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A Comprehensive Roadmap on Bangla Text-Based Sentiment Analysis

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Abstract

The effortless expansion of Internet access has eventually transformed the dissemination behavior towards E-Mode. Thus the usage of online or, more specifically, 'Digital' texts has expanded abruptly. 'Bangla', the seventh most spoken language globally, has no different nature. Communication in the Bangla language has also been exposed on the Internet, which describes the feelings of individuals in any specific context. These enormously generated data from diverse sources have drawn the interest of the researchers working in the Natural Language Processing domain. Despite its relatively complicated structure, a lesser amount of annotated data, as well as a limited number of frameworks and approaches, exist. This lacking of resources has kept several stones unturned in this diverse, emotion-rich and widely spoken language. To bridge the lacking and absence of resources, this article aims to provide a generalized deduced working procedure in this domain. To do so, the existing research work in the domain of sentiment analysis using Bangla text has been collected, evaluated and summarized. Also, in this article, the techniques used in pre-processing, feature extraction, and eventually used algorithms have been identified and discussed. Considering these facts, this research work sketches a tentative blueprint of sentiment analysis using Bangla text. Additionally, this article discusses existing regional language corpora such as Tamil, Urdu, and Hindi, as

well as English and methodologies used to extract emotional essence from Bangla language comparing other languages. That will assist in determining the probable chosen path of exploring Bangla in a more deeper aspect. Moreover, this work has deduced and presented a generalized framework that will direct aspiring researchers to decide the pathway of choosing data vis-à-vis methodologies based on their interests.

Keywords: Sentiment Analysis, Emotion Recognition, Sentiment Analysis in Bangla, Natural Language Processing, Low-Resource Language, Text Classification

1 INTRODUCTION

Sentiment analysis (SA) is the technique for determining an individual's polarity in any given context based on the language shared on any medium whether social media or another platform [1]. Similarly, SA from Bangla text also refers to the similar process where the polarity of emotion is determined from a particular version of Bangla text [1]. Correspondingly, Emotion Recognition (ER) is the state of a specific emotion in a particular text. Therefore, SA and ER are associated internally since SA refers to a text's polarity and ER determines a person's specific feelings. For instance, if a user expresses a negative emotion, such emotion can be sad, angry, or disgust. Therefore, ER is required to know the actual feelings of a circumstance. Accordingly, as the concept of SA and ER focuses on understanding the communicated language, thus this field of study is a subset of Natural Language Processing (NLP) [1]. As a result, SA and ER in several languages have evolved into a significant area of study, as the availability of texts is expanding rapidly.

SA and ER from the Bangla language have also come into the picture as it is the 7th most spoken language with 272.7 million native speakers all over the world [2]. In addition, the lacking of linguistic material used in the establishment, development and evaluation of language processing applications is known as low-resource language. [3]. However, the initial focus of the research was on the rule-based lexical and morphological analysis of Bangla. This field of study is expanding at a rapid pace over a period. However, there are some dilemmas in this domain, including a lack of data and inadequate tools and techniques [2–5] etc. Though retrieving a large volume of text from various platforms is more straightforward, there is a dearth of properly annotated computer-readable data [6]. For these reasons, this language is still considered to be a resource-constrained one. And the complex structure is also responsible for not having available tools and techniques for this language [7, 8]. As a matter of fact, extracting sentiment from Bangla text has become challenging for researchers [9].

[1] https://brand24.com/blog/sentiment-analysis/
[2] https://www.ethnologue.com/guides/ethnologue200
[3] https://medium.com/sciforce/nlp-for-low-resource-settings-52e199779a79

Several research studies in this domain presented several aspects to understand the current trends. A recent review on SA illustrates the domain-specific pre-processing techniques, research methodologies, corresponding dataset, and evaluation metrics for significant works on SA in Bangla [10, 11]. Additionally, this article found some publications on disambiguating words using three algorithmic strategies [12]. Another study [13] of NLP on Bangla text explored classical (Dynamic Time Wrapping (DTW), Hidden Markov Model (HMM), Linear predictive coding (LPC) etc), Machine Learning (ML) based, and Deep Learning (DL) based methods for a variety of domains. That includes SA, text summarizing, speech recognition etc. On the other hand, remarkable research contributed to the advancement of Bangla NLP tasks using an individual and consolidated dataset providing promising performance with transformer-based models [6].

This article is a noble approach to explore the previous research works in the area to comprehend the state of SA and ER in Bangla. This article further investigates the constraints of this field and outlines a roadmap Figure 8 for aspiring researchers in this domain, as SA and ER from the text are growing into an eminent research domain in this era. Therefore, this research is required in order to acknowledge the current SA and ER conditions for aspirants as well as to have a comprehensive direction to work in this domain. However, due to the lack of properly labeled data and the complexity of Bangla's structure [14–18], it is necessary to acknowledge the current corpora that are frequently used in this field so that the researchers can explore them and contribute to expand the dataset in this field. Following research questions are formulated in order to understand the mentioned phenomena better.

- What are the most used data sources in the Bangla language?
- What are the main applications of SA and ER in the Bangla language?
- What might be the outlined framework for conducting SA or ER in Bangla?

The rest of the paper is organized as follows: section 2 refers to the design of this research. Section 3 covers the related work on SA and ER in the Bangla language. Section 4 covers the discussion of overall observation in this domain that includes existing corpora and the mostly applied approach for SA in Bangla. This section also covers the generalized process of SA in Bangla language. Section 5 covers the detailed comparison of different approaches based on emotions. Section 6 covers the entire work we have done and conclusion of this article.

2 RESEARCH DESIGN

The overall purpose of this study is to have a better understanding of the current situation of research works in a resource-constrained language like Bangla. This study mainly focuses on the review of SA in Bangla to address this phenomenon. The research entails selecting and evaluating prior research contributions, analyzing and summarizing the findings in a way that draws

Table 1 Summary of Searching Procedure and Results

Source	Category	Time Period	Search Query	No. of Papers	Duration
Google Scholar	Articles, reviews, book chapters	2015-2021	"(Sentence AND Bengali) AND (sentiment OR emotion)"	110	10-17 October, 2021

clear conclusions about the progress of this versatile research domain. In addition, this paper aggregates the existing corpora and applied approaches for the Bangla language altogether. Various regional language corpora, code-mixing corpora, English corpora, and available strategies for these languages have been demonstrated in order to locate the cause of still being under-resourced and unavailable tools and techniques in the Bangla language. As a result, a compilation of existing works has been outlined to serve as a handbook for aspirants in the field of Bangla NLP.

