learning models would be easier to train and evaluate.

4.2 Performance Analysis

The performance analysis is the most crucial part since it will say which model works the best. We have calculate accuracy for each model we applied. We also evaluate the model using F1 score, Precission, Recall. We also determine the confusion matrix.

4.2.1 Accuracy

Accuracy is the ratio of all correctly predicted cases to all cases.

$$Accuracy = (TP + TN) / (TP + FP + FN + TN) \quad (1)$$

4.2.2 Precision

Precision is the ratio of true positive predictions to all positive predictions, including both false

positives and true positives.

$$Precision = TP / (TP + FP) \quad (2)$$

4.2.3 Recall

Recall is the ratio of true positive predictions to the total number of actual positive occurrences, including both

true positives and false negatives.

$$Recall = TP / (TP + FN) \quad (3)$$

4.2.4 F1 Score

F1 Score balances the trade-off between precision and recall by considering their harmonic mean.

$$F1\text{-}Score = 2 \times (Recall \times Precision) / (Recall \times Precision) \quad (4)$$

4.2.5 Confusion Matrix

The confusion matrix is a table that summarizes the performance of a classification algorithm. It displays the counts of TP, FP, TN, and FN. The CM helps visualize how well the model is distinguishing between classes and it gives insights into specific areas where the model might be making errors.

4.3 Results and Discussion

We applied both deep learning and machine learning model to detect emotion from Bangla text.

A table is given that is showing accuracy, precision, recall, F1 score :

TABLE 4.3.1 Performance Analysis Metrics

Model	Types	Accuracy	Precision	Recall	F1 Score
Logistic Regression Model	Macro Avg Weighted Avg	69	70	69	68
Random Forest Classifier	Macro Avg Weighted Avg	73	74	73	72
Multinomial Naïve Bayes	Macro Avg Weighted Avg	66	70	66	66
SVM	Macro Avg Weighted Avg	71	72	71	71

Gradient Boosting Classifier	Macro Avg Weighted Avg	69	71	69	69
CNN	Macro Avg Weighted Avg	89	88	89	88
Bangla Bert	Macro Avg Weighted Avg	86	86	86	85
RNN	Macro Avg Weighted Avg	88	88	88	88
DNN	Macro Avg Weighted Avg	87	88	87	87

We will be visualizing the machine learning model and deep learning model results.

