A CONTEXT-BASED APPROACH FOR EMOTION RECOGNITION FROM BANGLA TEXT

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APPROVAL

This Project titled **"A Context-Based Approach for Emotion Recognition from Bangla Text"**, submitted by Shumaiya Akter Shammi and Sajal Das, ID No: 191-15-12179 and 191-15-12381 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfilment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on *25 January, 2023.*

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ABSTRACT

Due to the reliability on various online platforms, numerous texts are spreading all over the world through internet. These texts are employed to enhance user experience, service quality, and other factors. Emotion recognition (ER) is essential in the present day since it is necessary to address user opinion in order to comprehend consumer demand and to properly recognize perceptions. For the purpose of extracting sentiment from various languages, numerous studies have been undertaken. Bangla, a language with limited resources, has recently gained popularity in the field of emotion recognition due to its accessibility on social media. Sentiment analysis (SA) and emotion recognition in Bangla have been applied into a number of works. Multiclass ER has been more widely incorporated in emotion recognition. Though several works have been done on this domain, this language is still resource constrained due to its scarcity of proper tools and techniques. An extensive literature review was used in this study to grasp the state of this field. After that, a compiled framework was developed to serve as advice for those wishing to enter this field. Then, a substantial corpus has been developed to distinguish emotion in a novel approach. The unique aspect of this research is the context-based annotation of the data. After that, emotions are detected known as context-based multilabel emotion recognition. There is no work has been done on this issue. After that, the performance of multilabel ER has been incorporated applying several algorithms. Finally, a web application has been made to acknowledge the performance of the best performer among all the algorithms. Therefore, this research generalizes a roadmap of SA and multiclass ER of existing literature as well as build a comprehensive corpus to detect context-based multilabel ER.

Keywords: Sentiment Analysis, Emotion Recognition, Natural Language Processing, Low-Resource Language, Text Classification, Multilabel Emotion Recognition.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Sentiment analysis refers to a collection of approaches, strategies, and instruments for identifying and extracting subjective data from language, such as attitudes and opinions [1, 2, 3]. Basically, Sentiment Analysis (SA) is the technique of determining the polarity viz. positive, negative, and neutral of a particular language. On the other hand, Emotion Recognition (ER) is the process of detecting identical emotions in a particular text[1]. For instance, a positive sentence may have multiple emotions – happiness, enjoyment, hopeful, etc. As a result of the increased ease with which people are able to articulate their thoughts and feelings, sentiment analysis is rapidly evolving into a technique that is indispensable for analyzing and making sense of sentiments present in all kinds of data. By automatically evaluating customer feedback, such as comments in survey replies and online networking conversations, companies can learn what keeps customers interested or discouraged. This enables the companies to modify their products and services to better meet the requirements of their customers[1].

Furthermore, SA and ER from the Bangla language have also entered the picture, as it is the world's seventh most spoken language, with 272.7 million native speakers worldwide[2]. However, understanding the feeling or emotion of a document requires understanding the text structure, definition of words, syntax, and intent. Natural Language Understanding (NLU) aids in understanding these circumstances, while Natural Language Processing (NLP) aids in text processing[3]. As a result, SA and ER are subsets of NLP. The SA and ER processes are based on Artificial Intelligence (AI), with NLP, ML, and DL-based algorithms used to identify text polarity. Furthermore, data is important in this arena because it improves the accuracy of assessing sentiment and emotion.

[1] https://monkeylearn.com/sentiment-analysis/#what-is-sentiment-analysis
[2] https://www.ethnologue.com/guides/ethnologue200
[3] https://www.expert.ai/blog/natural-language-processing-and-sentiment-analysis/

Many studies have been conducted in this area since SA and ER from the text are becoming a hot topic. In this field of research, it is common practice to determine the polarity of a sentence from Bangla text [4, 5, 6, 7, 8]. However, the number of works based on emotion detection in Bangla is slightly less [9, 10, 11, 12, 13, 14]. Despite the fact that people can communicate a wide range of emotions, it is not essential to explore every one of them from the text. Additionally, people are working on multiclass emotion detection which lacks the proper emotion detection from a text. A single text can convey a variety of feelings. However, there isn't a comprehensive study for multilabel emotion recognition in Bangla. There have only been a few papers that match these requirements [9, 15, 16]. Consequently, multilabel emotion detection is required. However, there are a few reasons why there aren't any appropriate multilabel ER-based works. Few studies have been conducted because of inadequately annotated data, the Bangla language's complex structure, and a lack of accessible tools and approaches. As a result, Bangla is regarded as a resource-constrained language [4, 17, 13, 18].

To acknowledge the current state of this field, a thorough evaluation of SA and ER has been conducted in this work. As a result, a compiled framework has been designed to serve as the basic direction for anyone seeking to enter this field. After then, a corpus is constructed to cover the gap left by the language's low resource status. To address the need for context-based multilabel ER in Bangla, some popular techniques have been addressed to meet the criteria of this domain.

1.2 Motivation

The fundamental motivation for this work is to determine why Bangla is resource-constrained since it is regarded as a low-resource language. However, despite its growth in popularity, SA in Bangla has made a very small impact in this area. Concise works on several emotions have been done in the Bangla language. Therefore, this research intended to understand the current state of SA and ER in the Bangla language. The next concern of this study is to create an outlined structure based on the existing literature. The construction of a corpus for this field is one of the main motives so that it can benefit this under-resourced language. Last but not least, a tool for the context-based Bangla ER is required to accurately recognize the emotions. Therefore, the inspiration for this research is to understand the existing state of affairs and build a tool for multiple ER in the Bangla language.

1.3 Rationale of the Study

The domain of SA and ER research is now in high demand across the world. Because SA and ER help to understand customer satisfaction, desire, and requirement of a system. Customer service, market research, social media monitoring, brand monitoring, and other areas have all employed SA and ER to take into account user requirements [19]. This is the reason why this area of study has expanded throughout time. However, SA and ER in Bangla are also expanding, yet there is still a demand for this language. In order to make it simpler to understand the need for this domain, the goal of this study is to present the available literature. Bangla is a low-resource language; hence it is important to understand why it is confined. Accordingly, numerous studies on multiclass and few works on multilabel ER have been conducted in various languages [20, 21, 22]. However, due to a lack of appropriate tools and methods, multilabel emotion recognition is not defined properly in the Bangla language. Therefore, proper tools and techniques need to be developed to overcome this obstruction. The motive of this study is to identify the reasons for being a low-resource language as well as the current situation to determine an outlined general framework for SA and ER. Finally, this work aims to create a tool for multilabel emotion detection because there is a severe absence of multilabel ER.

1.4 Research Questions

This research aims to perceive the following criterion to understand the research gap in this domain more efficiently and find a way to acknowledge the solution of this desideratum:

i. What is the current situation of SA and ER in Bangla?
ii. What are the well-known approaches for SA and ER in Bangla?
iii. What might be the compiled framework for conducting SA or ER in Bangla?
iv. What type of ER needs to be done in Bangla?
v. What might be the procedure for predicting multilabel emotion in Bangla?

1.5 Expected Output

Locating the tasks that have to be accomplished in this field is the anticipated outcome of this investigation. The state of the art of Bangla SA and ER must be acknowledged in the accessible research works in order to achieve this. As a result, a thorough evaluation is necessary to satisfy this requirement. This study attempts to describe a compiled framework for the aspirants so that they can acquire the general information necessary for practicing in this subject by taking into account the present circumstances. After that, a corpus must be built in order to enrich this language with few resources. Eventually, a tool for multilabel emotion classification is the final expected outcome of this literary work. There are several works have been done on SA in Bangla, ER in Bangla, and some works have been done on multilabel ER. But context-based multilabel ER has not been done yet. Therefore, this is another outcome of this study. Accordingly, this language is rarely used for multilabel ER. As a result, a multilabel ER tool is essential for this field. This is anticipated that this work will be able to fulfill the demands in consideration of the findings.

1.6 Project Management and Finance

This research followed a unified process for the development of the whole work which works as an iterative and incremental process. A design for the research has been used after establishing a connection with the corresponding authors. The modeling and construction of the study have been addressed in accordance with the planning. Firstly, a peer review based on the resources already in existence has been formed, aiding in the creation of a roadmap for Bangla SA and ER to provide direction to the aspirants. A thorough corpus has been constructed to add to this topic based on the previous works. The dataset was subsequently utilized to assess different multiclass and multilabel ER models in Bangla. The initial plans have been altered at various stages of the work that establish the incremental and iterative process of this research. However, no outside funding has been required to carry out the work. Nevertheless, we will need financial assistance if we wish to annotate the entire dataset that has been gathered. Because processing such a large volume of data will take a long time. Therefore, it is necessary to give the annotators a financial reward. After that, funding will be required for the creation of the appropriate software or application if this research is utilized in a project relating to ER in Bangla.

1.7 Report Layout

The rest of the thesis is structured as follows.

Chapter 2: The existing literature, sentiment and emotion classification approaches have been described in this chapter. Additionally, the scope of the problem, its importance, and challenges in this domain have been incorporated in this chapter.

Chapter 3: Based on the existing research, this work has found the challenges and the aspects that need to be done. Therefore, this chapter has explained the detailed procedure of the proposed model which enhances challenges to overcome. The data collection techniques, data preparation, data annotation, feature selection, and algorithmic approaches have been described here.

Chapter 4: The final outcome of the proposed tools for multilabel ER in Bangla has been outlined in this chapter. After that, a peer discussion of the overall process is also done in this segment.

Chapter 5: The impact of this research on society, its importance, and the sustainability of this work have been discussed in this section.

Chapter 6: Finally, the overall concise description of this research has been incorporated in this section. Then the limitations of this work are expounded here. After, some recommendations and further scope of the research are also mentioned.

CHAPTER 2

BACKGROUND

2.1 Preliminaries

The branch of computer science known as natural language processing (NLP) is a subfield of artificial intelligence (AI) that focuses on giving computers the ability to grasp written and spoken words in a manner that is comparable to how individuals are able to do so. Combining linguistic anthropology research with statistical, machine learning, and deep learning models is what natural language processing, or NLP, does. Computers are now able to process human language in the form of text or audio signals and completely grasp what is being said or written, including the intents and feelings of the speaker or writer. This is made possible by the technologies described above[4]. Thus, NLP's sentiment analysis, also known as opinion mining, determines a text's polarity. Many organizations utilize this to get perspectives about a product, service, or concept[5]. On the other hand, NLP enables us to determine identical emotions from text such as review, conversation, recommendation, etc. ER refers to the actual identification of emotional state from a given context or text.

A rising number of intelligent systems now use emotion detection models to improve their human-computer interaction. This is significant because it enables the systems to modify their replies and behavioral patterns in reaction to the human's emotions, improving the relationship [23]. Consequently, over time, SA and ER are growing in popularity. Positive, negative, and neutral emotions are the three most typical identifying sentiments for SA. Ekman's emotion, on the other hand, is the conventional method of emotion detection. Ekman's emotion detection system recognized six fundamental emotions, including fear, anger, joy, sadness, disgust, and surprise[6]. After

[4] https://www.ibm.com/cloud/learn/natural-language-processing
[5] https://www.techtarget.com/searchbusinessanalytics/definition/opinion-mining-sentiment-mining
[6] https://www.careershodh.com/popular-theory-of-the-6-basic-emotions-by-paul-ekman/

that, these emotions have been expanded to include seven emotions: joy, sorrow, surprise, fear, anger, disgust, and contempt[7].

Additionally, a variety of methods, including Machine Learning (ML), Deep Learning (DL), adaptive neuro-fuzzy systems, ensemble methods, tropical techniques, rule-based approaches, combination approaches, etc. [24, 25, 26, 27] have been utilized to extract sentiment and emotions from Bangla text. Commonly used ML techniques for SA and ER in Bangla include Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Logistic Regression (LR), Random Forest (RF), Decision Tree (DT), Naive Bayes (NB), Multinomial Naive Bayes (MNB), etc. [28, 29, 30, 31, 32]. On the other hand, DL for SA and ER has made use of techniques based on Long Short Term Memory (LSTM), Bidirectional Long Short Term Memory (BiLSTM), Gated Recurrent Unit (GRU), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN) [33, 34, 35, 36]. In rule-based approaches, lexicon-based approach and transformer-based approach have been used [17, 37, 38, 39, 40]. Multilingual BERT (Bidirectional Encoder Representations from Transformers) is another popular algorithm in the field of SA and ER.

Therefore, while emotion detection focuses on identifying the emotional or psychological state or mood, sentiment analysis prioritizes polarity. Thereby emotion identification is more accurate and objective, and sentiment analysis is more subjective.