Google scholar has been used to retrieve papers for this research, with the following keywords: "(Sentence AND Bengali) AND (sentiment OR emotion)". Accordingly, the exact search was conducted for this article on other repositories like IEEE Xplore, Semantic Scholar, and Arxiv. Nevertheless, those platforms provided fewer articles compared to Google Scholar due to their indexing methods. For instance, a search on IEEE Xplore using the following keywords returned only 17 papers, of which five were not in the interest of this work. A similar pattern of results has been observed on Arxiv where it returned only five papers. Whereas, Google Scholar facilitates the discovery of all relevant content in one result as an overall perspective of a particular domain. That's why, this platform has been used due to its inclusiveness and accessibility.

The details of the search keyword are shown in Table 1. These articles are compiled focusing a specific timeframe: 2015-2021. There are two reasons for selecting this particular timeframe. Firstly , this field has grown substantially over the last few years, and the second reason is to understand the current state-of-the-art of SA in Bangla. Through a keyword search on Google Scholar, around 5000 papers were published between 2015 and 2021. However, 110 articles were acquired from it because others conflict with the focused domain. As the primary center of attention was SA and ER in Bangla and only a handful amount of research has been conducted in this domain. Therefore, the search results returned various similar language based works such as Hindi, Tamil, English, Telugu, Manipuri, Kannada, Urdu etc. The search results presented similar low-resources languages especially from the Indian subcontinent. Additionally, there were many articles in the result beyond the main focus rather than the building blocks of SA and ER precisely. Thus, several duplicate articles also need to be excluded. After applying the inclusion and exclusion

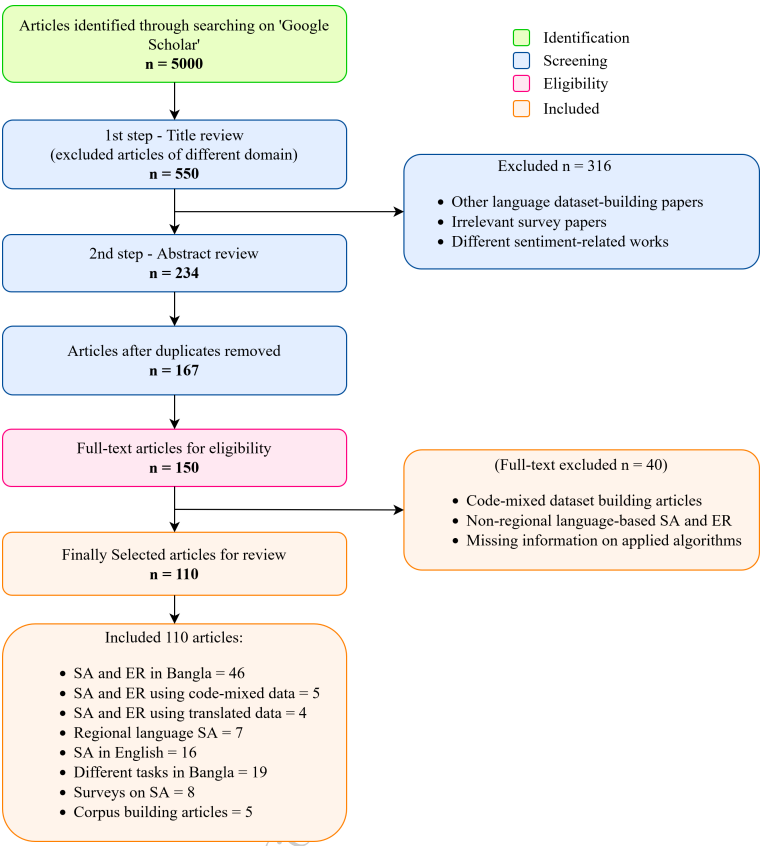

Fig. 1 Attrition of Papers through Screening

criteria, 110 research articles were collected which are fit into the research interest of this work. These articles include 46 articles on SA and ER in Bangla, 19 articles that used Bangla data for various tasks, 5 articles that used code-mixed data for SA, 4 articles that used translated data, 7 articles that used other regional languages for SA, 16 papers on SA in English, 8 surveys on SA, and 5 corpus building articles. A detailed flowchart outlines the final outcome of inclusion and exclusion criteria 1. Beyond the focused research papers on Bangla language, some relevant studies have also been incorporated. This has been done to understand and outline the availability of resources, tools etc. in different similar languages.

3 RELATED WORK

SA is the contextual mining of texts [1] that identifies the point of view of a text or conversation. There are two types of sentiment: subjectivity/objectivity identification and feature or aspect-based identification [4]. On the other hand,

[4] https://www.kdnuggets.com/2015/12/sentiment-analysis-101.html

ER is the elaboration of that point of view that acknowledges the exact feeling of a particular text. SA began in ancient Greece with the concept of Doxa [5] (Common beliefs or popular opinion), based on popular opinion and gave semantic orientation, and algorithms by the evolution of time. Basically, SA was started at the beginning of 20th century based on public opinions [19]. The first research study on SA was published in 1940 [20], and by the middle of the 1990s, computer-based methods were beginning to be discussed. SA was catered majorly by the Association for Computational Linguistics founded in 1962. Additionally, subjectivity analysis was carried out by the computational linguistics community in 1990 [19]. Following that, SA and ER have become more and more popular in recent years. 99% of research articles on SA were published after 2004. Precisely, 1039 articles had been published by 2010 and the number of papers has increased by 6996 by 2016. The availability of text on the internet and the automated crawling of data make it possible for such a large number of works [21].

Furthermore, to understand the sentiment or emotion of a text, it is essential to understand the text structure, definition of words, along with syntax and intent. Natural Language Understanding (NLU) helps to understand these circumstances and NLP helps to process the text [6]. Therefore, SA and ER are the subsets of NLP. The process of SA and ER is done based on Artificial Intelligence (AI) where NLP, ML, DL-based algorithms are implemented to define the polarity of texts. Moreover, data plays a vital role in this domain because it enhances the accuracy of determining sentiment and emotion. The higher the volume of data, the more satisfactory versatility can be achieved.