4.3.1 Logistic Regression

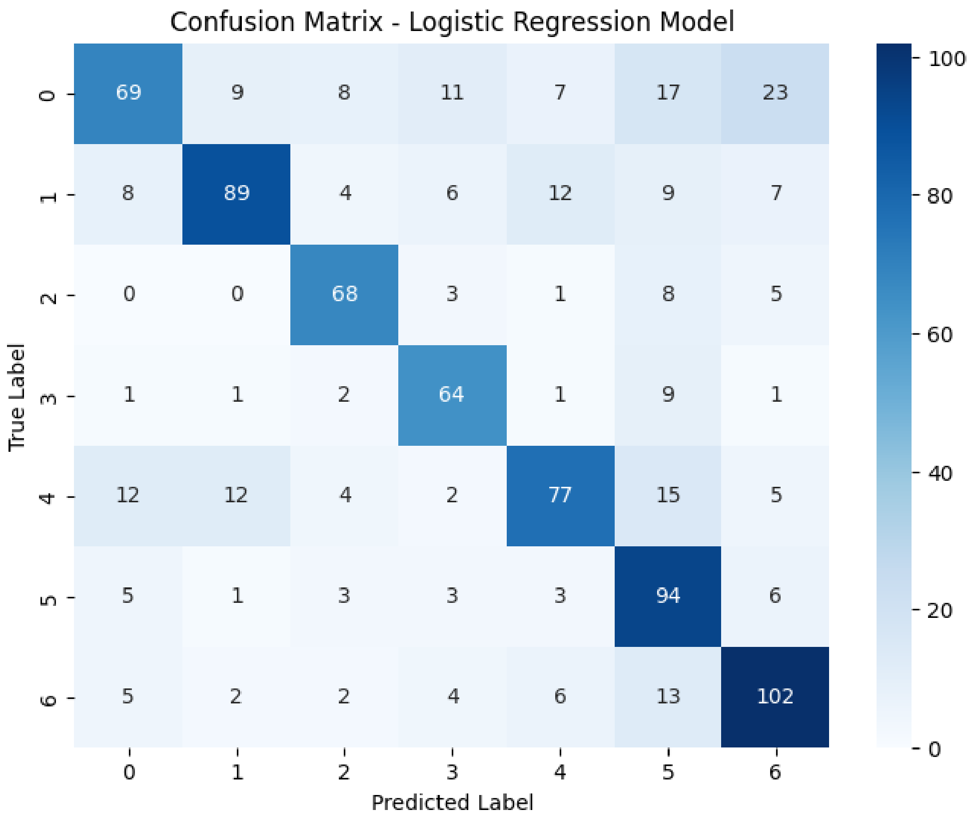


Figure 4.3.1.1 Confusion Matrix Logistic Regression

4.3.2 Random Forest Classifier

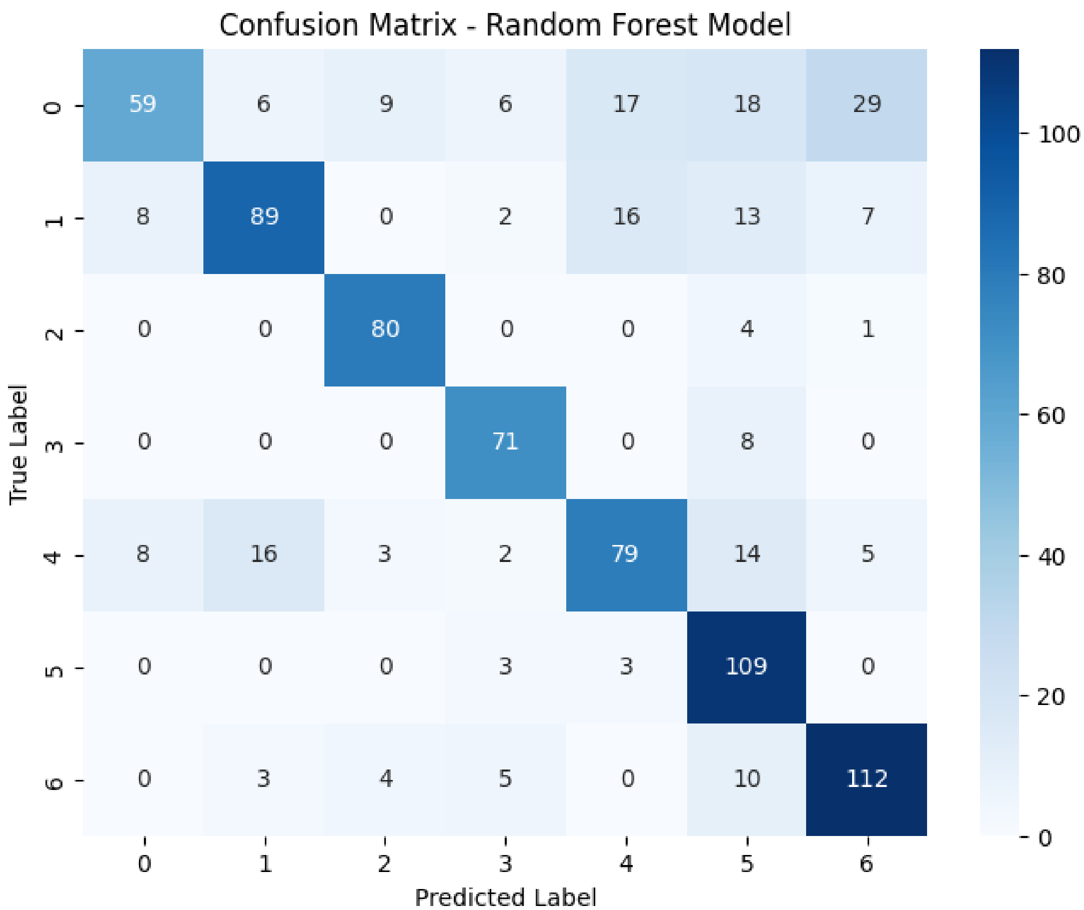


Figure 4.3.2.1 Confusion Matrix Random Forest Classifier