2.2 Related Works

Evolution

Over the years, SA and ER have gained significant popularity, and the sector has evolved as a result of the contents [41]. People are dependent on the internet in today's technological era, there are a ton of texts available online. As a result, these texts are used for SA and ER to comprehend user opinions and enhance user experience. SA, which supplied semantic direction and algorithms across time, had been initiated in

[7] https://www.paulekman.com/universal-emotions/

ancient Greece utilizing the concept of Doxa (Common beliefs or popular opinion)[8]. Traditionally, sentiment analysis-based works had been started in the 20th century, and the earlier research work related to public opinion analysis was published in 1940 titled "The Cross-Out Technique as a Method in Public Opinion Analysis" [42]. Three articles were then produced in 1945 and 1947 based on the popular perception of the participating nations in World War II. Then, in the middle of the 1990s, computer-based methods had begun to emerge. The conventional SA was initiated by a community called Association for Computational Linguistics, where an earlier study was concerned with extracting subjective statements from narrative sentences 1990 [43].

However, the publication of related works was very low for years. 99% of the paper have been published after 2004. There had only been 37 papers published overall by 2000, and 101 papers by 2005. The number of papers increased to 1039 by the end of 2010 and, finally, to 5699 by the end of 2015 [1].

SA and ER in Regional Language

Bangla is an Indo-Aryan and principal language in Bangladesh and the state of West Bengal in India [44]. There are 272.7 million and 70 million Bangla native speakers in Bangladesh and West Bengal respectively[9]. However, there are several regional languages in India and many works have been done for SA and ER in those languages as well as the establishment of comparison of those languages has also been incorporated. The popular regional languages for SA and ER in India are Hindi, Bangla, Tamil, Telugu, Manipuri, Kannada, Urdu, etc. [45, 46, 47, 48, 49, 50]. Additionally, supervised and unsupervised ML based approaches, DL based approaches have been implemented to detect sentiment or emotion in these languages.

Using code-mixed Bangla and Telegu data, a study was conducted in SA. In this study, they used CNN, a DL-based method, to classify the sentiment into three categories: positive, negative, and neutral [51]. Accordingly, this DL-based method has been employed in another research study to identify the same sentiments in datasets of Hindi,

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8 https://devopedia.org/sentiment-analysis
9 https://en.wikipedia.org/wiki/States_of_India_by_Bengali_speakers

Bangla, and Tamil [52]. On the other hand, the same sentiments have been identified in Bangla and Tamil tweets using probabilistic and decision tree classifiers [53]. Some works have been incorporated using only the Hindi language [47, 48, 49]. However, some studies on reviews of SA in various regional languages have been conducted [44, 45, 54, 55]. For instance, researchers have conducted a study on opinion mining in Bengali, Hindi, Tamil, Manipuri, Telugu, and Kannada languages, outlining the works and giving a brief summary of each work [45]. Accordingly, a survey of the literature on SA in various regional languages, including Hindi, Bangla, and Tamil with the Indian code-mixed language, has been accomplished [44]. Therefore, SA and ER in various regional languages have become a growing concern.

SA and ER in Bangla

There are numerous web communities where people can express their thoughts, and they are at ease doing it in their own language. Because of this, SA and ER have grown to be crucial for comprehending customer demand across multiple languages [56, 57, 58, 59, 60]. Accordingly, it is very natural that people in Bangladesh express their thoughts in Bangla because it is the country's native language. As a result, understanding sentiment and emotion in Bangla has gained attention. However, the Bangla language has a relatively complex structure due to its variety of regional dialects [61, 62, 63, 64].

In recent years, a number of SA and ER-related works in Bangla have been completed. Due to the difficulty of understanding Bangla, the majority of articles on this topic have focused on sentiment analysis. Since determining a sentence's polarity is the main goal for determining sentiment and this is a well-known problem in this field, the majority of research has only focused on measuring the polarity [65, 66, 67, 17, 68, 69]. The classification of emotion from Bangla text is a growing topic nowadays though there is a dearth of proper works on this criterion. Some works have been incorporated to detect emotion from the text [38, 70, 71, 40]. However, fundamental emotion recognition from text is a prevalent element in this field. The most well-known emotions for the emotion classification in Bangladeshi literature are Ekman's six fundamental emotions [9, 71, 40]. These six emotions have been extended to seven emotions including joy, sorrow, surprise, fear, anger, disgust, and contempt where contempt is the newly added emotion in Bangla Text.

On the other hand, multiclass emotion detection refers to the process of identifying a specific emotion across multiple classes. Several works for multiclass emotion detection have been done in Bangla [29, 30, 63]. But there is another category of work is existing that is done in different languages except for Bangla. Multilabel emotion detection is a task of NLP that determines multiple emotions from a given text [72, 73]. Very ignorable works have been done on this perspective in the Bangla language [9, 15, 16]. However, this field is expanding day by day as it is the 7th most spoken language in the world, as well as, texts are available everywhere. Therefore, more nourishment is required for this field in order to improve the current status.

2.3 Comparative Analysis and Summary

This section illustrates the comparative analysis of corpora, existing tools and their performance, and the mostly identified emotions and sentiments in this field.

Corpora Analysis

SA and ER in Bangla is a challenging task due to the insufficient resources of data. Several works have been done using a low volume of data. For instance, only 2000 Facebook comments were used to detect positive and negative sentiments that determine resource insufficiency [6]. On the other hand, 3200 Facebook posts were used to determine five types of sentiments: positive, strong positive, negative, strong negative, and neutral [74]. This low data volume has a significant effect on the outcome since the high data volume contributes to improving the accuracy rate. In another research work, researchers collected 15325 Bangla news headlines to identify sentiments. But they removed the neutral data from the corpus which lessened the accuracy of the classification result [65].

Furthermore, there is a dearth of properly annotated data in the Bangla language. As Bangla is considered a resource-constrained language, many researchers used translated data for SA and ER. Some researchers collected English data and translate them into

Bangla to detect sentiments or emotions from them [75, 15]. On the contrary, some researchers have converted Bangla data to English since SA and ER tools and methods are more appropriate in English [76].

Correspondingly, the unavailability of properly annotated data is responsible for collecting data from multiple sources. Several works have been incorporated in collecting data from multi-sources [17, 13, 38, 18]. These sources included Bangla articles and blogs, Facebook, e-commerce websites, Twitter, online newspapers, YouTube, movie reviews, sports comments, several social media platforms, textbooks, direct speech, depression-related Bangla posts, Bangla novels, poems, and quotations [77, 71, 78, 79, 80]. Collecting data from multiple sources generates a jumble of data sources. As a consequence, hybrid data reduces the data integrity which may result in a lower accuracy rate.

Tools and Techniques Analysis

Being a low-resource language and having inherent complexity in its structure, there is a lack of proper tools and techniques for analyzing sentiment and emotion in the Bangla language [81, 82]. Though proper tools are not available in Bangla SA and ER, this section describes the existing and mostly applied tools for SA and ER. Mainly ML-based techniques, DL-based techniques, and hybrid approaches are popular in this field.

In a research article, 10,000 Bangla texts have been used to detect positive, negative, and neutral sentiments where SVM performed better than other ML algorithms [66]. In another study, supervised, unsupervised, lexicon-based, and transfer-learning-based methods have been applied in which supervised SVM showed the highest accuracy of 93% [37]. On the other hand, a distinct classification has been done that identified religious and abusive comments along with five different emotions: happy, sad, angry, surprised, and excited [10]. TF-IDF has been used as feature selection in this work and ML approaches have been applied. From the ML algorithms, SVM performed better. On the contrary, MNB performed well in some literature work [29, 83, 30]. Therefore, SVM shows the most prominent results in most of the articles because SVM performs properly labeled data. And data labeling is the primary data preprocessing technique in every research related to SA and ER [28].

Moreover, DL-based approaches have been applied in this linguistic research where LSTM, hybrid LSTM, CNN, RNN, BiLSTM, and GRU algorithms are prominently used [7, 9, 84, 85]. In several instances, CNN performed admirably in terms of deriving sentiments accurately [86, 87, 11]. In addition, hybrid models outperformed non-hybrid models when CNN was combined with other DL models [63, 86]. From the DL algorithms, LSTM and CNN perform better than other DL approaches. In some cases, CNN performs well than LSTM because CNN is better for multiclass text identification [87].

In some circumstances, hybrid models perform better than non-hybrid models. Basically, ML models hybridization, ML with DL model hybridization, and multiple DL model hybridization have been implemented in different research works. KNN-SVM performed better in ML algorithm hybridization. Conversely, RNN-LSTM, CNN-LSTM, and CNN-BiLSTM showed better performance in terms of multiclass emotion detection [88, 62, 63, 86, 15]. However, better preprocessing techniques help to enhance better prediction. The majority of research studies use data cleansing, tokenization, and labeling as common preprocessing procedures. N-gram, BoW (Bag of Words), count vectorizer, TF-IDF (Term Frequency - Inverse Document Frequency), and POS (Parts of Speech) tagger are therefore well-known feature extraction techniques in most of the articles.

Classified Emotion Analysis

Measuring the polarity of a text is known as SA whereas identifying the actual feeling or emotion is called ER. Due to the ability to enhance user experience, SA and ER from the text have been done in several languages. But SA and ER in Bangla have become popular in recent years. Therefore, a number of research works have been conducted in the Bangla language though there is a lack of properly annotated data, and unavailable tools, and techniques.

For analyzing sentiment, there are basically two types of works that have been conducted in the Bangla language. Identifying positive and negative sentiments is one of them [65, 89, 69, 90]. Another type of work is to detect positive, negative, and neutral sentiments [91, 67, 92, 93]. Some researchers have sometimes worked for identifying more polarity of sentences such as strongly positive, positive, strongly negative, negative, and neutral [74, 9].

On the other hand, a limited number of researchers worked on emotion classification. However, there are two kinds of studies is appeared in the Bangla language for emotion classification: multiclass emotion detection and multilabel emotion detection [74, 94, 40, 14, 95]. From these two approaches, most of the articles worked for multiclass emotion detection in Bangla. Multiclass emotion detection refers to the recognition of only one emotion from multiple emotions. Conversely, multilabel emotion detection determines multiple emotions from a given text. Though a text can express multiple feelings, there is no prominent research work has been conducted on multilabel emotion classification. Accordingly, identifying the level of emotion by degree level is another important task in this area. Degree level of emotion means how extreme the emotion is, for instance, if the highest level of a particular emotion is 3, then what level is carrying the sentence 1 or 2 or 3? Therefore, these types of research can be more useful to improve user experience. Additionally, various works have been done on extracting multiple emotions from images and some approaches are available for this aspect [96, 97, 98]. But the resource for multilabel ER for text is one of the limitations of this domain. Hence, future research works need to focus on multilabel emotion detection to meet the criteria. However, this research generalized a compiled framework based on the existing literature. The framework shows the popularly applied algorithms for SA and ER in several fields. Figure 1 illustrates the compiled framework for the existing study to provide guidance to the aspirants.