Beyond academic interests, SA is widely utilized in market analysis and research because there are distinct online platforms to share opinions [1, 7, 22] and these opinions are important in improving user experience. These online platforms have different types of users from different countries and SA comes in that way in different languages [23–32]. Data pre-processing, feature extraction, applying classifier algorithms are the basic steps to discover the correct sentiment from text. Though many languages are available, people share their thinking using their native languages primarily. Language-based SA has evolved due to the popularity of using native languages in terms of communication across the online platforms as well. Still, English is the dominating language worldwide with 1.5 billion native speakers [7] as this language is internationally recognized, easy to learn [8] and the most spoken language in the world. Eventually, SA in English became popular and many tools and techniques have been implemented for this language.

Being the dominant language, there are a lot of available tools and techniques along with domain-specific data are available for the English language as the volume of native speakers is fertile [28, 33–35]. Consequently, data annotation has relatively a trouble-free job for this research domain [36–38]. But there

[5] https://devopedia.org/sentiment-analysis
[6] https://www.expert.ai/blog/natural-language-processing-and-sentiment-analysis/
[7] https://www.ethnologue.com/guides/ethnologue200
[8] https://www.ynsitu.com/en/8-reasons-english-is-the-dominant-language/

is a lack of adequate domain-specific data for regional languages like Bangla [1, 39–46]. The major setback is the lack of enough annotated data [31, 47, 48] and for this reason, this language is still considered as a low-resourced language [26, 49–51]. On the other hand, resource-building support is also limited in this language [6]. Hence, plenty of work has been done with the help of translated data [14, 50, 52–54] and code-mixed data [55–58]. Positive, negative, neutral [47, 48, 51, 54, 59–65] are the common sentiments classified in any language, and Ekman's six emotions [42, 50] are the familiar emotions detected in the Bangla language. However, lack of adequate tools and techniques, it is tough to filter other emotions in all types of dataset. Due to the availability of social media on the internet, SA from text has become popular day by day and the work in this domain is also increasing. Some comprehensive review works have been done and this kind of comprehensive analysis is crucial to get the central idea of any language. Similarly, these comprehensive analyzes have been done on other languages as well [3, 4, 66, 67]. Additionally, several approaches have been implemented to review SA in the Bangla language from different perspectives, for instance, highlighting the DL methods [2], and multilingual social media approaches [3], bring out lexicon-based approaches [10], monolingual and multilingual model comparison for NLP tasks [6] and so on. These research works presented their work from an individual point of view [2, 6, 10–13]. Multilingual models are trained in several languages, but Bangla is still depreciated [68]. There is infrequent work in different areas of BNLP (Bangla Natural Language Processing) [6]. Still a broader understanding of the comprehensive approach to dictate the general path of SA in Bangla is missing. This paper aims to bridge this gap by revisiting the existing literature and combining these divergences. This directional path has been drawn using a comprehensive review of SA in Bangla. Furthermore, this research work has extracted a framework for SA in Bangla from the existing research works for beginners so that one can get the preliminary path of this versatile research domain.

4 DISCUSSION

4.1 Existing Sentiment Corpora

There are 46 articles focused on several types of dataset in the Bangla language that have been assessed in this research work. In the due process, the most frequently used corpora from these articles were retrieved, and categorized as review, social media, etc. According to the patterns observed from these articles, the most popular data sources include Facebook posts / comments, newspapers (Prothom-alo, Ananda Bazar, etc), Bangla book reviews, restaurant reviews, e-commerce site reviews/comments, YouTube comments, tweets, google play store reviews, Amazon product reviews, ABSA (Aspect-Based Sentiment Analysis) dataset, article and blog comments, movie reviews, sports comments, short stories, Kaggle dataset, and news headlines. This section covers the demonstration of existing corpora with some significant categories.

4.1.1 Low-resourced Corpora

SA from the Bangla language is an intensely challenging task. The inadequate resource in the language resulted in the translated data based works, (translated English data to Bangla with google translator) [14, 50, 54]. Some of the research works performed vice-versa [52] because of the absence of adequate tools and techniques. Though social media is one of the most common data collection sources [31, 49, 69], several articles used a handful amount of data for assessing the sentiment. Such as, 2000 Facebook comments [49] were used to detect two types of sentiment and 70 people were involved in acquiring the dataset, and Naive Bayes (NB) was applied for the SA. Another study [69] used 3200 Facebook posts to classify emotions into five categories: positive, strong positive, negative, strong negative, and neutral. Unigram, bigram, and countvectorizer were used to extract the features, and the ML-based algorithm. e.g., Support Vector Machine (SVM) produced the best results for their pre-processed data. The concept of detecting positive, negative, and neutral sentiment is a well-known aspect of SA. However, another article [61] eliminated neutral headlines from their corpus containing 15325 Bangla news headlines. As a result of omitting this diverse set of data, their dataset became small-scaled, and lessened the accuracy level even though they used the most popular ML algorithms for SA (SVM, Boosted Tree, Logistic Regression (LR)). However, SVM outperforms all other algorithms (79.6%) on their corpus [61].

4.1.2 Multi-sourced Corpora

Due to the unavailability of annotated data, many researchers collect data from a variety of sources, including Bangla articles and blogs [47, 51, 59, 70], Facebook [10, 47, 51, 70, 71], e-commerce websites [47], Twitter [51, 71], online newspapers [10, 51, 70, 72, 73], YouTube [70, 71, 73], movie reviews [71], sports comments [72], several social media [73], textbook [10], direct speech [10], depression-related Bangla posts [74], Bangla novels, poems and quotations [74]. Since Bangla is a resource-constrained language, most of the datasets are the compilation of different sources. As a consequence, hybrid sources of data generate a hotchpotch of data sources. However, a comprehensive attempt has been made to compile a lexicon-based dictionary containing 5100 sentiment words using these sources [51]. This article used the dictionary to determine the polarity of Bangla texts that have both positive and negative sentiments. They used tokenization, punctuation removal, stop word removal, and stemming to perform pre-processing, and then proposed a model called polarity identification. Furthermore, they compared the result with several ML models including NB, Decision Tree (DT), and SVM. Their proposed model (lexicon-based [51]) achieved a 92 percent accuracy rate.