4.3.3 Multinomial Naïve bayes

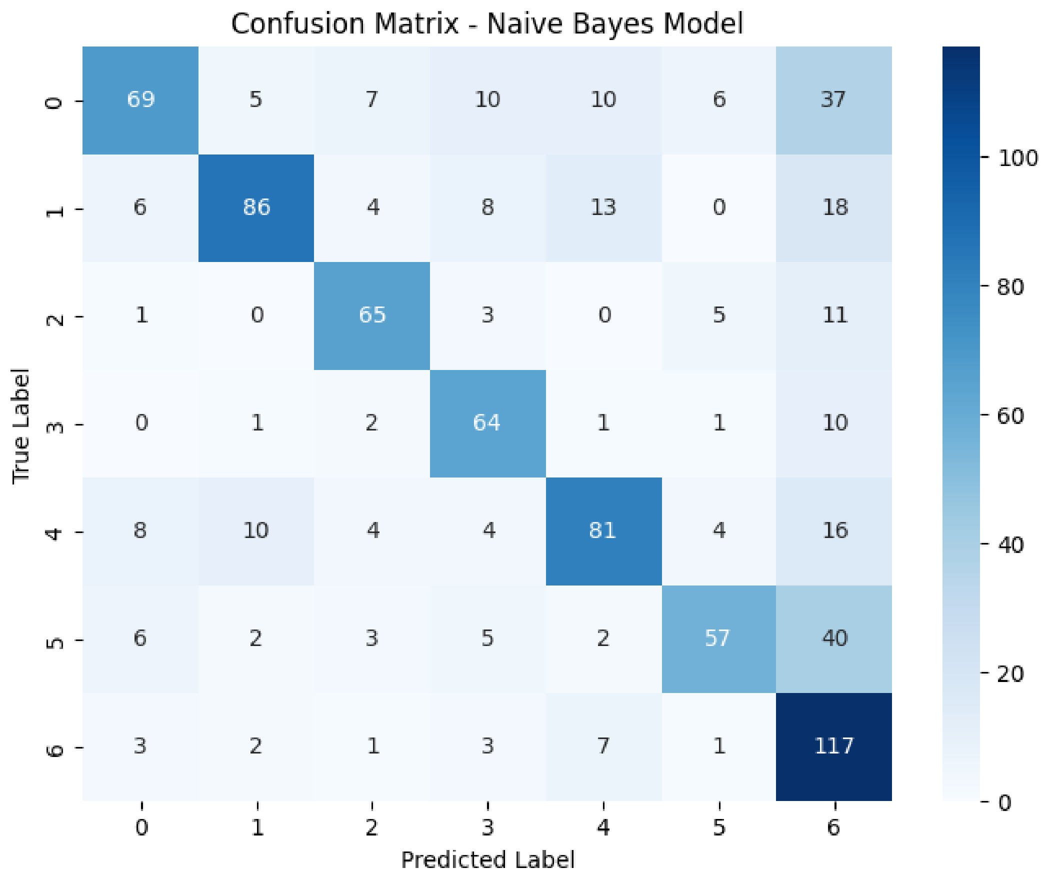


Figure 4.3.3.1 Confusion Matrix Multinomial Naïve bayes

4.3.4 SVM Model

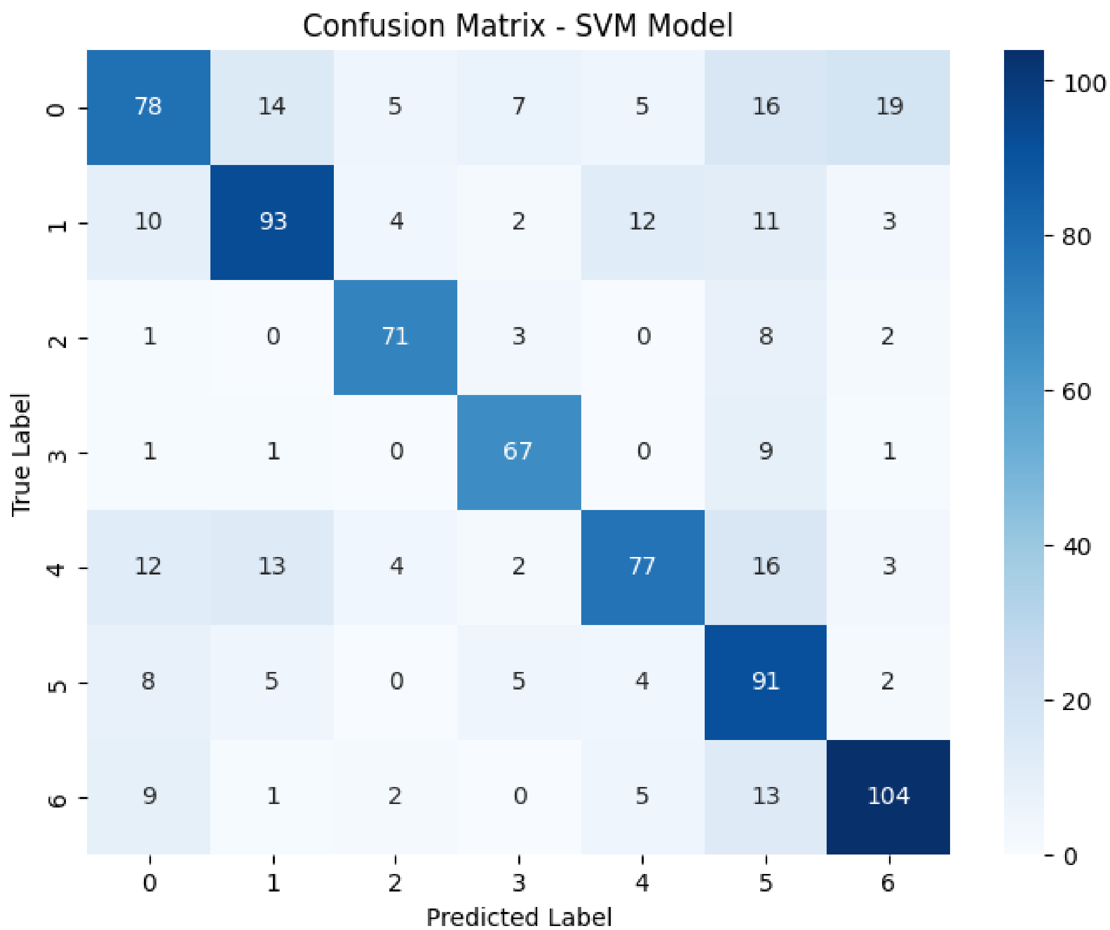


Figure 4.3.4.1 Confusion Matrix SVM Model