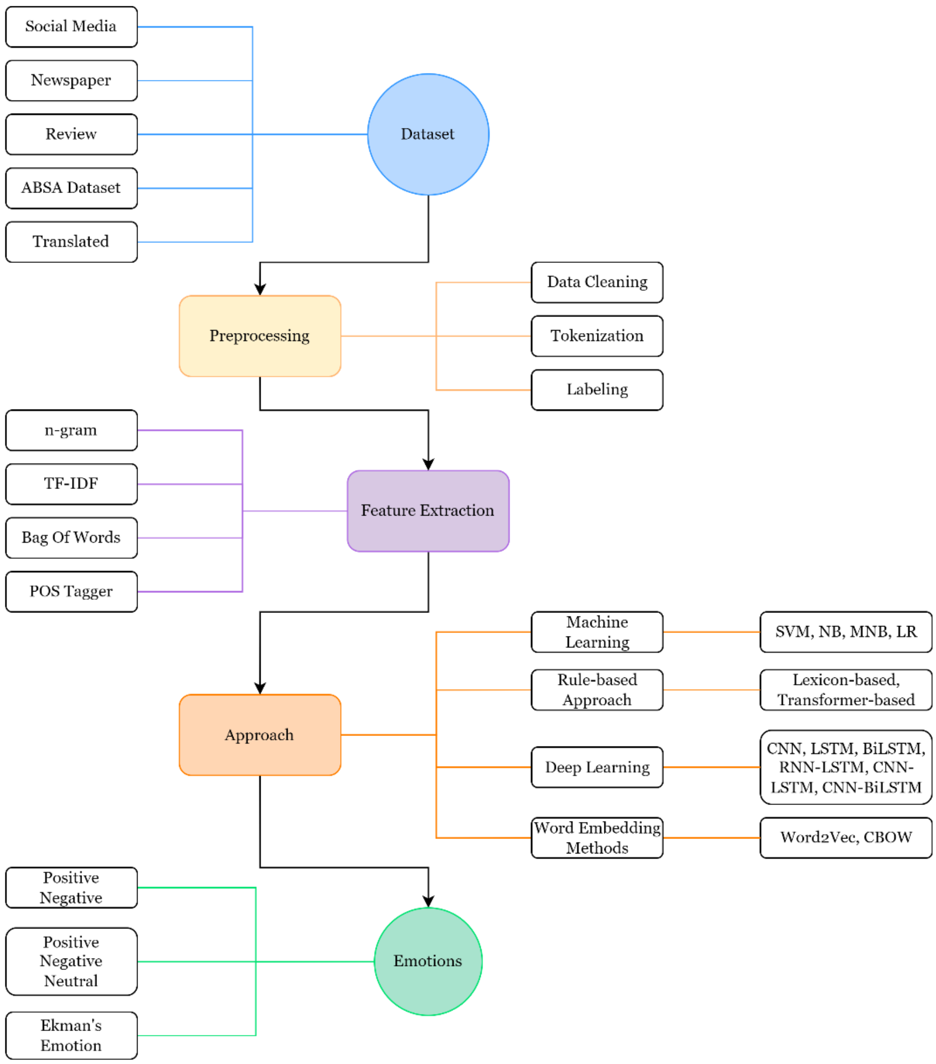

Figure 1: Generalized Framework for SA and ER in Bangla

2.4 Scope of the Problem

In this era of technology, retrieving text from various online sources is easier. However, Bangla is still depicted as a language with limited resources. The language resource constraint is caused by the lack of properly labeled computer-readable data [99]. Contrarily, Bangla has a very complex structure, which accounts for the dearth of appropriate methods and tools for this language [100, 101]. As a result, one of the difficult issues in this field is now sentiment analysis, or accurately identifying the emotion from Bangla text [102].

However, positive, negative, and neutral sentiments are prevalent in a number of studies that have been done on this subject. Accordingly, some fundamental emotions, including Ekman's emotions, are well-recognized emotions in this area. Hence, the major goal of this study is to comprehend the current state of affairs in this field. The second goal of this article is to create a properly annotated Bangla corpus in order to address the data shortage in this area. That is why each data annotation was performed by three annotators. In order to assure more accurate emotion from a text, three annotators contribute their emotional feedback for each given paragraph. Additionally, the data annotation process has been done based on the context of data to understand the emotions of people more accurately. Moreover, this kind of work is required because multilabel emotion detection makes it possible to extract various emotions from a text. Therefore, due to the dearth of context-based multilabel emotion classification work in Bangla, this study has taken this issue into account. Finally, this work has addressed some techniques to detect context-based multilabel ER in Bangla.

2.5 Challenges

SA and ER in Bangla is a demanding task due to several reasons. This section depicted the major challenges of this domain that are responsible for being a difficult task.

Scarcity of Resources

Large amounts of training data are necessary to create an AI or ML model that behaves like a human. A model must be trained to comprehend certain facts in order for it to make judgment calls and take action. For AI applications, data annotation entails categorizing and labeling the data[10]. The diversity of human languages is the key factor contributing to text annotation's importance in NLP. Despite their increasing intelligence, systems still have a lot of room for improvement in context and hidden meanings. Machines receive that information from annotation[11]. In terms of SA and ER, data labeling is one of the significant tasks for supervised learning. Data annotation helps to learn to model the context of the data. Nevertheless, there is a dearth of properly

[10] https://appen.com/blog/data-annotation/
[11] https://www.defined.ai/blog/what-is-text-annotation-in-machine-learning/

labeled data in Bangla and for this reason, this language is still resource-constrained which makes this field difficult and overcome challenges.

Processing Inability

Data preprocessing, a pivotal stage in the data mining process, is described as the manipulation or elimination of information before usage in order to ensure or improve performance[12]. Data preparation may have an impact on the capacity to interpret the outcomes of the final data processing. When the evaluation of the findings is a significant concern, this should be appropriately considered. Data pre-processing for SA and ER has a great impact on a better understanding of the outcome. It helps to acknowledge the behavior, structure, and context of the data and then helps the predictor to predict the best result. But there is a shortage of proper pre-processing techniques for Bangla data due to its complex structure and multiple dialects.

However, the mostly applied pre-processing approaches included data cleaning, tokenization, and data labeling. Data cleaning contains multiple techniques, for instance, stop word removal, symbol removal, punctuation removal, data stemming, unnecessary character removal, and emoticon removal. However, other languages such as English has built-in stop word dictionary and lexicon-based dictionary. But there is an immense lack of these dictionaries in Bangla. A limited number of researchers have worked for building these dictionaries [103, 104]. Conversely, the popular feature selection techniques include n-gram, BoW, count vectorizer, TF-IDF, and POS tagger. Therefore, these are the most familiar approaches in the existing literature. Moreover, there are many built-in libraries for other languages viz. English. But Bangla does not have proper tools for better understanding of data and making better predictions. Therefore, more approaches need to be conducted to understand the anatomy of data.

[12] https://en.wikipedia.org/wiki/Data_pre-processing

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

Emotion Recognition or Sentiment Analysis is a subset of Natural Language Processing in the field of Artificial Intelligence. This research focuses on Emotion Recognition in Bangla, one of the most resource-constrained languages. This study explains the purpose of ER, current work assessment in Bangla, Regional, and other languages, generalizing a comprehensive roadmap of SA or ER, constructing a large corpus of Bangla text, and bringing a comparative analysis of alternative model implementations. Figure 2 depicts the hierarchical area structure of this domain.

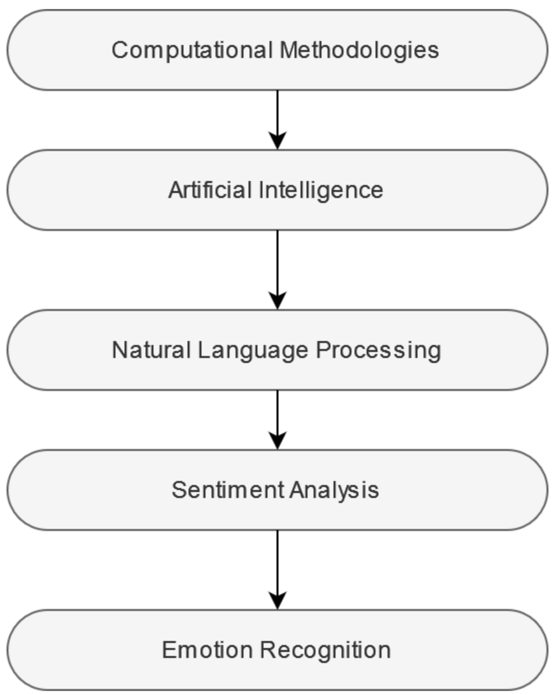

Figure 2: Research Subject

Building an extensive corpus is an essential component of this research instrumentation. The comprehensive literature study of this research revealed alternative platforms for collecting data for Bangla text. According to multiple data sources, the most popular platform for individuals is social media, where people share and upload massive volumes of data on a daily basis [83, 17, 105]. As a consequence, a social media platform was chosen to collect data to evaluate several types of algorithms.

3.2 Data Collection Procedure

The dataset is the most important aspect of this research since a complete collection of data for sentiment analysis or emotion detection in a low-resource language like Bangla is not accessible. As a result, one of the most challenging tasks of this study is to develop a complete corpus of Bangla text on SA or ER. One of the most prominent social media networks, Facebook, was utilized as the data source. There has also been other research on Facebook data in SA and ER [6, 10, 94]. Few researchers have utilized the Facebook Graph API to acquire data from Facebook, which only allows them to access the pages or groups to which they have access [7, 74, 86]. In other research, the author collected the status or comments from various categories of pages and groups in order to attain a large quantity and diversity of data [30, 13, 106, 38]. However, this research developed an automated data collection scraping algorithm to collect data.

A comprehensive corpus is composed of a variety and huge volumes of data. To build such a dataset, a researcher must consider the diversity of information available and select the source of that data. Since the Graph API cannot collect data from any other public group or page without access, the Web or Browser Automation approach comes into play. Though it is time-consuming and computationally demanding, it meets the requirement for scraping or crawling data wherever. In this study, the dataset was primarily collected via the web automation approach, with python-based Selenium, one of the most prominent open-source browser automation libraries, being used to finish the entire process.

Source of Data

First, we have chosen the 11 most controversial recent incidents in our nation that have had an influence on the entire country and have been widely shared on social media platforms. The most popular news portal's Facebook pages such as Prothom Alo, BBC Bangla, BD News 24, Bangla Tribune, Kaler Kantho, Daily Jugantor are picked to take public comments. The news posts are then filtered depending on the number of comments made from the chosen news portal's Facebook pages. Following a manual collection of posts, a total of 130 posts for 11 news topics were obtained and converted into a CSV file with the news id, news portal id, post id, post link, and comment counts.

Data Scraping Algorithm

However, a scraping algorithm has been built to collect all the data. TABLE 1 pseudocode denoted as Data Scraper Algorithm and the visualization using flowchart for the whole process is addressed in Figure 3. First of all, the links are needed to be read from the CSV file to extract information from each link. After that, two empty lists are created to hold the comments in *comment_texts* and the *link_index* variables. Then an iteration process is started which starts from the first link to the last to scrap all the comments from each link. A *link* variable is declared to be used for allocating the link url by index from the DataFrame posts and accessing the link using *driver.get()*, which is specified as the web driver for this selenium project at the start.

TABLE 1: PSEUDOCODE OF DATA COLLECTION AND PROCESSING

Algorithm: Data Scraper

```
function comment_crawl(i)
    comments ← find_elements()                         ▷ Find all comments.
    for comment ← comments do
        cmnt ← comment.text.strip()
    if cmnt! = ‘’ and cmnt not in comment_texts then
        comment_texts.append(cmnt)
        link_index.append(str(i))
end if
end for
end function
function replies_crawl(i)
    comments ← find_elements()                         ▷ Find all comments.
    mentions ← find_elements()                         ▷ Find all mentions.
    l ← 0
    for comment ← comments do
        cmnt ← comment.text.strip()
    try
        mntn ← mentions[l].text.strip()
        if mntn in cmnt then
            cmnt ← cmnt.replace(mntn)
            l ← l + 1
        end if
```

```
    except
        pass
    end try
    cmnt ← comment.strip()
    if cmnt! = ‘’ and cmnt not in comment_texts then
        comment_texts.append(cmnt)
        link_index.append(str(i))
    end if
    end for
end function
posts ← read(‘posts.csv’)
comment_texts ← list()
link_index ← list()
for i ← 0 < length(posts) do
    link ← posts.loc[i][‘link’]
    driver.get(link)                          ▷ Visit the page.
    while True do
        comment_crawl(i)                      ▷ Go to the function (1).
        replied_btn ← find_elements()         ▷ Find replied buttons.
    try
        for j ← 0 < length(replied_btn) do
            replied_btn[j].click()            ▷ Go to replies page.
            replies_crawl(i)                  ▷ Go to the function (2).
            time.sleep(1)
            driver.back()                     ▷ Back to previous page.
        end for
    except StaleElementReferenceException
        pass
    end try
    try
        more_btn ← find_element()             ▷ Try to find view more comments.
        more_btn.click()                      ▷ Go to next page.
        time.sleep(1)
    except NoSuchElementException
        break
    end try
    end while
    comments df ← DataFrame(link_index, comment_texts)
    comments df.to_csv(‘dataset.csv’, ‘a’)
end for
```

During this process, another iteration process will begin to retrieve the comments from the page that contains the news post. At that time, the *comment_crawl(i)* function is called that starts finding the elements with xpath of that webpage and putting them on the *comments* variable. Then, a verification was applied among all identified comment elements to remove empty spaces and assigning it to the *cmnt* variable. It verifies if the *cmnt* cannot be empty and is not found in the prior comments stored on the *comment_texts* list; if it satisfies, it adds the *cmnt* to the *comment_texts* list and also adds the index to the *link_index* list before terminating the function and returning to the previous iteration.