On the other hand, researchers applied LR, K-Nearest Neighbor (KNN), DT, Random Forest (RF), Multinomial Naive Bayes (MNB), SVM, and Stochastic Gradient Descent (SGD), where the unigram MNB obtained the highest accuracy of 87% [47]. Another article collected a substantial amount of

data containing 40,000 sentences from multiple sources, e.g. Facebook, Twitter,YouTube comments, reviews [71]. But the accuracy was lower than the others (84.53%), which was achieved by the LSTM (Long short-term memory) algorithm. The phenomenon of relative lower accuracy dictates the challenge of dealing with the hotchpotch data from various sources. Additionally, an article employs an attention-based Convolutional Neural Network (CNN) to detect three distinct types of sentiment [72]. Another paper [73] demonstrated the word2vec approach, Continuous Bag of Words (CBOW), and a skip diagram model in which CBOW was the highest scorer (Accuracy - 76.22 percent). But a different approach using RNN-LSTM (Recurrent Neural Network with Long Short-Term Memory) showed a significant outcome with 98% accuracy [74]. Consequently, in another study [70], data were categorized into six different emotions: anger, fear, disgust, sadness, joy, and surprise, known as Ekman's emotion whereas others were limited to two or three emotions.

4.1.3 Social Media Corpora

Many people share their emotions using Facebook as this medium is prominently used for networking. Hence, this particular platform draws relatively more attention from the researchers for Bangla SA. ML-based approaches have been evaluated by cricket analysis comments retrieved from Facebook [31, 75] and another popular dataset named ABSA dataset [31]. And tokenization was used as the pre-processing method and the Term Frequency-Inverse Document Frequency (TF-IDF) vectorizer was used as a feature extraction technique. Accordingly, researchers also prepared a dataset containing cricket sports opinions of Bangladeshi people [41] to determine the three popular sentiments: positive, negative, and neutral. TF-IDF vectorizer as a feature extraction technique is very popular and common where they have chosen countVectorizer [41] to extract the features. Supervised approaches are generally used for SA, so they applied SVM, LR, and NB algorithms as they are supervised ML approaches where LR performed better with 83% accuracy based on the n-gram features. Another method has been applied for the cricket dataset which is a part of the ABSA Bangla text dataset [15]. And this approach is based on DL named RNN-LSTM gave a satisfactory result, 95% accuracy. Not only that, but to process their data, they have used a Natural Language-based approach which is different from others.

4.1.4 Code-Mixing Corpora

In this modern era, code-mixing is a very familiar phenomenon. As a consequence, Bangla and English code-mixed data is used to analyze sentiment in several research works [23, 76, 77]. ML algorithms performed better with code mixed features by achieving 72.5% accuracy where the data source was Twitter and Facebook [23]. On the other hand, a combination of word-based and semantic features has been implemented using Bangla, English, and Hindi code-mixing social media data that showed 68.5% accuracy [56].

4.1.5 Other Regional Language in SA

Bangla is an Indo-Aryan and primary language spoken in Bangladesh and the state of West Bengal [66]. We have observed few works from Indian authors as West Bengal has 70 million Bangla native speakers [9]. It is found that Indian researchers tried to implement SA or ER in several regional languages (i. e. Hindi, Bangla, Tamil, Telugu, Manipuri, Kannada, Urdu, etc.) and established comparison among them [26, 57, 66, 67, 78–83]. While extracting Sentiment from these languages, researchers have implemented different approaches: CNN, supervised and unsupervised ML algorithms (i. e. SVM, LR, NB, etc.), DL approaches, Recurrent Neural Network (RNN) approaches [26, 57, 66, 67, 78–82]. Therefore, these are the popular methods to classify sentiments and emotions.

4.1.6 Different Category Works using Bangla Data

There are some other works also done for the Bangla language except SA. These works can be broadly classified as: synthetic and legitimate sentence detection [84], interrogative sentence detection [85], irony detection [86], hate speech detection [87], abusive and non-abusive detection [88], news categorization [7, 22, 45, 89–91], document categorization [1, 92, 93], document summarizing [94], text classification [95], text summarizing [96], extreme guilt and grave fault [44].

4.2 Sentiment Extraction Approaches

There is a shortage of proper linguistic tools and techniques for SA in Bangla as it is a resource-constrained language and has inherent complexity [1, 11]. However, this section illustrated the existing tools and techniques applied for SA and ER.

4.2.1 Machine Learning

ML algorithms are widely used in the field of opinion mining. From the assessment conducted in this work, it is evident that the most applied algorithms for SA are SVM, KNN, LR, RF, DT, MNB etc. [16, 18, 29, 30, 41, 48, 54, 60–63, 65, 75, 86, 97–103]. SVM showed the most outperforming results from all of these ML approaches [27, 31, 35, 62, 69, 87, 88, 99, 104]. On the contrary, RF showed better results among the other ML algorithms for the classification of depression-related posts [100]. A dataset containing 10,000 Bangla texts extracted from the google play store and divided into three sentiment classes: positive, negative and neutral [62]. In this research work, SVM performed better with 5-fold and gradient boosting performed well without 5-fold. In another article, researchers used a series of pre-processing methods and then applied ML approaches where online newspapers were the source of data that contained 1619 data [48]. For pre-processing of the data, add contraction, stop

[9] https://en.wikipedia.org/wiki/States_of_India_by_Bengali_speakers

word removal, unwanted character removal, vocabulary count were used in this article.

Furthermore, combined ML and DL-based approaches have been proposed such as KNN-based SVM, Principal Component Analysis (PCA) with CNN, RF, LR, where KNN-SVM performed relatively better [63]. Online business is growing day by day and people give product reviews through e-commerce sites. So, e-commerce sites are becoming a popular platform for retrieving Bangla data. People collected Bangla data from e-commerce websites and trained their model using ML approaches and got better result using SVM [18, 65, 97, 98]. A more comprehensive approach of assessment implemented on a corpora of 11807 Bangla sentences using supervised, unsupervised, lexicon-based and transfer-learning-based methods [65]. Among the supervised ML classifiers, SVM gave the highest accuracy of 93%. Also, LR, RF, and Extremely Randomized Trees (ET) were applied to test the corpus. In the lexicon-based approach, VADER (Valence Aware Dictionary for Sentiment Reasoning), TextBlob, and SentiStrength were used where TextBlob gave the highest accuracy of 82.79%. Among the ML-based approaches SVM shows the highest accuracy: 98.7% even with 6000 Bangla horoscope sentences [60]. This dataset was collected from Bangla newspapers to evaluate the sentiments in the text. A different classification was done where 10,000 comments were classified into two classes: abusive and religious; along with five different emotions: happy, sad, angry, surprised, and excited [27]. They used a feature selection technique called TF-IDF and applied ML-based approaches. From the supervised ML, SVM gave a decent accuracy of 62%.