4.3.5 Gradient Boosting Model

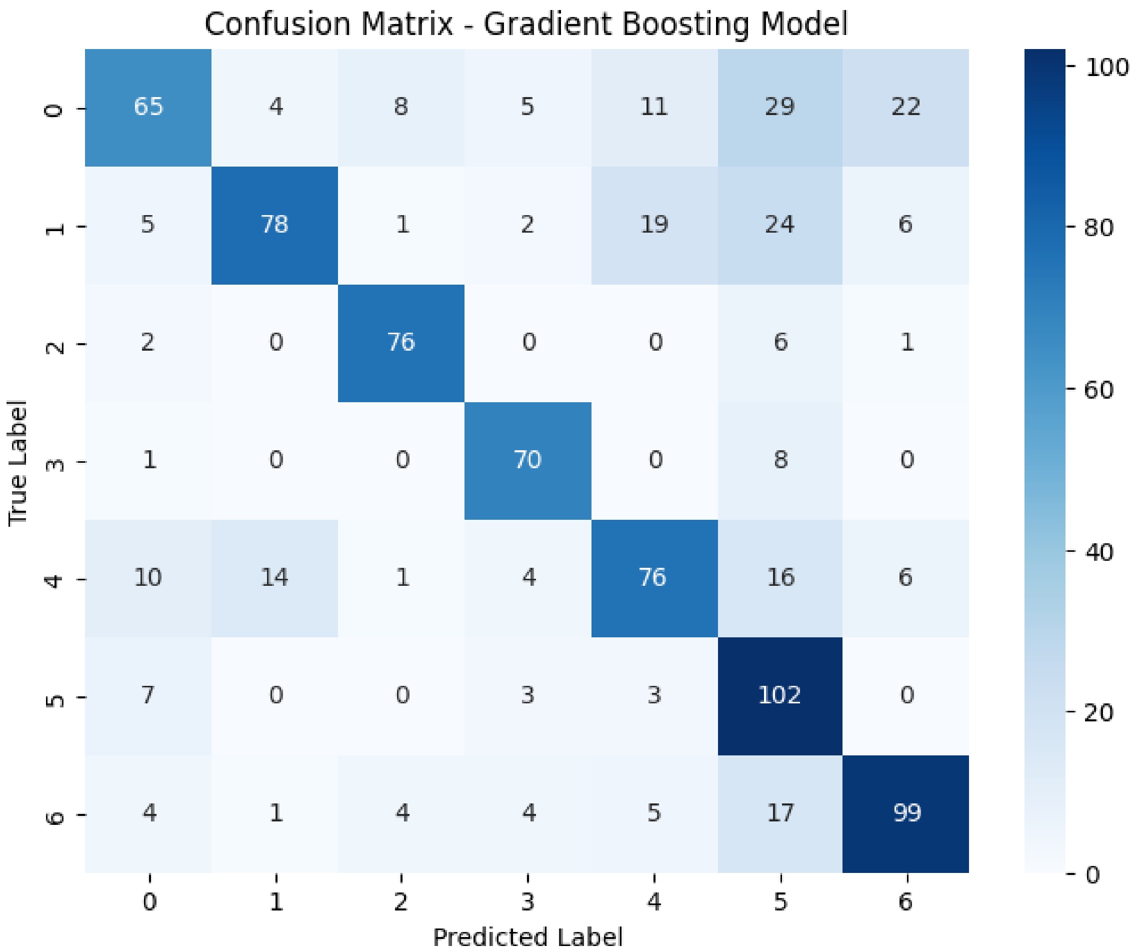


Figure 4.3.5.1 Confusion Matrix Gradient Boosting Model

4.3.6 CNN

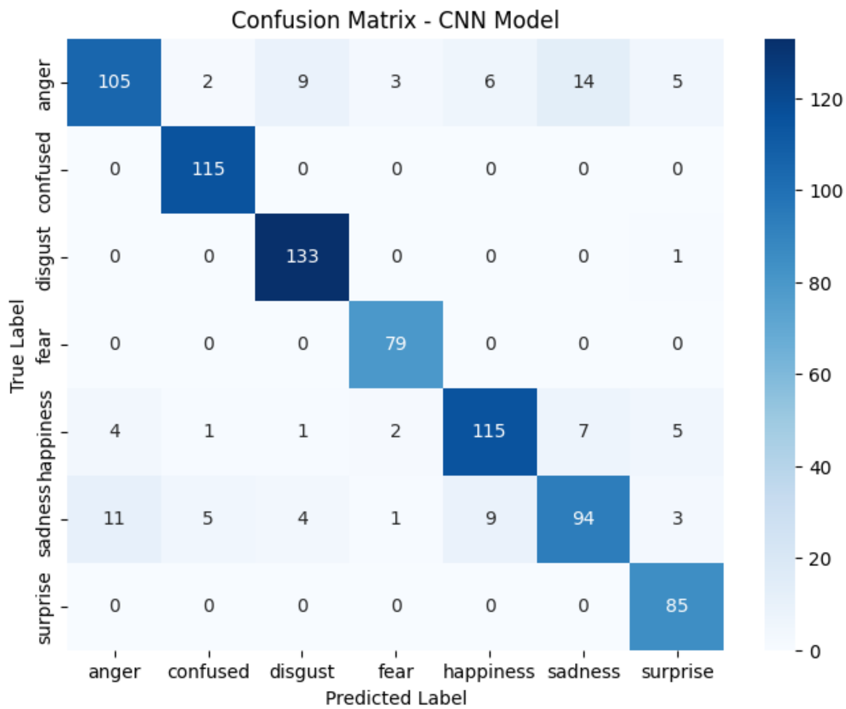
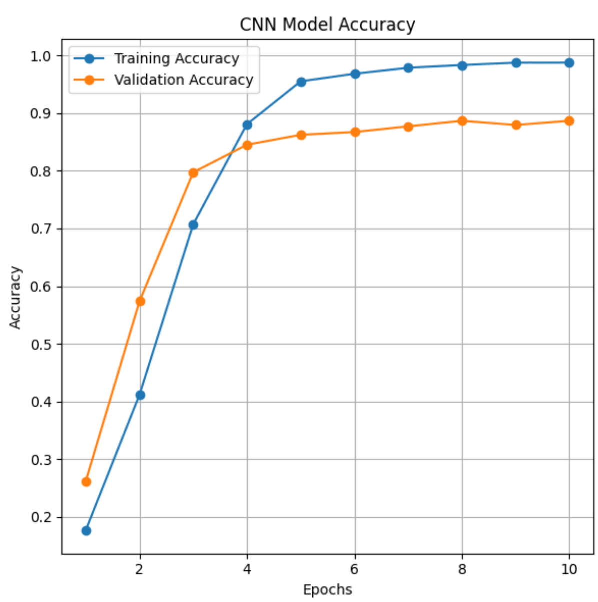