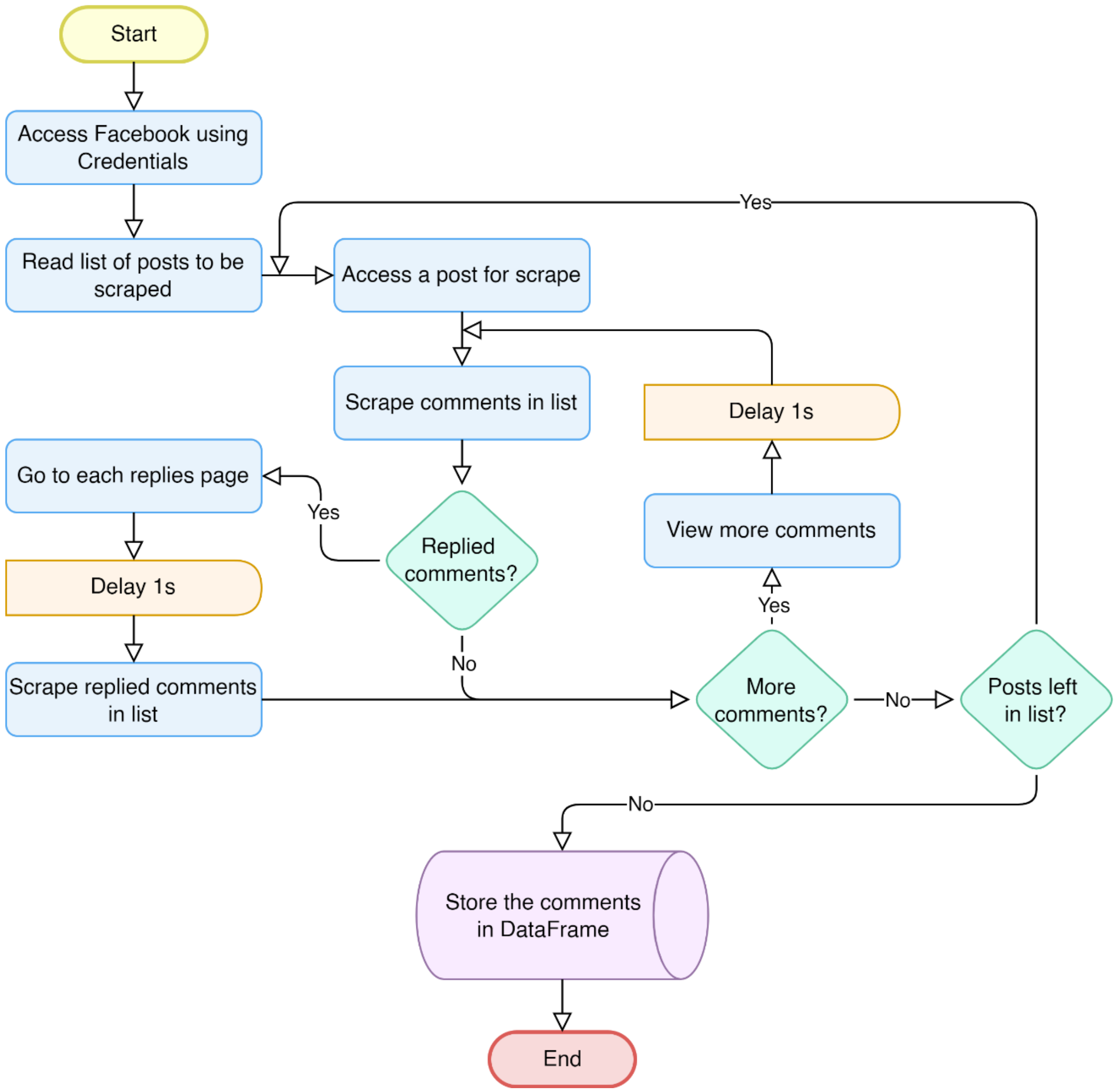

Figure 3: Data Scraping Algorithm Flowchart

After the completion of the *comment_crawl()* function, the algorithm starts finding the reply buttons to scrape the replies of the corresponding comments. After arriving at the replies page, it invokes the function *replies_crawl(i)* and begins finding the elements of comments by xpath on variable *comments*, as well as the elements of mentions by xpath on variable *mentions*. A variable *l* with the value 0 is declared and used as a flag for processing the mentions in the comments. Then, it goes over all identified comment elements, stripping comment text to remove empty spaces and assigning it to the *cmnt* variable. A try-except tries to remove or replace the mention name from the *cmnt* by taking the *mention[l]* on *mntn* and stripping it, and an *if* condition checks if the mention is present on the comment or not; if it is, the mention is replaced with an empty string on the comment, and value l is increased by one. Any exception will be passed by the following code segments, which will remove the comment and verify it, as well as add the comment to the *comment_texts* and *i* to the *link_index* lists.After collecting the replies' comments, a 1s time delay will bring the browser back to the previous page, and this loop will continue to cycle through all of the *replied_btn* accessible on the page. If there is an exception with an element reference, it will pass and finish this try-except to proceed. Then another try-except tries to find any view more comments button on this page using the find element method on the *more_btn* variable, and if it is found, it will move to the next page by clicking it, and a time delay of 1s helps to fully load the page. With the exception of no such element of *more_btn*, it will either terminate the while loop here or otherwise continue its iteration for the next page. Finally, the entire list of *comment_texts* and *link_index* list values were zipped to be stored on a DataFrame of *comments_df* and the DataFrame values were appended to 'dataset.csv'. This *for* loop will run the whole procedure for all post links and will terminate when the last post link is completed. Finally, the total number of comments is 136,583 after gathering all of the comments data using the above algorithm.

3.3 Statistical Analysis

Popular news portals have been utilized to extract comments in this study. As a consequence, it becomes easier to collect a higher number of comments. But a huge number of comments have to be eliminated due to the various diversity of data such as English comments, bang-lish comments, spam comments, etc. However, TABLE 2 shows the details calculation of each news comments.

TABLE 2: COMMENTS RATIO OF COLLECTED DATA FOR EACH NEWS

News	Portal Names	Num of Posts	Num of Comments
News 1	Prothom Alo, BBC Bangla, BD News 24, Bangla Tribune, Kaler Kantho, Daily Jugantor	14	11294
News 2	Prothom Alo, BBC Bangla, BD News 24, Bangla Tribune, Kaler Kantho, Daily Jugantor	13	10098
News 3	Prothom Alo, BBC Bangla, BD News 24, Bangla Tribune, Kaler Kantho, Daily Jugantor	13	12192
News 4	Prothom Alo, BBC Bangla, BD News 24, Bangla Tribune, Kaler Kantho, Daily Jugantor	14	16582
News 5	Prothom Alo, BBC Bangla, BD News 24, Bangla Tribune, Kaler Kantho, Daily Jugantor	15	14973
News 6	Prothom Alo, BD News 24, Kaler Kantho	3	536
News 7	Prothom Alo, BBC Bangla, BD News 24, Bangla Tribune, Kaler Kantho, Daily Jugantor	13	7302
News 8	Prothom Alo, BBC Bangla, BD News 24, Bangla Tribune, Kaler Kantho, Daily Jugantor	15	22930
News 9	Prothom Alo, BBC Bangla, BD News 24, Bangla Tribune, Kaler Kantho, Daily Jugantor	9	5723
News 10	Prothom Alo, BBC Bangla, BD News 24, Bangla Tribune, Kaler Kantho, Daily Jugantor	17	33188
News 11	Prothom Alo, Channel i, Daily Manab Zamin	5	1765
	Total	**130**	**136583**

Figure 4 illustrates the comments ratio for every news. It is shown that news 6 has the smallest ratio of comments. The number of comments for news 6 is 536. On the other hand, news 8 has the highest number of comments which is 22,930. And the average number of comments for the news are around 15,000. However, small number of data has been annotated as it requires more annotators. A total of 13,600 data have been annotated and the annotation ratio is shown in Figure 5 for multilabel ER.

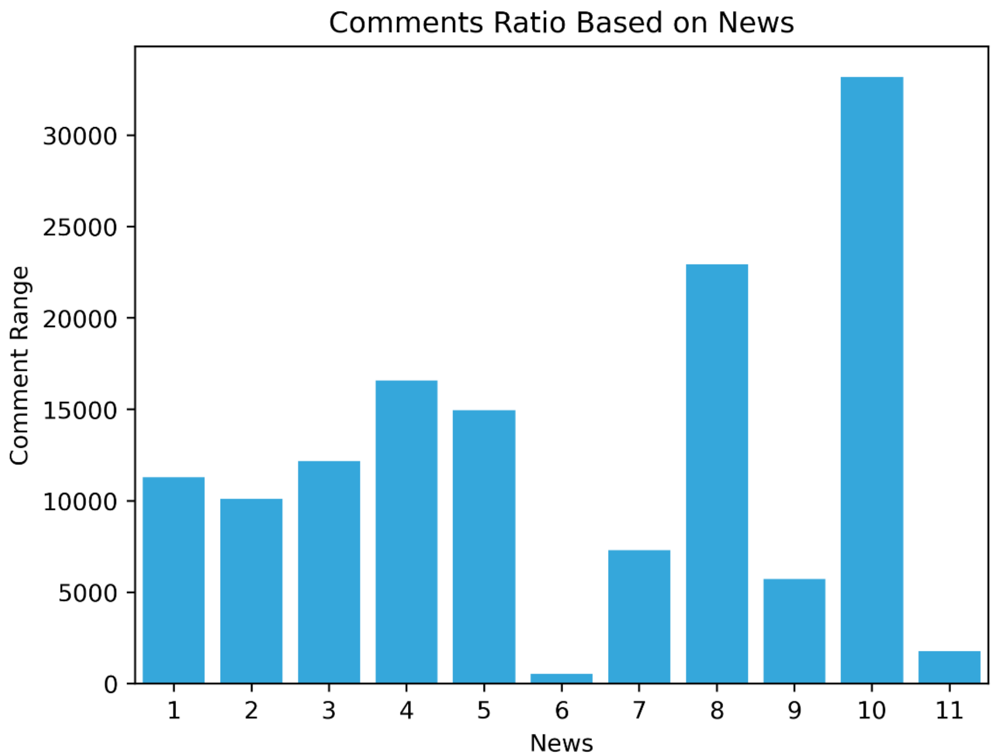

Figure 4: Comment Ratio Based on News

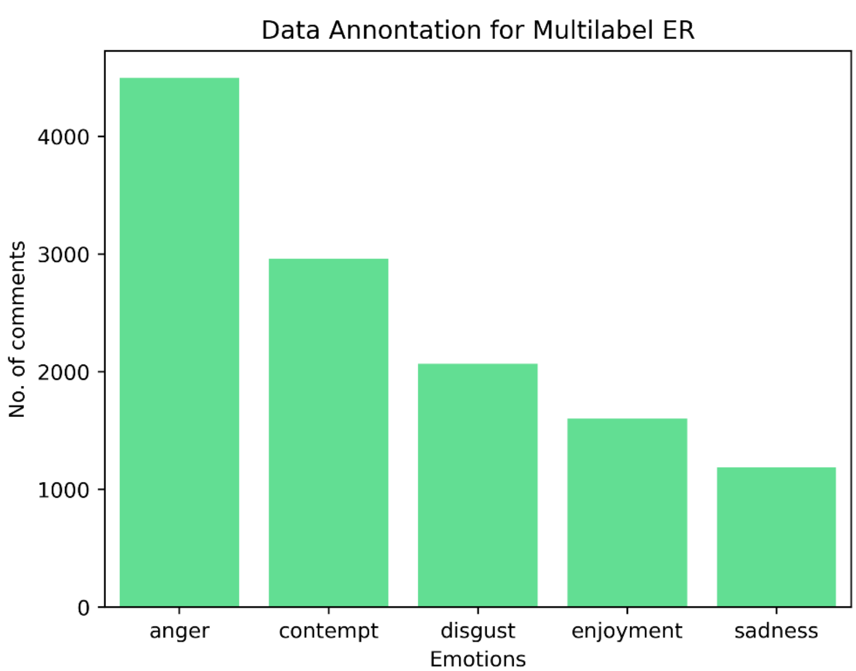

Figure 5: Data Annotation for Multilabel Emotion Recognition

3.4 Proposed Methodology/Applied Mechanism

This study follows the suggested roadmap based on the existing literature for the proposed methodology. The popular and frequently used preprocessing steps and feature extraction techniques have been utilized in this research. After that the suggested algorithms from various fields as well as some other popular algorithms for Bangla language have also been explored in this study. The following sub sections have illustrated the whole process of methodology.

Data Preprocessing

The entire dataset was processed in three levels or phases to eliminate redundant data as well as unnecessary data. The levels are a step-by-step approach for cleaning and obtaining only relevant data. The preprocessing steps are distinguished into several phases to make understandability of the process since the process is long.