However, MNB is prominently used in NLP which is a probabilistic learning algorithm. As being a part of NLP, MNB is used to classify sentiments and it performed comparatively better [16, 29, 101]. Authors have classified their data with three basic emotions: happy, sad, and angry [101]. Also, they have used two primary feature extraction techniques - Bag of Words (BoW) and word embedding separately. While using BoW, LR and MNB classifiers have been applied. Accordingly, Artificial Neural Network (ANN) and CNN classifiers have been employed with word embedding. Among these approaches, the MNB classifier gave the best accuracy of 68.27%. On the other hand, an accuracy of 86.67% was achieved by implementing MNB to detect happiness and sadness emotion from Bangla posts that are collected from different social media platforms [29]. Different pre-processing and feature selection techniques such as text segmentation, emoticons handling, stop word removal, stemming, TF-IDF, bigram, Parts of Speech (POS) tagging have employed [16] to detect multi-class emotions: happy, sad, angry from 4200 comments. And their accuracy applying MNB was 78.6%.

4.2.2 Deep Learning

From DL approaches, LSTM, hybrid LSTM, and BiLSTM (Bidirectional Long Short-Term Memory), Gated Recurrent Unit (GRU) played the pivotal role in giving a better performance (in terms of accuracy) in this linguistic research

[24, 25, 39, 46, 64, 105–107]. An accuracy level of 77.85% [24] and 91.35% [46] were achieved respectively using BiLSTM. Moreover, a hybrid LSTM approach called RNN based LSTM attained 85% accuracy applied to Bangla newspapers data [39]. They classified their data as positive, negative, and neutral. Three dataset which covered 7,293 data and was collected from Apurba, ABSA Sports, and ABSA restaurant dataset having positive and negative sentiments used to assess the SA [39]. In another study [105], authors tokenized 400 comments collected from online repositories that were preprocessed using stop words removal, lemmatizing, lexicon replacing. As a result, they obtained an accuracy of 84% by applying the LSTM algorithm.

Moreover, CNN is a popular model for image segmentation, but many researchers used this approach to classify the emotions from text [17, 30, 40, 43, 108]. In some cases, CNN gave a significant performance in terms of accuracy for extracting sentiments. Simultaneously, the hybridization of CNN with other DL models performed better than non-hybrid models [17, 40] . For instance, 5000 Bang-lish [10] short paragraphs were annotated by labeling sad, help, abuse, funny, angry, etc. where CNN has been applied with LSTM [17]. Accordingly, other researchers also used the same approach and got 90.49% accuracy which was an appreciable result [40]. Another research article [108] has demonstrated the application of CNN and LSTM separately, where CNN performs better than LSTM. Using CNN, they got 97.24% accuracy whereas LSTM showed accuracy of 95.33%.

4.2.3 Other Approaches

This article has found some distinct approaches that were implemented in these research works [42, 55, 68, 97, 109–114]. These articles did not follow the traditional ML or DL-based approaches.

One of these works applied an adaptive neuro-fuzzy system in their work which is slightly unfamiliar for SA, as per the observation of this work [109]. They applied POS tagging, normalization and tokenization as pre-processing methods. Another research proposed a stacked ensemble model that gave them the best accuracy [110, 115]. Two MNB with different subsets of features such as word n-gram and SentiWordNet features, character n-gram and SentiWordNet features, and SVM-based model with linear kernel combined within a stacked ensemble by Multilayer Perceptron (MLP) was used for the classification task in this paper. Another research work demonstrated a multilingual BERT (Bidirectional Encoder Representations from Transformers) model that analyzed sentiment in Bangla from online news comments [111].

An automated system known as the topical approach was proposed with an accuracy of above 90% [42]. Meanwhile, another work represented a bilingual approach where they compared the results between the Bangla and English data [113]. Additionally, some research works comparing SA in Bangla and English corpora were observed [55, 97]. Some of the studies used multiple dataset that detected several sentiments and emotions from multiple corpus

[10] Bangla sentences written with English characters

[112]. Another approach for SA is found where researchers modified the features of English VADER to directly classify the sentiments from Bangla texts without any requirement of Bangla to English translation tools [114]. Another great work to reduce the barrier of embedding the low resource language is done very recently that describes the limitations of low resource language understanding and builds a pre-trained model BanglaBERT [68].

4.2.4 Approaches for English Corpora

Social media is a widely used platform for sharing our thoughts and emotions. As a consequence, these sharing data such as comments, posts, and tweets are the immense source of text data. From these popular sources, Twitter data are most commonly used for English SA [35, 99, 104, 116–120]. ML algorithms have been applied in these tweets where SVM provided better performance [35, 104]. Meanwhile, NB was applied on the dataset collected from Facebook graph API (Application Programming Interface) and English conversation correspondingly [28, 33]. Another dataset from the Amazon product review was used applying two different models [34, 121]. The first one is NB giving 98.39% accuracy whereas MLP gives 92% accuracy [121]. Also, NB, LR, and Linear Regression were found to give reasonable results in a few works. Hence, Word2vec technology including the CBOW model and Skip-gram model gave a better performance with an accuracy of 91.54% than LSTM, RNN, CNN, and NB on an experimental corpus of hotel comments [37]. SENN (Semantic-Emotion Neural Network) model was proposed to recognize the emotion of annotated data collected from multiple sources (i.e. dialogues, tweets, fairy tales, blogs, and news headlines) [122]. Md Shad Akhtar and the group [36] experimented their model using Single-task learning (STL) and Multi-task learning (MTL) for the proposed approach on a multi-modal dataset consisting of 3,229 videos spanning over 23,000 utterances. A restaurant recommender system was proposed based on SA provided a remarkable result of 92.8% precision score using NLP [123]. Most of these works related to SA from the English corpus gained more than 90% accuracy due to the available resources, tools and techniques.