Figure 4.3.6.1 Confusion Matrix CNN Model



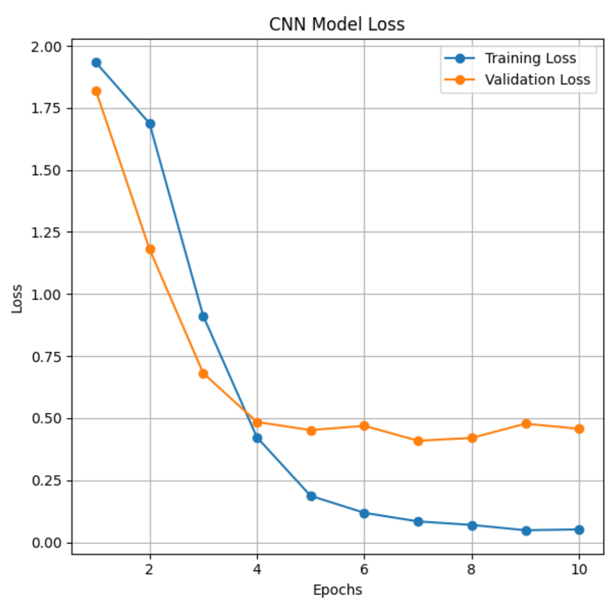


Figure 4.3.6.2 CNN Training and validation Accuracy

Figure 4.3.6.3 CNN Model Training and validation loss

4.3.7 Bangla Bert

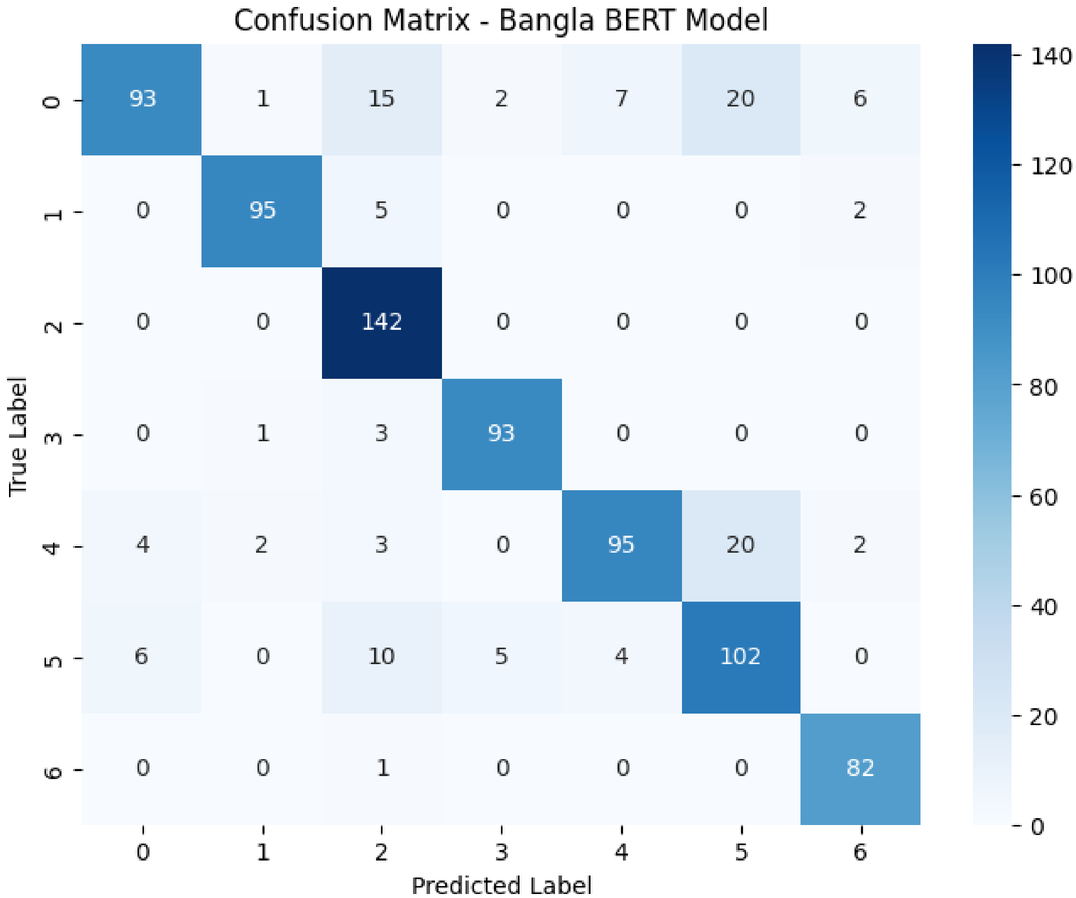


Figure 4.3.7.1 Bangla Bert Confusion Matrix

4.3.8 RNN Model

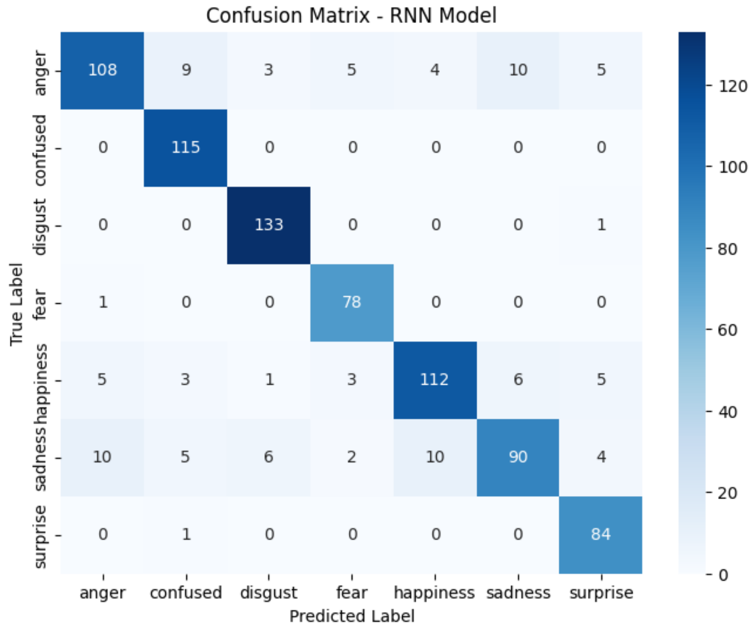
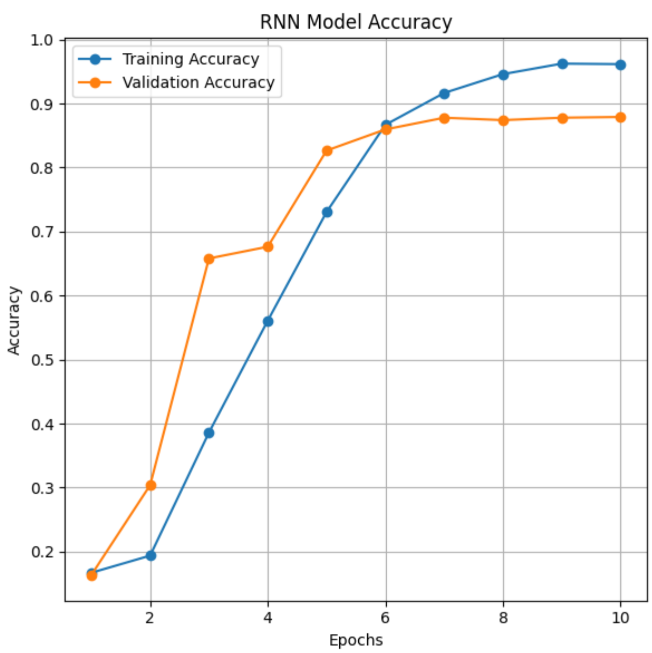


Figure 4.3.8.1 RNN confusion matrix



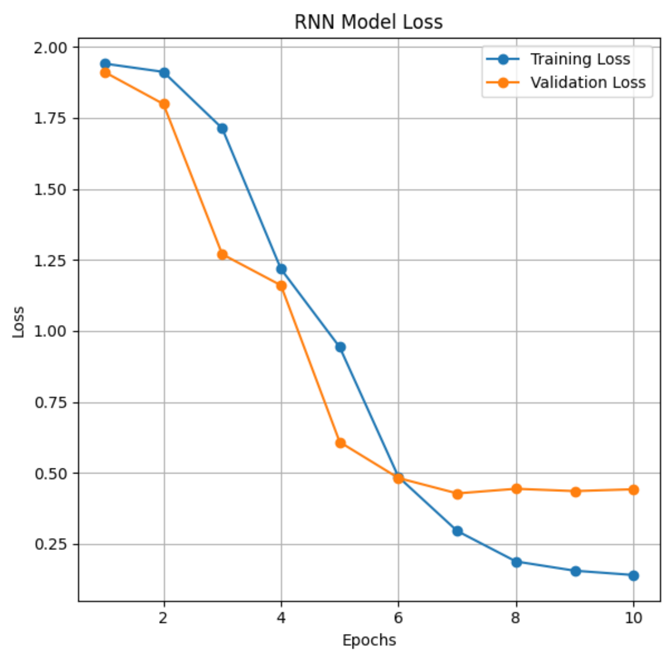
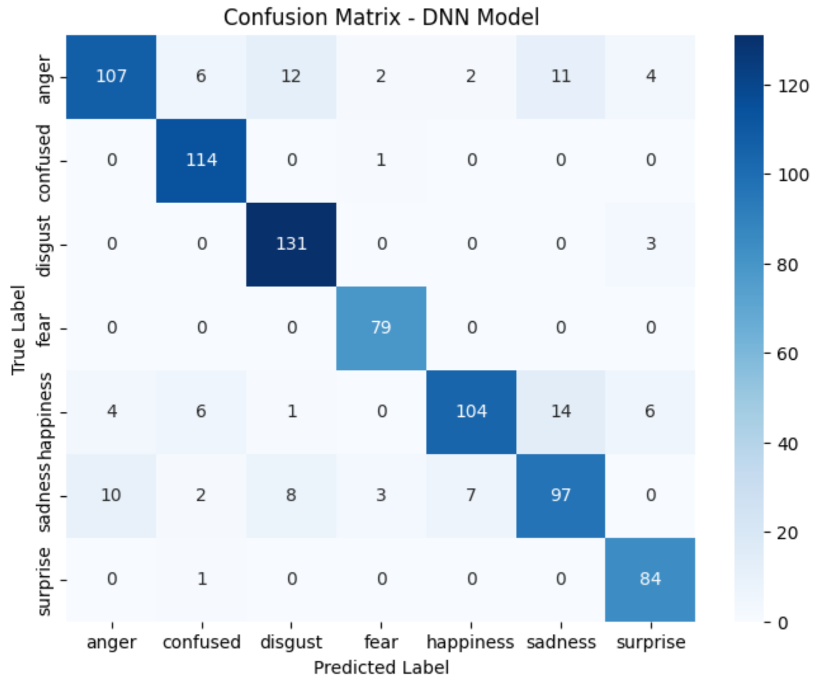