Preprocessing (Phase 1):

Phase 1 preprocessing is the initial level of cleaning, and it includes emoji separation, non-bangla word separation and removal, and the elimination of extraneous whitespace from comments. A regular expression of all emoji patterns comprises emoticons, symbols, and pictographs, transport and map symbols, and flags of all platforms that are used to detect and distinguish emojis from comments. Another regular expression that may identify the Bangla characters in the comments and is used as a false condition to separate and exclude the other characters from the comments. After the regex removes the foreign characters, it generates such whitespaces in the comments that all double spaces are transformed with one space and whitespaces are eliminated. This phase is basically the primary steps for processing the data.

Preprocessing (Phase 2):

Following an automatic cleaning of the comments, phase 2 involved a few human actions such as discarding null comments, resetting comment indexes, and manually screening for and deleting irrelevant comments. Empty, meaningless comments are removed from the

CSV file, and index resetting is performed to enhance the efficiency of subsequent actions. Then, a manual method is used to check each remark for relevance to the news, spam, and duplicate comments. It was deleted from the dataset as it was discovered to include irrelevant, spam, or duplicate remarks. This manual procedure is primarily handled by the researchers of this study.

Preprocessing (Phase 3):

The final phase of data preprocessing consists of converting English numerals to Bangla and converting punctuation to Bangla. On the phase 1 cleaning, a Bangla regex was used to detect and erase characters other than Bangla. Another regex was used in this stage to detect only English words and eliminate them from the comments. Following that, there are many lines in the comments that are written entirely in Bangla yet include just digits typed in English, therefore these sentences are processed to convert the English digits to Bangla digits. For example, 500 was changed to ৫০০, ১00 was turned to ১০০, 4 was transformed to Bangla digit ৪. Finally, English punctuation such as | was converted to ।, which is used as a full stop in Bangla sentences, and was changed to Bangla punctuation.

Following this complete data preprocessing procedure, the total number of comments was 108,950, which will be utilized as the final dataset.

Data Annotation

The most crucial stage for ensuring data completeness is data annotation or labeling. Annotated data can be trained against a model to predict labels. An experimental setup was employed in this work to pick the data for annotation; TABLE 5 displays the specifications of the data selected. A total of 20,000 comments are chosen depending on the number of comments included in the news posts. Moreover, 20 news posts have been selected among 11 popular news except news 6, which has a relatively low number of comments. Every post contains over 1000 comments, which were chosen to create 5 sets of excel sheets, each containing 200 comments. Following that, each set of sheets was generated for three distinct annotators to enhance the model's labeling. A set of 100 folders has been created containing 300 sheets based on the 20,000 comments used to annotate the dataset.

To label the first 50 sets (extended to 150, 3 copies of each set) containing 10,000 comments, 36 native Bangla speakers worked together. By interpreting the context of the news and labeling the comments, each annotator was given a separate set of sheets with the news posts. The data has been annotated into five emotions [40, 107, 108]. The selected news relevant emotions, such as anger, contempt, disgust, enjoyment, and sadness were emphasized for the emotion's classes [14, 109, 71]. Annotators labeled the comments as 0 to 5-degree levels for each emotion, with a higher degree number indicating better emotion efficiency. The annotated emotions are denoted as 1 in the dataset for training and testing. Furthermore, 11 Bangla native speakers labeled 18 sets with 54 sheets and 3,600 comments for solely multilabel emotions. So a total of 47 persons labeled 13,600 comments, with three distinct annotators for each set. TABLE 3 shows a sample dataset with annotated comment labels in multilabel emotion classification.

TABLE 3: SAMPLE DATA WITH ANNOTATED EMOTION

Comment	**Multilabel emotions**
আর কত নাটক তোরা করবি	Anger, Disgust
শোষিত জনগন এইটাই আশা করেছিল!!!	Anger, Disgust
শুধু লজ্জা বলতে পারি	Anger, Sadness
মানুষ মানুষের জন্য	Enjoyment
এই মানুষগুলোর মুখের হাসিতে প্রান জুরায়ে যায়।	Enjoyment

Finally, this article has done some concluding preprocessing after completing the annotation phase of data. In this phase, the unnecessary punctuations were removed using a different regex that is not used in any of the phases yet. And the comments containing more than two words were taken for final evaluation of the model.

Feature Extraction

Tokenization and TF-IDF are employed as feature extraction technique in this research. Tokenizers are used to transform text into numbers. Because machines cannot understand text, the data must be transformed into machine-accessible language. Tokenizers are used in various studies to preprocess the text data [110, 111, 112, 113]. But Deep Learning implementation focuses on tokenization to make the data as features before feeding the input to the model [113, 34, 114, 115]. Therefore, this study utilized tokenization as feature extraction in deep learning models. Furthermore, sequences are constructed from the tokenized data and then transformed into pad sequences to provide a complete feature for model implementation in this work. In preprocessing, the data is broken down into individual words or peripherals before being vectorized and used in the subsequent Machine Learning process.

On the other hand, the Term Frequency-Inverse Document Frequency (TF-IDF) determines the significance of a word in a sentence or document. It is accomplished by multiplying two metrics: the frequency with which a word appears in a sentence or document, and the inverse document frequency with which the word appears across a collection of sentences and documents [94, 88, 116]. In this work, the TF-IDF vectorizer and transformer are primarily employed in the construction of machine-learning algorithms. In addition, the transformer converts the count matrix into a normalized TF-IDF feature matrix. After that, a tri-gram feature has also been used as a feature where the maximum number of features is 5000. And finally, a tokenizer is used in TF-IDF. Several NLP researchers experimented with their features utilizing the TF-IDF vectorizer and transformer [10, 75, 89].

Applied Algorithms

In this research, some popular techniques that are usually applied for sentiment analysis and emotion recognition are employed. A framework has been developed in this research based on the existing literature. This research accomplished the suggested approaches of the generalized framework to observe the performance of context-based multilabel ER in Bangla. Machine learning, Deep learning, and one of the most popular approaches in recent years BERT have been incorporated for multilabel ER in Bangla. The following subsections describe the applied approaches for several domains.

Machine Learning

Logistic Regression (LR)

Logistic regression is a mathematical technique for building supervised machine learning models with binary or dichotomous dependent data points. It describes data and the relationship between one predictor variables and one or more target variable [117, 118, 105]. The type of the predictor variables could be ordinal, nominal, or interval. It uses the activation function called sigmoid, to assign probabilities to discrete outcomes, which turns numerical outputs into a probability expression between 0 and 1.0. The probability is either 0 or 1, depending on whether or not the event occurs. With a cut-off of 0.5, you may divide the classes into two groups for binary predictions. As formula shows, p(x) is the probability of the input data, β_0 is the intercept of y, the line's slop is β_1, and x represents the x coordinate value [7, 8, 65].

$$p(x) = \frac{1}{1 + \mathrm{e}^{-(\beta_0 + \beta_1 \mathrm{x})}}$$

In this work, Logistic Regression is used in conjunction with a classifier chain technique to predict multilabel emotions. This method is followed by training for each label and then adding the label with the feature. The predicted label is inserted as a sparse dense matrix. The model's parameters were 12 units of inverse regularization strength and default units for the remainder.

Random Forest (RF)

The machine learning technique known as random forest is beneficial when dealing with issues with regression and classification [5, 10, 11]. It employs ensemble learning, a method that pools the power of multiple classifiers to address intractable issues. This method is constructed from a collection of decision trees. Using the predicted outcomes from the decision trees, it arrives at a conclusion. The results of multiple trees can be predicted by averaging or calculating the mean. As more trees are added, the accuracy of the results increases. The benefits of a decision tree approach are retained while their downsides are removed. It enhances precision by lowering the likelihood of data being overfit [119, 93]. As a result, the decision tree approach was included in this work, and essentially random forest was used for both datasets. In the model implementation, the default parameters were utilized to predict the emotions. As the ensemble of decision trees grows, the algorithm sprinkles in randomization, creating the impression of a forest. By breaking up a node into multiple parts, the algorithm can examine multiple features at once, increasing the number of possible combinations and thus the quality of the resulting model.

Multinomial Naive Bayes (MNB)

One of the most well-known Bayesian learning techniques used in NLP is the Multinomial Naive Bayes algorithm [75, 89, 29]. The algorithm determines what kind of content, like a comment or a story, it is based on the information provided by the Bayes theorem. It takes a sample and determines the probability of each tag, then returns the tag with the highest probability. Each of the individual algorithms that make up the Naive Bayes classifier assumes that the features being classified have no correlation with one another. There is no correlation between the presence or absence of one feature and the decision to include or exclude a different characteristic. It's great at evaluating incoming text and figuring out problems that span multiple categories of objects [94, 68, 61]. As Bayes theorem is applied to proceed for Naive Bayes algorithms, it is required to first understand the concept of the Bayes theorem [120, 85]. Thomas Bayes developed this probability model, which can be expressed as:

$$P\left(\frac{A}{B}\right) = \left(\frac{P(A \cap B)}{P(B)}\right) = \frac{P(A) * P\left(\frac{B}{A}\right)}{P(B)}$$

In the formula, A's prior probability of appearance (PA) is compared to the probabilistic reasoning of B (PBA) if A occurs, and the probability of A (PAB) if B occurs (PB). In this work, Multinomial Naive Bayes is used in combination with a classifier chain method to predict multilabel emotions. This method is followed by training for each label and then adding the label with the feature. The predicted label is inserted as a sparse dense matrix. The model utilized the default parameters to classify the emotions.

Support Vector Machine (SVM)

To solve problems involving two classes through the use of classification techniques, SVM is a prominent supervised machine learning model. After supplying an SVM model with sets of labeled training data for each category, it is able to classify new text. Support vector regression (SVR), an expansion of support vector classification (SVC), is one type of SVM that can be used for particular ML tasks [74, 10, 121]. As opposed to other classification strategies, SVMs pick the distance measure that minimizes the average distance to the closest data point for all classes.

Decision boundaries generated by SVMs are often maximum margin classifiers or maximum margin hyperplanes. A straight line is drawn between the two categories in a simple linear SVM classifier. Assigning all data points on one side of the line to one category while assigning all data points on the opposite side of the line to a different category [95, 122]. This suggests that there is potentially an infinite number of paths to choose from. When compared to other algorithms like k-nearest neighbors, the linear SVM approach stands out since it chooses the best line to classify your data points [94, 66]. It picks a line that is the greatest distance from the nearest data points and still separates the data. To predict multilabel emotions, Support Vector Machine is employed in conjunction with a classifier chain technique in this work. Following this, training for each label is performed, and the label is then associated with the feature. As a sparse dense matrix, the anticipated label is entered. To categorize the emotions, the model used the default parameters.

K-Nearest Neighbors (KNN)

The KNN algorithm is a method for classifying data that uses the proximity of neighboring data points to predict which of two categories a given data point belongs to. To solve classification and regression issues, it employs a supervised machine learning technique [5, 10, 89]. However, its primary use is in resolving categorization difficulties. It is known as a lazy learning algorithm or lazy learner since it does not do any training when given training data [19, 69]. Instead, it just saves the data throughout the training period and makes no computations. It does not create a model until a query is run on the dataset [123, 83, 11]. As a result, KNN is great for data mining. KNN is also applied with the classifier chain method in this work. In its simplest form, KNN relies on a voting procedure to determine the category of an unseen observation. This means that the data point will be assigned to the class that received the most votes. Researchers will only use the nearest neighbor criterion to determine a data point's classification if K = 1. If K is ten, then the K nearest neighbors is used, and so on.

Deep Learning

LSTM

LSTM networks are Recurrent Neural Networks with the ability to learn order dependence. RNN uses the output of the previous step as input for the following step. It addressed the issue of RNN long-term dependence, which happens when an RNN cannot anticipate words stored in long-term memory but can make more reliable projections based on current input. As the gap length expands, RNN performance degrades. By default, the LSTM may store information for an extended duration [85, 13, 124]. LSTM is capable of processing sequential data such as video, text, audio, and so on [125, 126, 127]. It is frequently used in machine translation, language modeling, video analysis, sentiment analysis, speech recognition, and many other applications. The difficulty with Recurrent Neural Networks is that they merely keep the prior data in their "short-term memory" [9]. When the memory in it runs out, it simply deletes the most recently hosted data and replaces it with fresh data. By preserving just chosen information in short-term memory, the LSTM model seeks to avoid this difficulty. This short-term memory is kept in the Cell State. There is also the hidden state, which is familiar from regular neural networks [92, 87, 128, 129].