Moreover, though this work demonstrates the popularly used corpora along with tools and techniques, there are some limitations in this domain. For instance, some researchers have worked with translated data due to the unavailability of proper data sources and proper tools and techniques [14, 50, 54]. In addition, few works have been done translating the Bangla data into English which shows one of the significant limitations of this domain. On the contrary, researchers collected data from multiple sources as there is a lack of properly annotated data [51, 59, 71, 73]. This is why Bangla is still considered a resource-constrained language. Accordingly, this article observed some advantages and disadvantages of existing tools and techniques. For instance, SVM is the primarily used algorithm for SA and ER because of its high performance on properly labeled data. But, it cannot perform with better accuracy results when the data is not properly labeled. Furthermore, punctuation removal and

tokenization with n-gram features enhanced this accuracy level. On the other hand, LSTM is the most used algorithm in the DL area (than BiLSTM and CNN). And DL approach performs well on TF-IDF, unigram and word2vec feature extraction techniques. The article addressed detailed findings of each methods in the comparison section entitled 'comparative landscape'.

4.3 Observations

4.3.1 Corpora Observations

Based on the existing research, newspaper headlines [26, 48, 60, 61, 64, 94], Facebook [23, 24, 49, 69], YouTube comments [25, 53, 70, 71, 87, 88, 112], tweets [78, 86, 109], and multiple website comments/reviews [14, 18, 47, 51, 62, 63, 65, 72, 124–128] were the common and prominently used sources of data . Though these datasets are frequently used in this field, the Twitter dataset is more prevalent for English and others are popular for the Bangla language. The span of the dataset used for SA or ER is 1000 to 50,000. Therefore, several articles presented corpus-building strategies with annotations for SA in Bangla [53, 129–131]. Observing these works, the most commonly accessed dataset are categorized into five categories: social media, newspaper, review, ABSA Dataset, and translated dataset. In addition, most current datasets are labeled and classified into two or three fundamental sentiments: positive, negative, and neutral. Whereas others are annotated by some other emotions such as happy, sad, angry, joy, and others. This summarizes that researchers have focused on classifying fundamental emotions. But there are more emotions that can be extracted which is found to be another limitation in this research area.

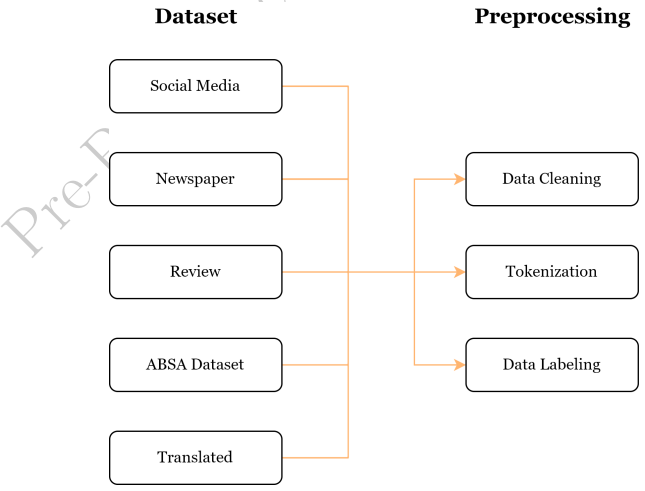

Fig. 2 Most Prominent Data Pre-processing Techniques

4.3.2 Most Practiced Pre-processing Methods

In data pre-processing, most of the publications used three main strategies such as data cleaning, tokenization as well as data labeling. Data cleaning encompasses a few methods such as stop word removal, symbol removal, punctuation removal, data stemming, unnecessary character removal, and emoticon removal. Accordingly, few works established their own stop word sets to construct more efficient corpus [60, 63]. Similarly, another stop word detection strategy has been proposed that achieves simpler and faster data pre-processing [132, 133]. On the other hand, Data labeling is mandatory for preparing the dataset [27, 101, 111]. Few articles have demonstrated their own approach to categorize emotions manually to meet their classification criteria whereas others used previously labeled data [27, 101, 111]. Figure 2 indicates the generally utilized pre-processing procedures that are usually applied to the dataset we have specified.

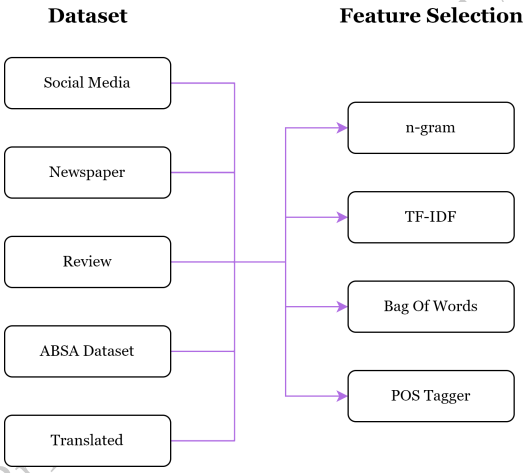

Fig. 3 Most Practiced Feature Selection Techniques

4.3.3 Most Applied Feature Selection Techniques

Feature selection is the most beneficial activity for SA and emotion detection as better features can deliver the best outcome by applying the algorithms. For feature extraction, most of the articles accomplished unigram, bigram, and trigram-based feature selection methods known as n-gram features. They also used BoW, countvectorizer, TF-IDF, and POS tagger. A Prediction Maximization Model (PMM) has been proposed in an article [134] for Bangla POS tagging where HMM is applied with tag mapping and scoring in PMM to maximize the accuracy. The summary of feature selection recommendation is addressed in Figure 3 that can be applied on the mentioned corpora.

4.3.4 Leading Classification Approaches

Existing research indicates that, ML, rule-based approaches, DL, word embedding techniques, and Combination approaches of DL are currently leading the field of SA. These methodologies can be useful to analyze sentiment based on the most often used dataset displayed in Figure 4.