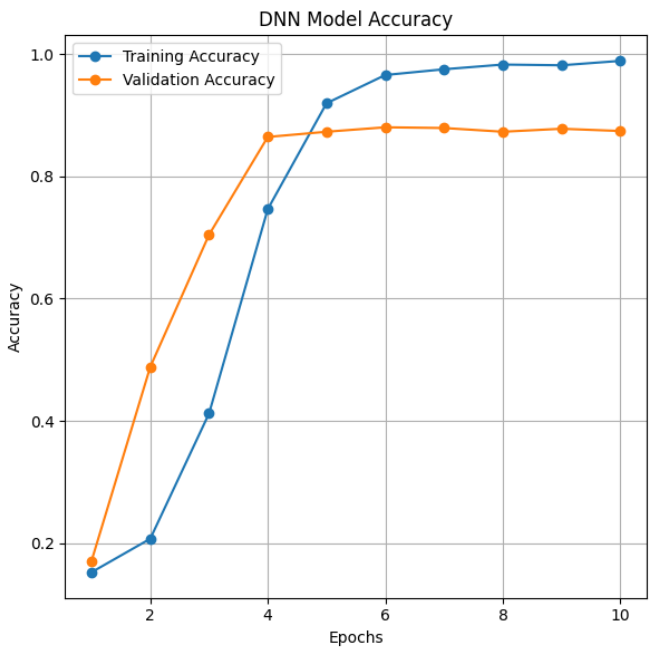
Figure 4.3.8.2 RNN Training and Validation Accuracy

Figure 4.3.8.3 RNN Training and Validation Loss

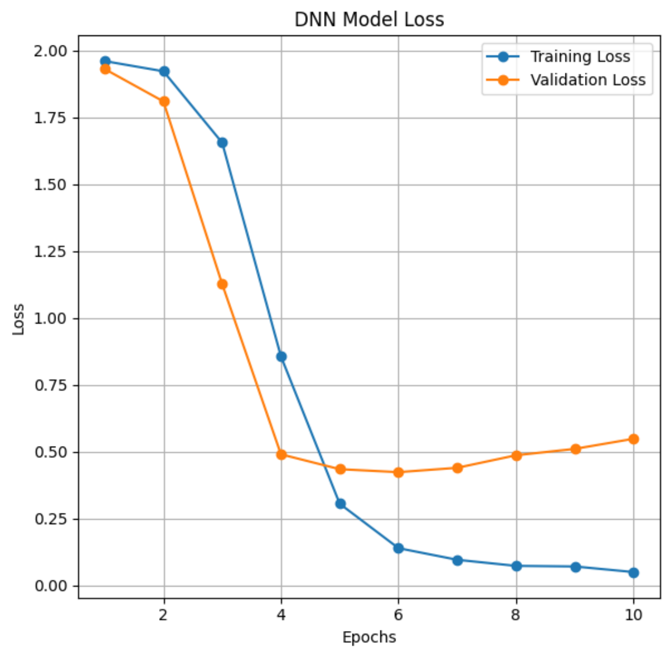
4.3.9 DNN Model



4.3.9.1 DNN Model Confusion Matrix



4.3.9.2 DNN Model Testing and Validation Accuracy



4.3.9.23 DNN Model Testing and Validation Loss

4.4 Summary

We have demonstrated the models result, F1-score, Precision, Recall, Confusion matrix in this section. CNN model gave us the highest accuracy. Overall, deep learning model is performing better than the machine learning models. We have shown training and validation accuracy for all the deep learning model applied here except Bangla Bert. We have also shown the training and validation loss of all the deep learning model applied here except Bangla Bert. Logistic regression, Random Forest Classifier, Multinomial Naive Bayes, SVM, Gradient Boosting Classifier, CNN, Bangla Bert, RNN, DNN accuracy respectively is 69%, 73%, 66%, 71%, 69%,89%,86%, 88%, 87%. The second highest accuracy we got from RNN.

CHAPTER 5

Engineering Standards and Design Challenges

In this section we have discussed about the engineering standards and design challenges.

5.1 Compliance with the standard

The Bangla text emotion detection system provides several benefits in terms of societal, environmental, and ethical impact while contributing to the need for sustainable practices. This section will discuss its broader implications and outline a sustainability plan.

5.1.1 Communication Standards

For this thesis paper I had to consult with a psychologist for annotation validation.
Thus, I had to communicate with the psychologist. I had to discuss with my supervisor for conducting this thesis paper.

5.2 Impact on society, Environment & Sustainability

5.2.1 Impact on Life

Mental Health Support: The system can help in the identification of emotions in Bangla text on social media or chat platforms, which could help identify signs of mental distress, anxiety, or depression; thus, enabling timely interventions that can save lives.
Improved Communication: It will allow machines to understand human emotions in Bangla, hence allowing better interaction in applications such as chatbots and virtual assistants. This will help improve user satisfaction and experience.
Educational Tools: The system can aid in creating emotion-aware educational tools, enhancing emotional intelligence and language learning among Bangla-speaking

individuals.

5.2.2 Impact on Society, Environment

Empowering Bangla Speakers: This research addresses the linguistic gap in NLP technologies, providing Bangla-speaking communities with tools that resonate with their language and cultural context, fostering inclusivity in technology.