It takes three inputs: long-term memory, short-term memory, and E, which can be either a training example or new data. On their path to a new Cell State and Hidden State, these three values pass via a few particular gates. Forget Gate; it is determined which current and prior information is retained and which is discarded. This contains the prior run's concealed state as well as the current status. In the Input Gate, it is determined how valuable the current input is for achieving the goal. The current input is multiplied by the hidden state and the weight matrix from the previous run for this purpose. The output of the LSTM model is then determined in the Hidden State through the Output Gate. A four-layer LSTM model was utilized in this work, with a sequential model built by combining the embedding layer, two LSTM layers of 128 and 64 neurons, and an output Dense layer of 1 neuron with a sigmoid activation function. This LSTM model was utilized for each label particularly to match the classifier chain approach in deep learning. Also, it learned in $3x10^{-4}$ Adam learning rate to train the model.

BiLSTM

Bidirectional LSTM (BiLSTM) is a recurrent neural network that is mostly used for natural language processing [7, 33, 15]. In contrast to conventional LSTM, input flows in both directions, and information from both sides may be utilized. It also simulates the sequential interactions between words and phrases in both directions. In conclusion, BiLSTM is an extension of LSTM that switches the direction of information flow [130, 33, 40, 131]. It indicates that the input sequence is reversed in the additional LSTM layer [132]. The outputs of both LSTM layers are then concatenated using a number of operations, such as the mean, sum, product, and concatenation. This style of paradigm offers numerous benefits for real-world problems, especially in NLP. This is due to the fact that each input sequence component contains information from both the present and past. By combining LSTM layers from both sides, BiLSTM is able to provide a more appropriate output. In this study, a four-layer BiLSTM model was constructed, consisting of an embedding layer, two Bidirectional LSTM layers of 128 and 64 neurons, and an output Dense layer of 1 neuron with a sigmoid activation function. Also, the BiLSTM model was utilized for each label particularly to match the classifier chain approach in deep learning.

Hybrid Deep Learning Algorithms

An algorithm that combines two or more other algorithms to solve the same problem is called a hybrid algorithm. It is a strategy that fuses many varieties of deep neural networks with probabilistic methods for dealing with model uncertainty. Recurrent neural networks can learn from context, but the ordering of words causes bias. The Convolutional neural network (CNN) text analysis approach may collect significant text properties by pooling, however it is difficult to obtain contextual information [76, 15, 133].

This work built two hybrid deep learning models, CNN-LSTM and CNN-BiLSTM [63, 86, 107]. A sequential model combining the embedding layer, a Convolutional layer with 32 filters and 3x3 kernels and a relu activation function, a Max Pooling layer with pool size 2, an LSTM layer of 100 neurons, a Dense layer of 32 with sigmoid activation function, and finally an output Dense layer with 1 neuron with sigmoid activation function was used for CNN-LSTM. A sequential model combining the embedding layer, a Convolutional layer with 32 filters and 3x3 kernels and a relu activation function, a Max Pooling layer with pool size 2, a Bidirectional LSTM layer of 100 neurons, a Dense layer of 32 with sigmoid activation function, and finally an output Dense layer with 1 neuron with sigmoid activation function. These models were utilized for each label particularly to match the classifier chain approach for all of the emotions.

BERT Approaches

Bidirectional Encoder Representations from Transformers (BERT) is a transformer-based approach for natural language processing. It was developed by Google AI Language researchers in 2018 and provides a one-stop solution for more than 11 of the most common language tasks, including sentiment analysis and named entity identification. BERT utilizes Transformer, an attention protocol that discovers contextual associations between words (or sub-words) in a text. It comprises of two separate mechanisms: an encoder that reads text input and a demodulator that develops a forecast for the task. Since the objective of BERT is to develop a language model, only the encoder mechanism is necessary. In contrast to directional models, which read text input sequentially, the Transformer encoder reads the entire sequence of words simultaneously (left-to-right or right-to-left). Therefore, it is considered bidirectional when it would be more accurate to say nondirectional. This capability allows the model to learn the semantics of a word based on its circumstances (left and right of the word).

Few studies have examined specific Bangla Natural Language Understanding (NLU) tasks, such as sentiment analysis and emotion detection. As a result, Bangla NLU has yet to conduct a thorough, unifying study. BanglaBERT is the country's first Bangla Language Understanding Benchmark (BLUB). A few more transformers, such as Bangla-ELECTRA, Bangla-BERT-Base, and Multilingual-BERT were also constructed and published as hugging face frameworks [12, 40, 134]. However, there is still a lot of work to be done in the research of BERT in Bangla.

BanglaBERT was trained with 27.5 GB of collected Bangla pretraining data (named "Bangla2B+") extracted from crawling 110 popular Bangla websites [40, 135]. They offered two downstream task datasets on natural language inference and question answering in addition to benchmarking on four distinct NLU tasks, including text classification, sequence labeling, and span prediction. For both multiclass and multilabel data, this study applied all of the BERT transformers outlined in this section. The applied BERT algorithms are BanglaBERT, multilingual BERT, Bangla-Bert-Base, and Bangla-

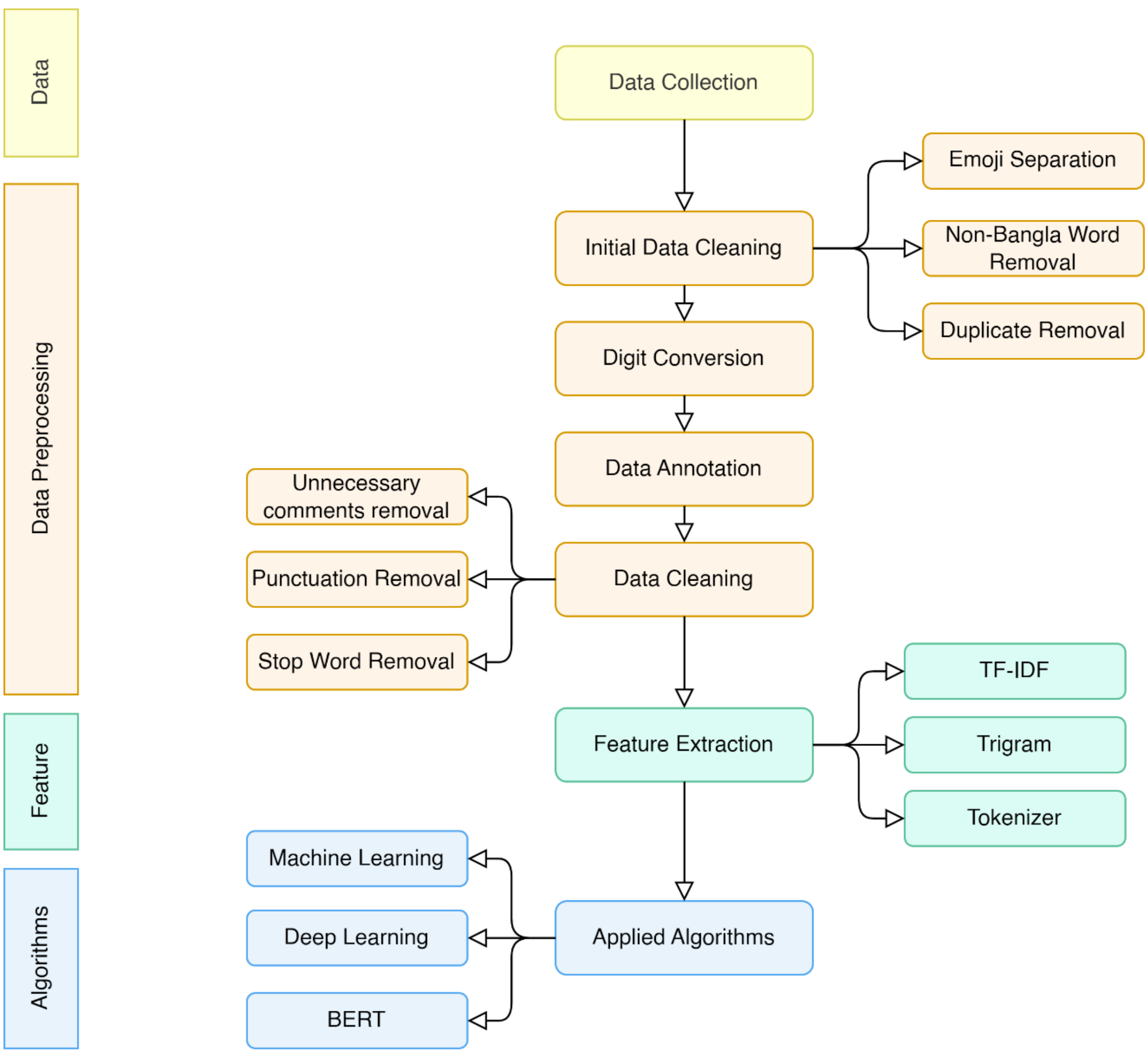

Figure 6: Applied Methodology for Multilabel ER in Bangla

Electra. Bangla-Bert-Base outperformed not just the BERT techniques, but also the ML and DL approaches. Therefore, several algorithms have been evaluated from different fields for the emotion recognition in Bangla. Figure 6 illustrates the general methodology that have been incorporated in this study.

The figure of the proposed methodology implies the overall procedure of this research. Moreover, data collection process is one of the vital parts of this study. After that, the emotion classification using the context-based data brings the novelty of this work. Therefore, the outcome of the applied algorithms as well as the prior discussion has been incorporated in the following chapter.

3.5 Implementation Requirements

This research does not require a high configured device for data collection and methodology applied in this study. But there is a minimum requirement for the device specification that anyone has to maintain for applying the scraping algorithm as well as the related methodologies. The general requirements of the Central Processing Unit (CPU), Random Access Memory (RAM), and Graphics Processing Unit (GPU) are shown in TABLE 4. Accordingly, the device specification of this research is also addressed in the table. Additionally, the minimum requirements are especially needed to maintain for applying the deep learning approaches. However, Google Colab has also been used to perform heavy deep learning algorithms.

TABLE 4: IMPLEMENTATION REQUIREMENTS

Terminology	**Used in this Research**	**Minimum Requirement**
CPU	8 cores and 3.6GHz (AMD Ryzen™ 7 3700X)	4 cores and 2.6GHz (Intel® Core™ i3-9100E, AMD Ryzen™ 3 2200G, or higher)
RAM	16 GB	8 GB
GPU	6GB GDDR6 (Nvidia GeForce® GTX 1660 SUPER)	Nvidia GPU 6GB VRAM and CUDA architectures 3.5, or higher (Nvidia GeForce® GTX 750, 780)

CHAPTER 4
EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

A well-structured dataset is necessary to evaluate the models from various fields such as Machine Learning, Deep Learning, Hybrid Approaches, and BERT (Bidirectional Encoder Representations from Transformers). Hence, a detailed explanation of the dataset before the experiment is given in TABLE 5.

N.B. EC - Each Comment

TABLE 5: SELECTED COMMENTS FOR ANNOTATION OF EACH NEWS

News	Number of Posts	Number of Comments	Number of Sentence (EC)
News 1	3	3000	Single and Multiple
News 2	2	2000	Single and Multiple
News 3	1	1000	Single and Multiple
News 4	2	2000	Single and Multiple
News 5	3	3000	Single and Multiple
News 6	0	0	Single and Multiple
News 7	2	2000	Single and Multiple
News 8	3	3000	Single and Multiple
News 9	1	1000	Single and Multiple
News 10	2	2000	Single and Multiple
News 11	1	1000	Single and Multiple

To maintain the consistency in the dataset, same news portal and the same number of comments from each post have been selected for annotation. However, news 6 contained less than 1000 comments in each post. For that reason, no comments have been selected from news 6 for annotation. And 1000 comments have been selected randomly from each post to label the data. After the selection process, each data labeling has been done by three annotators and some preprocessing steps have been applied to train the model properly.

4.2 Experimental Results & Analysis

Multilabel emotion recognition is the main aspect of emotion identification that is the focus of this study. Five relevant emotions based on the news are classified in this research. Anger, contempt, disgust, enjoyment, and sadness are the recognized emotions. Therefore, multiclass emotion recognition means identifying a particular emotion from a single text [136, 86, 14]. However, many algorithms from various domains, including machine learning, deep learning, and BERT, have been used to assess emotions. Frequently used machine learning techniques for classifying emotions include KNN, Support Vector Machine, Logistic Regression, Random Forest, and Multinomial Naive Bayes. Additionally, the literature review of this study claims that SVM performs admirably in multiclass ER [137]. After that, various deep learning approaches like LSTM, BiLSTM, CNN, CNN-LSTM, CNN-BiLSTM, RNN-LSTM are popular in this domain. Then some BERT approaches are also applied for multiclass emotion detection. But very few works have been incorporated for multilabel emotion classification in Bangla and there is no research has been employed for context-based multilabel ER in Bangla.