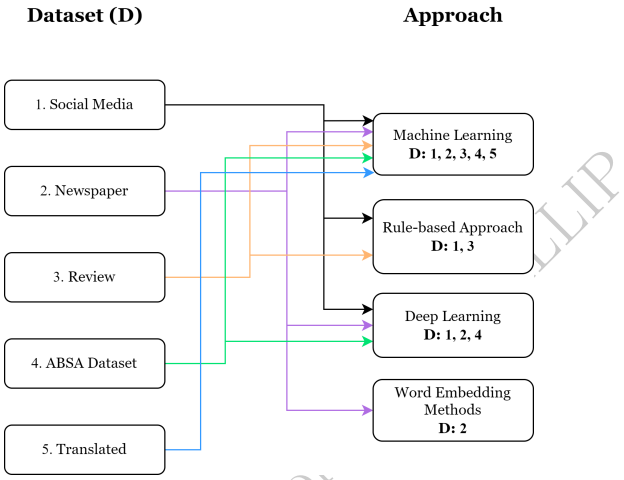

Fig. 4 Compiled Mapping of Dataset to Approach

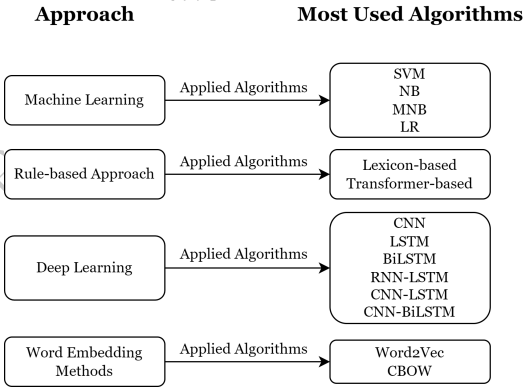

Fig. 5 Popular Algorithms from Different Approaches

For instance, ML, rule-based approaches, DL approaches, or a hybrid approach can be used if a researcher desires to extract emotion from a social media corpus (indicated in black indicators in fig:4). Similarly, ML and a combination of DL approaches can be applied to translated data. Likewise, these directions are the same for the rest of the data sources. Therefore, ML-based

methods are suitable for datasets: 1 (social media), 2 (newspaper), 3 (review), 4 (ABSA dataset), 5 (translated), denoted as D:1, 2, 3, 4, 5 in Figure 4. Accordingly, rule-based approaches are appropriate for datasets: 1 (social media) and 3 (review). These recommendations of corpora have been generated from the existing literature. Now the question is, which algorithms are applicable for particular approaches as there are plenty of algorithms in each field? A simple and inclusive pathway has been designed to facilitate this. Figure 5 illustrates the algorithms from each field deduced from the existing works in this domain. These particular algorithms are usually applied to classify sentiment.

The graphic illustrates how to apply the mentioned algorithms to each approach. SVM, NB, MNB, and LR are examples of ML approaches. Rule-based techniques can be implemented using lexicon and transformer-based technologies. In addition, DL approaches are dominated by CNN, LSTM and BiLSTM whereas word embedding techniques are based on Word2Vec and CBOW. Finally, there are three types of combination approaches extracted from the earlier works: RNN-LSTM, CNN-LSTM, and CNN-BiLSTM.

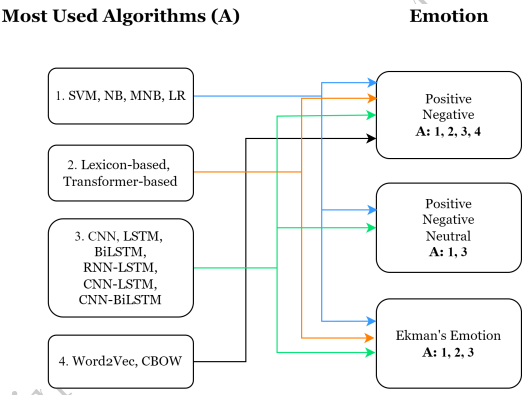

Fig. 6 Popular Used Algorithms to Detect Emotions

4.3.5 Commonly Identified Emotions

Based on the existing studies, positive and negative emotions are the most often discovered emotions in Bangla SA. Following that, a substantial number of articles classified positive, negative, and neutral emotions. Apart from this, few works have been done on more than three emotions such as Ekman's six basic emotions[25, 36, 42, 53, 70, 122, 135]. Though Ekman's emotions exemplify six fundamental human emotions, humans have more emotions than these polarities of sentiments. The relationship between the most used algorithms and the detected emotions is illustrated in Figure 6. The title "Most used algorithms" is defined as "A" where 1 (SVM, NB, MNB, LR), 2 (Lexicon-based, Transformer-based), 3 (CNN, LSTM, BiLSTM, RNN-LSTM, CNN-LSTM,

CNN-BiLSTM), and 4 (Word2Vec, CBOW) algorithms are applied to classify positive and negative emotions. Similarly, (positive, negative, neutral) and Ekman's emotions are visualized with the connectivity of corresponding most used algorithms in distinct colors Figure 6.

4.4 Roadmap to Sentiment Analysis

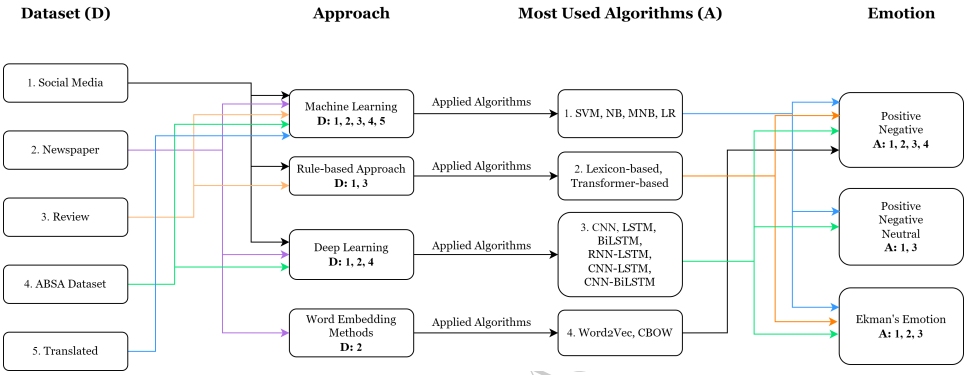

Fig. 7 A Detailed Framework of SA and ER in Bangla (Compiled)

In this study, contemporary research has furnished knowledge about SA or ER methodology. The widely used pre-processing methods, feature selection techniques and approaches are described in the previous section.

Most of the researchers have employed SVM to classify sentiments as SVM showed more efficient results than all other models [12, 18, 27, 31, 48, 60–62, 65, 69, 75, 97, 98]. In the following section, all the methodologies and models utilized in existing works are compared, correlated, and evaluated for their stance on employing these models for SA in the Bangla language (Section 5). For better visualization of the extracted understanding, a detailed compilation of existing works has been illustrated in Figure 7.