Social Media Analysis: This will, in turn, analyze the sentiments and emotions of the general public in Bangla texts and help organizations and policymakers to understand the societal mood in various issues and address those issues effectively.

5.2.3 Ethical Aspects

Data Privacy: Emotion detection systems should handle user data in a secure and ethical manner. Data anonymization and data protection according to GDPR are crucial for building user trust.

Bias Mitigation: Making sure the model is fair to avoid amplifying biases present in the training dataset. This includes dealing with linguistic and cultural biases pertaining to Bangla.

Transparency and Accountability: Explanations of model predictions give transparency and allow users to trust the system, which is extremely important in applications like mental health or social media monitoring.

5.2.4 Sustainability Plan

Community Involvement: Involve the Bangla-speaking communities in the improvement cycle of the system through contributions of annotated data and feedback. This will keep the system relevant and inclusive.

Scalability and Accessibility: Develop this system into a cloud-based service; this will give the benefit of scalability to users like institutions of education, health sectors, or social platforms.

5.3 Project Management and Financial Analysis

For this project management we have calculated our budget. This is is the table given below:

Primary Budget:

TABLE 5.3.1 PRIMARY BUDGET

Category	**Details**	**Cost (Taka)**
Stake Holders	To verify the labeled data we need to visit a psychologist	1000 tk
Expert Help	Taking advices from an expert	2000 tk
Total		**3000 tk**

Alternate Budget:

TABLE 5.3.2 ALTERNATE BUDGET

Category	**Details**	**Cost (Taka)**
Stake Holders	To verify the data from my University psychologist	0
Expert help	Taking advices from an expert	1000
Total		**1000 tk**

5.4 Complex Engineering Problem

Complex engineering challenges often include related problems that need high-level technical knowledge, multidisciplinary collaboration, and creative solutions. The outcome of these kinds of problems is mostly unexpected, which needs rigorous research, design, and validation. This paper represents the first deep learning-based agriculture application for nut breed identification, integrating image processing with agricultural expertise to address real-world issues.

5.4.1 Complex Problem Solving

TABLE 5.4.1.1 Mapping with complex problem solving.

EP1 Depth of Knowledge	**EP2** Range of Conflicting Requirements	**EP3** Depth of Analysis	**EP4** Familiarity of Issues	**EP5** Extent of Applicable Codes	**EP6** Extent of Stakeholder Involvement	**EP7** Interdependence
✔	✔	✔				✔

EP1 Depth of Knowledge: We had to go through multiple previous works to understand our work better and how to improve our work. Thus, we gained deep knowledge in this area.

Ep2 Range of Conflicting Requirements: I have studied in Computer Science and Engineering. I am implying machine learning and deep learning here. But I am doing research on emotion. That is psychology area.

Depth of Analysis: A vast amount of analysis had to be done to do this thesis paper.

Interdependence: As I have said earlier, I had to study previous papers to know my work in details.

Mapping with Knowledge Profile for EP1

TABLE 5.4.1.2 Mapping with knowledge Profile (EP1)

K3 Engineering Fundamentals	**K4** Specialist Knowledge	**K5** Engineering Design	**K6** Engineering Practice	**K8** Research Literature
✔	✔	✔		✔

K3 (Engineering Fundamentals): Machine Learning and Deep learning models have been applied on the dataset.

K4 (Specialist Knowledge): An expert has verified the data.

K5(Engineering Design): In methodology the proposed diagram have been shown that is used to detect emotion from Bangla text.

K8 (Research Literature): To do this thesis paper we had to go through previous research papers.

Mapping with Knowledge Profile for EP3

TABLE 5.4.1.3 Mapping with knowledge Profile (EP3)

K2 Mathematics	**K3** Engineering Fundamentals	**K4** Specialist Knowledge	**K5** Engineering Design
✔	✔	✔	✔

K2 (Mathematics): To find out the accuracy we had to calculate the precision, recall, F1 score.

K3 (Engineering Fundamentals): We have used deep learning and machine learning in this thesis paper.

K4 (Specialist Knowledge): We have taken an expert approval that our labeling data is correct.

K5 (Engineering Design): In methodology the proposed diagram have been shown that is used to detect emotion from Bangla text.

Mapping with Knowledge Profile for EP7

TABLE 5.4.1.4 Mapping with knowledge Profile (EP7)

K1 Natural Sciences	**K2** Mathematics	**K3** Engineering Fundamentals	**K4** Specialist Knowledge	**K5** Engineering Design	**K6** Engineering Practice	**K8** Research Literature
	✔	✔	✔	✔		✔

K2 (Mathematics): To find out the accuracy we had to calculate the precision, recall, F1 score.

K3 (Engineering Fundamentals): We have used deep learning and machine learning in this thesis paper.

K4 (Specialist Knowledge): We have taken an expert approval that our labeling data is correct.

K5 (Engineering Design): In methodology the proposed diagram have been shown that is used to detect emotion from Bangla text.

K8 (Research Literature): To do this thesis paper we had to go through previous research papers.

5.4.2 Engineering Activities

Table 5.4.2.1 Mapping with complex engineering activities

EA1 Range of resources	**EA2** Level of Interaction	**EA3** Innovation	**EA4** Consequences for society and environment	**EA5** Familiarity
✔	✔		✔	✔

EA1: To conduct this paper variety of resources needed. Previous thesis paper, GPU, dataset.

EA2: To complete this thesis we had to come across supervisor and to verify the data we need to contact with a psychiatrist.

EA4: It has a contribution to society. To study about mental situation this study could help in the future.

5.5 Summary

This thesis reflects such an interdisciplinary element of Emotion Recognition in Bangla Text by effectively combining the effort of machine learning with psychological knowledge to look into difficult engineering problems. In this thesis, careful examination of previously related works and their contribution, deep learning-based model, and methods, precision computation, recall, and F1-score, come into play to construct such a system design that a suggested engineering design diagram here is verified for its accuracy of labeling. The study utilized several resources such as GPUs, datasets, and expert collaboration. This work shows the societal benefit, especially in mental health research. The study also reflects interdisciplinary cooperation in resolving the competing demands from the field of psychology and computer science.

CHAPTER 6

Conclusion

We have discussed the whole summary , limitation and future work in this section.