The concept of multilabel emotion identification from text is based on the fact that a single text might include several emotions. Recognizing several emotions from a single text is known as multilabel emotion recognition [9, 15]. This study identified multilabel emotions using machine learning, deep learning, and BERT techniques. TABLE 6 displays the effectiveness of ML approaches, with MNB offering the highest level of accuracy. And TABLE 7 shows the precision, recall, and F1 score of the MNB approach regarding all emotions. Accordingly, Figure **7** shows the confusion matrix to show the performance of MNB.

TABLE 6: MACHINE LEARNING APPROACHES FOR MULTILABEL ER

Algorithm	Accuracy (%)
SVM	80.72
MNB	**82.64**
LR	80.03
RF	79.11
KNN	70.87

The application of ML techniques like MNB, Support Vector Machine (SVM), Logistic Regression, Random Forest, and KNN is applied first. Due to the lack of a suitable algorithm for multilabel ER, certain well-known and arbitrary strategies have been employed to satisfy the requirements and MNB provided a satisfactory result among all the ML approaches.

TABLE 7: PRECISION, RECALL, AND F1 SCORE FOR MNB

Emotions	Precision (%)	Recall (%)	F1 Score
Anger	74.84	**66.63**	0.7
Contempt	72.84	42.07	0.53
Disgust	64.29	8.89	0.16
Enjoyment	89.94	59.61	**0.72**
Sadness	**90.91**	4.78	0.09

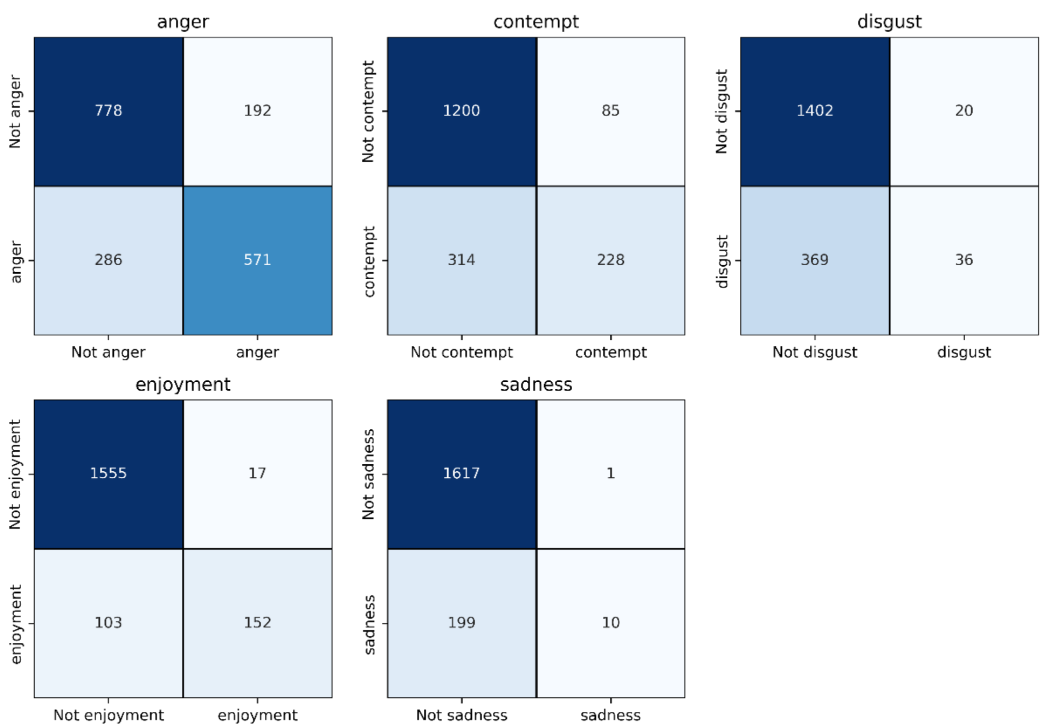

Figure 7: Confusion Matrix of MNB Performance

Accordingly, DL methods have been assessed to extract the multilabel emotions from Bangla comments. The LSTM, CNN-LSTM, BiLSTM, and CNN-BiLSTM algorithms are evaluated for multilabel. In this phase, BiLSTM scored better than other models. The corresponding outcomes of each method are described in TABLE 8 and the precision, recall, and F1 score are shown in TABLE 9 and the confusion matrix is shown in Figure 8.

TABLE 8: DEEP LEARNING APPROACHES FOR MULTILABEL ER

Algorithm	**Accuracy (%)**
LSTM	78.44
BiLSTM	**79.14**
CNN-BiLSTM	78.70
CNN-LSTM	78.29

TABLE 9: PRECISION, RECALL, AND F1 SCORE FOR BILSTM

Emotions	**Precision (%)**	**Recall (%)**	**F1 Score**
Anger	**68.88**	53.37	0.6
Contempt	65.54	41.61	0.51
Disgust	33.88	30.19	0.32
Enjoyment	60.0	**74.76**	**0.67**
Sadness	41.61	24.57	0.31

Bangla BERT has become popular nowadays for Bangla ER because this model is developed for only Bangla language [12, 40, 135]. BERT models are basically developed for multiclass emotion classification. And these models have their own developed values that cannot be modified. Though these models are for multiclass ER, this work applied them for multilabel ER also to observe the results they have shown in the Bangla language.

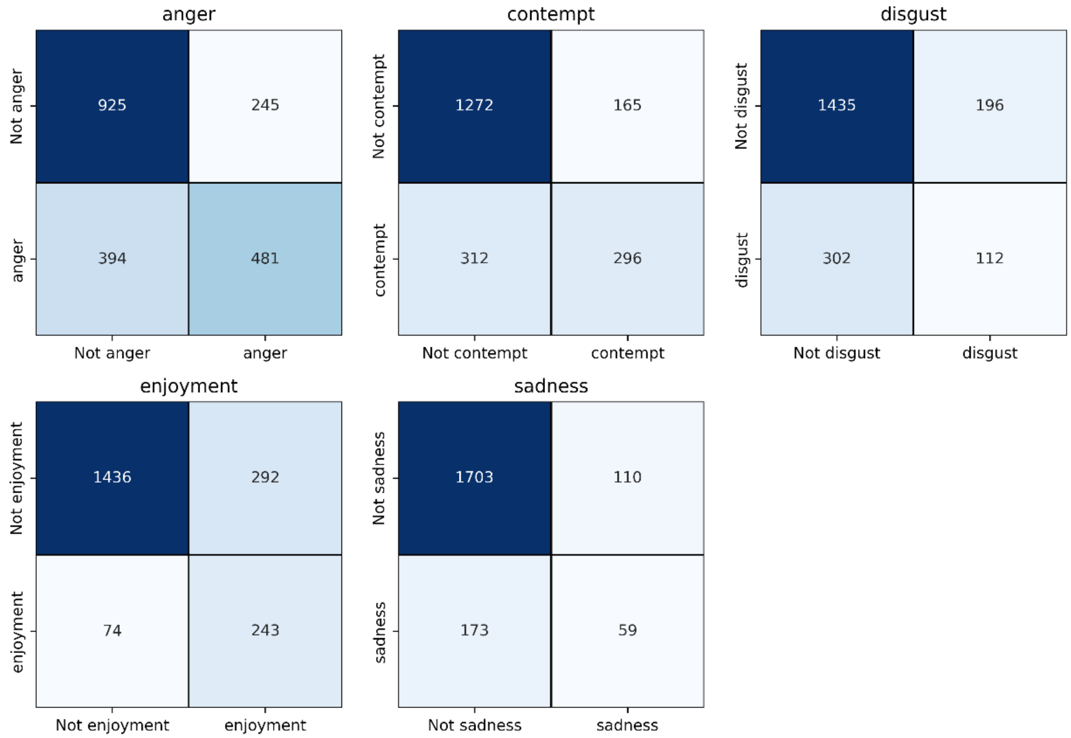

Figure 8: Confusion Matrix of BiLSTM Performance

There are various types of BERT models have been implemented for the Bangla language. Bangla-Electra, Bangla-Bert-Base, Multilingual Bert, and BanglaBert have been applied in the corpus to identify the expected emotions.

TABLE 10: BERT APPROACHES FOR MULTILABEL ER

Algorithm	**Accuracy (%)**
Bangla-Electra	81.79
Bangla-Bert-Base	**83.23**
Multilingual Bert	80.92
BanglaBert	82.21

TABLE 10 illustrates the performance of BERT algorithms where Bangla-Bert-Base performed better than other BERT algorithms. The precision, recall, and F1 score for Bangla-Bert-Base is shown in TABLE 11. Accordingly, the confusion matrix is illustrated is Figure 9.

TABLE 11: PRECISION, RECALL, AND F1 SCORE FOR BANGLA-BERT-BASE

Emotions	Precision (%)	Recall (%)	F1 Score
Anger	72.98	72.82	0.73
Contempt	66.85	61.21	0.64
Disgust	45.69	41.67	0.44
Enjoyment	**84.33**	**74.34**	**0.79**
Sadness	52.88	41.91	0.47

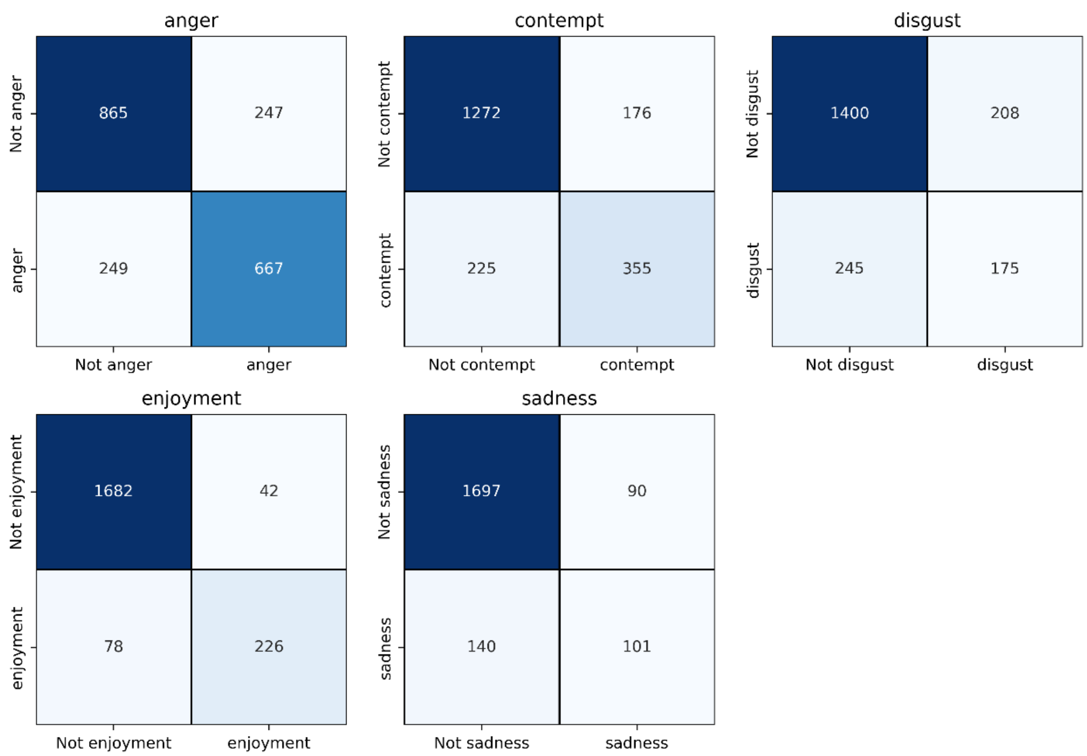

Figure 9: Confusion Matrix of Bangla-bert-base Performance

This study extracts multiple classes of emotions from Bangla text, where the data were categorized according to context. Therefore, this corpus has been used to comprehend and assess the performance of multilabel emotions in various models. With regard to multilabel emotions, the Bangla-bert-base performed admirably with an accuracy of 83.23 %.

Finally, a web app has been developed for Bangla emotion recognition. The web app is developed using the best performer bangla-bert-base. That means a user has to provide a Bangla comment in the comment box, then the pre trained bangla-bert-base model will identify the emotion of the given comment. Figure 10 illustrates a glimpse of the developed application.

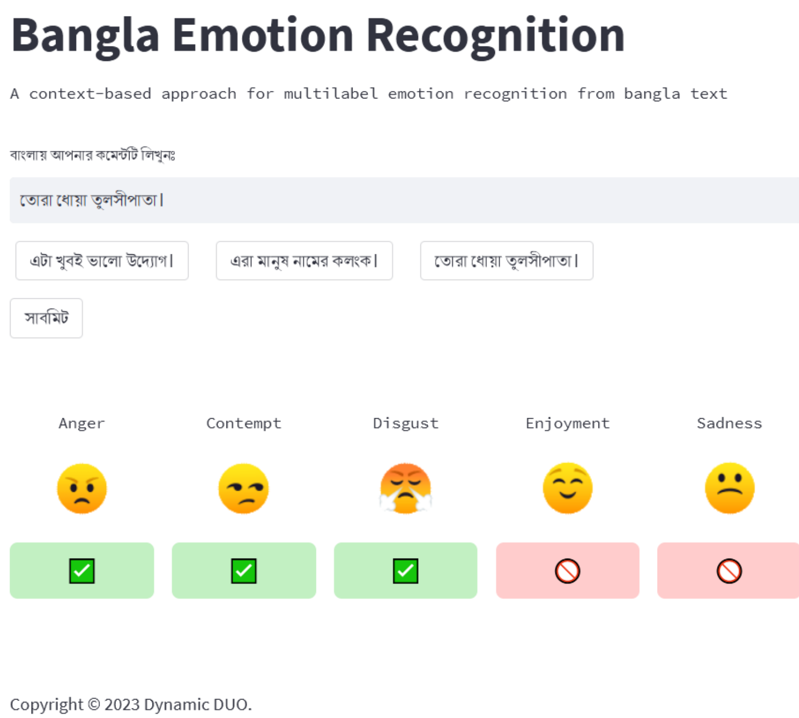

Figure 10: Interface of Web Application

An example is shown in the picture that a user provides a comment and the pre trained model predicts three emotions that is relevant to the comment. A framework has been used for the development of the application known as Streamlit and the pre trained model is deployed to detect the emotions properly. This web application can be used to identify emotions and three sample examples are also given in the interface so that a user can easily click one of them and check the result. Moreover, a user can provide a Bangla text by their own motive and the pre trained model will identify the emotions based on the training. Therefore, the interface of the application is easier to understand and animated emojis have been used for better look and understanding.

4.3 Discussion

Text-based ER has become a popular topic due to its high demand by various industrial companies to meet customer satisfaction. As a result, numerous works on ER have been produced in a variety of languages as well as in Bangla [51, 53, 38, 71]. Nevertheless, because of its structural complexity and lack of suitable data processing tools, Bangla is regarded as resource-constrained language. Despite having a highly complex structural design, a number of works have been done to address the issue because it is the seventh most spoken language in the world[13]. SA and multiclass ER from Bangla text is common in this field [10, 71, 40]. Many researchers work on identifying a single emotion from multiple classes known as multiclass ER from the text.

However, multilabel ER, or the detection of many emotions from a single text, is a difficult task in this field. Because very few works have been incorporated into this field in several languages [9, 15]. But no comprehensive work has been done on multilabel ER in Bangla which shows the challenge of this criteria. However, this study incorporates the challenge to understand the performance of multilabel ER in the Bangla language using some existing algorithms available in this field.

Context-based ER requires that a user comprehend the context before they can recognize emotion from the text. That implies that the emotion will be determined based on the fact after the context has been acknowledged. Context-based ER aids in more accurate emotion identification since it provides a thorough understanding of the text being studied. But there is no such work that has been done before in the Bangla language. Identifying emotions from a given comment is the general aspect of this domain. Due to this, this study utilizes this fact in a special approach in order to present a novel feature of this field.

Several algorithms have been applied from different domains such as ML, DL, and BERT. For multiclass ER, KNN, Support Vector Machine, Logistic Regression, Random Forest, and Multinomial Naive Bayes algorithms are commonly used algorithms for multiclass ER [137, 138, 139]. Accordingly, the generalized framework states that SVM, MNB, NB, and LR are frequently used in machine learning algorithms. On the other hand, MNB, Support

[13] https://www.ethnologue.com/guides/ethnologue200

Vector Machine (SVM), Logistic Regression, Random Forest, and KNN are applied from ML techniques for multilabel ER [20, 41]. Since any proper algorithm is not available for multilabel ER, some popular and random algorithms have been applied to incorporate the results. MNB provides the highest result among all applied ML algorithms which is quite satisfactory. On the other hand, LSTM, CNN-LSTM, BiLSTM, and CNN-BiLSTM were applied from DL approaches where BiLSTM with an accuracy of 79.14% which is the highest among DL approaches. Though BERT algorithms are developed for multiclass ER in Bangla, these algorithms are applied in multilabel ER to observe the performance. Bangla-Electra, Bangla-Bert-Base, Multilingual Bert, and BanglaBert are applied and Bangla-Bert-Base outperformed other algorithms with an accuracy of 83.23%. Therefore, Bangla-Bert-Base performed best than all other algorithms. Though the result of MNB and Bangla-Bert-Base is almost similar, the accuracy and other values such as precision, recall, and F1 score are quite satisfactory than MNB.

The approaches applied for ER are basically built for sentiment extraction and multiclass emotion classification. There is no approach has been implemented yet for multilabel ER in Bangla. The resource for multilabel ER for other languages is also unavailable. If general texts are used for this purpose, better result can be achieved. Because context-based data creates diversity in the data. For that reason, it becomes difficult to learn the structure of data for the machine. Therefore, it can be said that context-based data creates diversification that is responsible for lower accuracy. However, the corresponding result for multilabel ER is not outstanding but satisfactory. For the exact emotion retrieval, more research needed to be incorporated in this domain. For this, the data needs to be structured and concise as Bangla is a complex language regarding its structure.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT, AND SUSTAINABILITY

5.1 Impact on Society

The primary goal of this study is to discover the emotions that are influenced by various news articles posted by different persons on social media. The use of social media is expanding quickly, as well as the sharing of thoughts and feelings in a similar way. Additionally, a number of restaurants, online shopping-related websites, and e-commerce sites have the feature to solicit customer feedback. After receiving any service, consumers give comments and recommend excellent or terrible platforms to others based on their personal user experiences. As a result, the importance of user feedback for the business sector cannot be overstated. Based on customer feedback, these companies are attempting to enhance their services.

Therefore, one of the primary issues for every user-related business is emotion identification from the text. In order to improve this domain with a novel idea of emotion recognition that hasn't been done before, this research has been implemented. Therefore, the impact of this research on society is very essential. The data used in this research also be used in other works for the same purpose. Accordingly, this research can be used in various government projects related to enhancing user experience.

5.2 Impact on Environment

This research incorporates building a comprehensive corpus and emotion recognition from low-resource languages like Bangla. Thus, the purpose of this study is to advance the branch of computer science known as Natural Language Processing. Therefore, the purpose of this research is to aid in the creation of learning machines. Therefore, this research has no adverse effect on the environment.

5.3 Ethical Aspects

In this work, all ethical standards have been followed. First and foremost, the difficulty of this research required the use of an appropriate corpus. Using a Facebook scraper, data was collected maintaining all kinds of ethical standards. For instance, depending on some prominent news, Facebook comments have been gathered from several online news portals. People shared their opinions by leaving comments, and different opinions from different groups of people were available. Additionally, we gathered all the comments without paying special attention to any one group, political viewpoint, or religion.

Second, the data has also been ethically labeled. Each data annotation had three annotators, and each one identified a label to the data that reflected their personal viewpoint. During the data annotation phase, no direct interactions or observations of other people's data have taken place.

Thirdly, during data preprocessing, there was no data tampering or compromise. Preprocessing procedures have been made to reduce the complexity since preprocessing enables the provision of data that produces better outcomes when training the model. However, neither the data modification nor the security of the data was compromised in any way as a result of these actions. As a result, our research did not transgress any moral principles that might be detrimental to society, the environment, or people.

5.4 Sustainability Plan

Understanding people's emotions is an increasing concern in today's society since individuals are expressing their opinions through various social media platforms for various reasons. Because the utilization of these feelings, thoughts, and views helps to build applications more user-friendly, understand user demand, and enhance the user experience. Since more people are using social media and the internet every day, this research is applicable for a lifetime. The corpus created for this study is also reusable in the future, so anyone can use it to develop their models, for sentiment analysis or emotion identification tasks, or for any other activity requiring opinions. On the other hand, the scraping algorithm used in this study can potentially be used again for more data gathering. Since Bangla is the primary language of Bangladesh, the approaches that have been used in this work for detecting emotion can also be applied to other datasets, which may aid scholars working in this field as well as the general public and government purposes.

CHAPTER 6

SUMMARY, CONCLUSION, RECOMMENDATION, AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the Study

This study seeks to provide a thorough literature evaluation to comprehend the status in this field currently and to examine the resources already available for Bangla language. The first goal of this study was to determine the SA and ER status of distinct languages. The study then concentrates on Bangla, which is regarded as a low-resource language. This study also discusses the cause of resource constraints. The quantity of works, the significance of each work, and the causes of their popularity in this field are also taken into account in this study. The various sources for data collection and the overall methodology are also included in this study, along with popular preprocessing methods and frequently used algorithms. This study generalizes a compiled framework for the aspirants in this field based on an analysis of the existing literature so that they can learn about the literature and can acknowledge the tools and techniques that are now in use.

This study aims to establish a corpus because Bangla is a language with limited resources. Additionally, this study used a novel, never-before-used data annotation process. Each set of data had three annotators, and each set of data was annotated after the context of the data had been understood. That implies that the annotation process begins with the annotator reading the news and accompanying comments before annotating the data. A few well-known preprocessing methods have been used before and after the annotation process has been finished. The data is then used to identify emotions across multilabel. To observe the outcome of each criterion, machine learning, deep learning, and BERT models are applied. Although there have been a number of papers that combine multiclass ER, a suitable model for multilabel ER has not yet been devised. In this study, the widely used methods for emotion detection were used. However, because context-based data has not yet been employed, the result is satisfactory as compared to other research. Finally, a web application has been developed to show the performance of the model.

6.2 Conclusions

This study focuses on the existing literature to understand the current situation of this domain so that it can provide a generalized idea of existing works to aspiring researchers. Therefore, a comprehensive generalized framework for sentiment analysis and multiclass emotion recognition has been developed in this research. After that, a social media corpus has been built using our own scrapping algorithm. Popular online news portals are the source of this data. Then the data were preprocessed by popular preprocessing techniques and evaluated by the algorithms suggested by the generalized framework as well as some other algorithms. Among all the algorithms, the Bangla-Bert-Base model performed best and it shows 83.23% accuracy. On the other hand, machine learning also performed well and provides similar result to BERT approaches. Therefore, this study introduces a novel approach to emotion recognition by using context-based data that helps to understand emotions more effectively. Eventually, a web app is created for Bangla emption recognition so that a user can provide his desired comment and acknowledge the emotions.

6.3 Limitations of the of Study

The lack of appropriate resources is a significant limitation in this field. There are certain limitations on this study, though. The scraping algorithm has been used to gather a lot of data. However, not all data can be used to assess the models. Because it takes more time and requires more annotators to handle such a large volume of data. However, in this study, only 47 annotators annotated the data. A large number of annotators are required because the research requires three annotators for each annotation. On the other hand, if such a large amount of data is used for training and testing, a configured computer is required to analyze the models. The evaluation of the models takes a long time.

6.4 Implication for Further Study

Since this study has some limitations, actions can be performed in the future to go over such difficulties. The whole data gathered from online news portals can be used in subsequent studies to assess different models. These data can be utilized for unsupervised machine learning algorithms because not all of the data has been annotated yet. After properly annotating the data, the data can then be used to test alternative supervised learning and deep learning approaches. The lack of an appropriate algorithm for context-based multiclass and multilabel emotion detection can be addressed in future studies to help Bangla overcome the difficulties of context-based ER. We, therefore, aspire to fulfill the requirements for more research in future and make contributions to the field.

APPENDIX

SA – Sentiment Analysis

ER – Emotion Recognition

NLU – Natural Language Understanding

NLP – Natural Language Processing

AI – Artificial Intelligence

ML – Machine Learning

DL – Deep Learning

SVM - Support Vector Machine

SVC – Support Vector Classifier

SVR – Support Vector Regression

KNN - K-Nearest Neighbor

LR - Logistic Regression

RF - Random Forest

DT - Decision Tree

NB - Naive Bayes

MNB - Multinomial Naive Bayes

LSTM - Long Short Term Memory

BiLSTM - Bidirectional Long Short Term Memory

GRU - Gated Recurrent Unit

CNN - Convolutional Neural Network

RNN - Recurrent Neural Network

BERT - Bidirectional Encoder Representations from Transformers

PCA - Principal Component Analysis

BoW - Bag of Words

POS tagger - Parts of Speech tagger

TF-IDF - Term Frequency - Inverse Document Frequency

CPU - Central Processing Unit

RAM - Random Access Memory

GPU - Graphics Processing Unit

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