6.1 Summary

In this thesis, we have explored the problem of emotion detection from Bangla text, with a focus on addressing the challenges associated with low-resource languages. Through a thorough review of existing methodologies and the implementation of state-of-the-art techniques, we have developed a robust framework for single-label emotion classification. By combining both classical machine learning algorithms and modern transformer-based models, we have showcased the efficacy of these approaches to capture the nuances of Bangla emotions. The results here indeed confirm that a high-quality dataset, advanced feature extraction techniques, and contextual embeddings improve the performance of Bangla emotion detection.

6.2 Limitation

Despite these promising results, there were some limitations to this study. Because most Bangla datasets originate from a few sites, including blogs or social media, the breadth and diversity of the datasets used were limited. This, in turn, limits the capacity of the models to be applied under different situations. Moreover, the model's capacity to predict all emotions equally was affected by the unequal distribution of emotion categories in the datasets. While transformer-based models did perform well, they came with some defects, especially in low-resource settings, since they are so computationally expensive and require much training data. Though we have collected data manually but it was not enough, we need more data to measure more accurately. We have detected a single emotion at a time. But one sentence can express multiple emotion at a time. Right now, we haven’t developed an application.

6.3 Future Work

Future study can overcome these constraints by compiling bigger and more varied datasets covering a greater variety of Bangla text sources and emotional settings. The application of emotion detection algorithms may be further improved by developing domain specific datasets, such as those focusing on the customer service, medical, or educational fields. Further, investigating sophisticated architectures, such as pre-trained transformer models focused on Bangla, and using multimodal data, such as text combined with audio or visual inputs, could result in better performance and robustness. Another exciting future research direction is to expand into cross-lingual emotion recognition systems for Bangla and other South Asian languages.

REFERENCE

[1] D. G. Myers, Theories of Emotion, 7th ed. New York, NY, USA: Psychology Press, 2004.

[2] S. A. Hosseini, "Classification of Brain Activity in Emotional States Using HOS Analysis," February 2012.

[3] S. Azmin and K. Dhar, "Emotion Detection from Bangla Text Corpus Using Naïve Bayes Classifier," 2019 4th International Conference on Electrical Information and Communication Technology (EICT), Khulna, Bangladesh, 2019, pp. 1-6

[4] R. R. Rushan, S. Hossain, S. S. Shovon, and M. A. Rahman, "Emotion Detection for Bangla Language.

[5] H. A. Ruposh and M. M. Hoque, "A Computational Approach of Recognizing Emotion from Bengali Texts," 2019 5th International Conference on Advances in Electrical Engineering (ICAEE), Dhaka, Bangladesh, 2019, pp. 1-6.

[6] A. K. Das, A. A. Asif, A. Paul, and M. N. Hossain, "Bangla Hate Speech Detection on Social Media Using Attention-Based Recurrent Neural Network," Journal of Intelligent Systems, vol. 30, no. 1, pp. 525–540, 2021. doi: 10.1515/jisys-2020-0060.

[7] S. I. Khan, F. Bin Aziz, and M. U. Uddin, "Emotion Detection from Multilingual Text and Multi-Emotional Sentence Using Difference NLP Feature Extraction Technique and ML Classifier," International Journal of Advanced Networking and Applications, vol. 14, no. 3, pp. 5429–5435, 2022. ISSN: 0975-0290.

[8] M. R. Faisal, A. M. Shifa, M. H. Rahman, M. A. Uddin, and R. M. Rahman, "Bengali & Banglish: A Monolingual Dataset for Emotion Detection in Linguistically Diverse Contexts," Data in Brief, Available online: http://www.elsevier.com/locate/dib, July 20, 2024.

[9] M. A. Rahman and M. H. Seddiqui, "Comparison of Classical Machine Learning Approaches on Bangla Textual Emotion Analysis," arXiv preprint arXiv:1907.07826, Jul. 2019

[10] T. Akter, M. S. Akter, T. Mahmud, D. Islam, M. S. Hossain, and K. Andersson, "Evaluating Machine Learning Methods for Bangla Text Emotion Analysis," 2024 Asia Pacific Conference on Innovation in Technology (APCIT), 2024, pp. 1–6, doi: 10.1109/APCIT62007.2024.10673544

[11] S. A. Purba, S. Tasnim, M. Jabin, T. Hossen, and M. K. Hasan, "Document Level Emotion Detection from Bangla Text Using Machine Learning Techniques," *2021 International Conference on Information and Communication Technology for Sustainable Development (ICICT4SD)*, 2021, pp. 1–6

[12] M. Mahmudun, M. T. Altaf, and S. Ismail, "Detecting Sentiment from Bangla Text using Machine Learning Technique and Feature Analysis," International Journal of Computer Applications, vol. 975, p. 8887

[13] K. Sarkar, "Using Character N-gram Features and Multinomial Naive Bayes for Sentiment Polarity Detection in Bengali Tweets," in 2018 Fifth International Conference on Emerging Applications of Information Technology (EAIT), 2018, pp. 1–4.

[14] T. Rabeya, S. Ferdous, H. S. Ali, and N. R. Chakraborty, "A survey on emotion detection: A lexicon based backtracking approach for detecting emotion from Bengali text," in 2017 20th International Conference of Computer and Information Technology (ICCIT), 2017, pp. 1–7.

[15] D. Das and S. Bandyopadhyay, "Labeling emotion in Bengali blog corpus--a fine grained tagging at sentence level," in Proceedings of the Eighth Workshop on Asian Language Resources, 2010, pp. 47–55.

[16] H. Kavade, "A Logistic Regression Model to Predict Incident Severity Using the Human Factors Analysis and Classification System," M.S. thesis, Dept. Industrial Engineering, Clemson Univ., Clemson, SC, USA, Dec. 2009.

Emotion Detection from Bangla Text Using Seven Emotion Classes

ORIGINALITY REPORT

24%	17%	16%	14%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	dspace.daffodilvarsity.edu.bd:8080 Internet Source	4%
2	Sara Azmin, Kingshuk Dhar. "Emotion Detection from Bangla Text Corpus Using Naïve Bayes Classifier", 2019 4th International Conference on Electrical Information and Communication Technology (EICT), 2019 Publication	3%
3	Submitted to Daffodil International University Student Paper	2%
4	Submitted to United International University Student Paper	1%
5	www.mdpi.com Internet Source	1%
6	Abdelaziz Testas. "Distributed Machine Learning with PySpark", Springer Science and Business Media LLC, 2023 Publication	1%