This detailed outline will assist the researcher in locating the prominent Bangla data sources where one can apply the most suitable approaches and algorithms and obtain a classification of one of the emotion types from the given dataset. As a consequence, this deduced framework will help scholars to determine certain sentiments or emotions from the dataset to classify using the chosen approaches. Social media, for example, can be a massive source of data for this field. So after gathering the data, one can decide which processing technique and algorithms to apply as well as the emotions. The compiled framework demonstrates that ML, rule-based approaches, DL, and combinations of DL approaches are appropriate for this dataset. This finding will allow the researcher to select any algorithms while experimenting with the labeled emotions. Additionally, this detailed framework demonstrates the technique of the chosen dataset for the entire SA procedure.

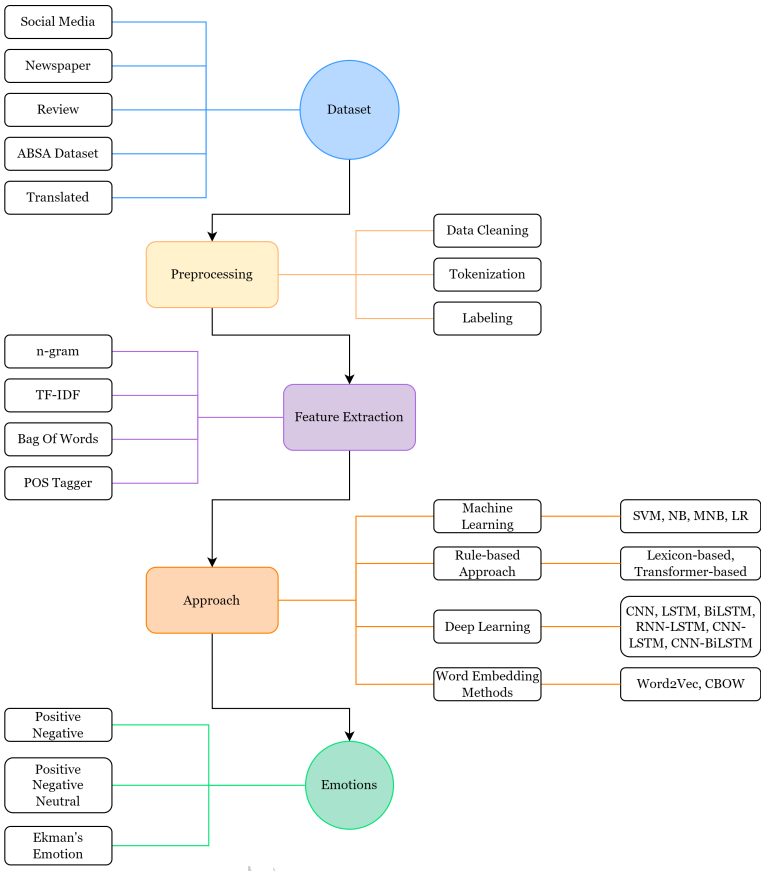

Fig. 8 The Generalized Framework of SA and ER in Bangla (Compiled)

On the other hand, this article shows a simplified representation of the entire process of SA and ER. This will assist individuals in grasping the entire task in a generic approach. Figure 8 depicts the generalized framework for SA or ER in the Bangla language extracted from the existing literature. This generic framework refers to the procedure of assessing sentiment where a dataset is an input and recognizing emotion or sentiment is the final outcome. This article exhibits the entire process based on the prominently used methodologies in collected research works. If anyone wishes to work in SA or ER without having any prior expertise in this area, this framework can lead the path to make one successful.

For instance, if a researcher wishes to use a newspaper dataset, data preprocessing approaches must be performed after collecting the data. Depending on the methodology, the feature extraction method may then be n-gram, TF-IDF, BoW, or POS tagger. The data should then be trained using a model and classify it further using an algorithm. From the generalized framework, it is clear that ML, DL, word embedding, and combination approaches are suitable

for newspaper data. Additionally, the model can generate outputs categorized as Ekman's emotion, positive, negative, or neutral. Therefore, as the first step in SA, the researcher can use this framework analogously for their chosen dataset and methodology.

However, the generalized framework is compiled and presented for the aspiring researchers to provide them a comprehensive direction to work in this domain. But this framework is neither proposed nor tested, it's only extracted from the literature considered in this study. The goal of this work is to present an overview of SA and ER in Bangla from the pool of existing literature so that researchers can have a general understanding of this domain.

5 A COMPARATIVE LANDSCAPE

Based on the identified emotions, a comparative landscape has been deduced that is divided into three major categories: two distinct types of sentiments (positive and negative), three distinct types of sentiments (positive, negative, and neutral), and multiple types of emotions. Some comparative pictorial depictions have been presented to anticipate the potential of the relationship in fig:9fig:12. These figures depict the relative accuracy levels of algorithms applied to a given dataset for different kinds of emotions. This article also discusses the comparison based on feature extraction methods and pre-processing methodologies in the thorough explanation of each criterion.

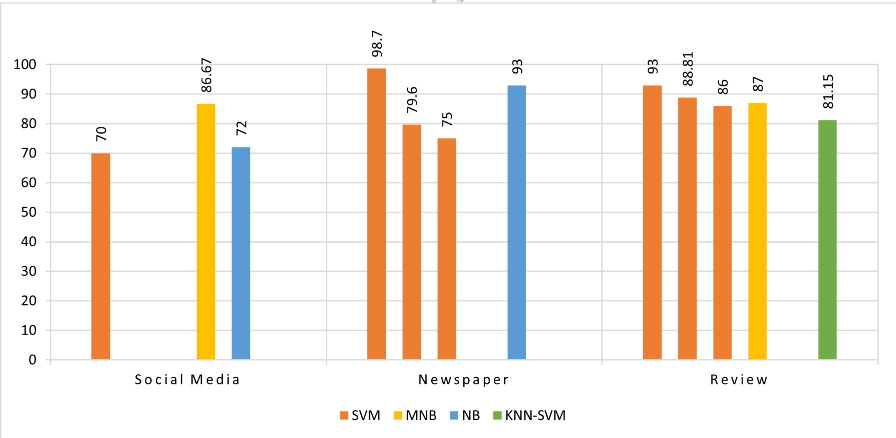

Fig. 9 Comparison Based on Two Emotions (Positive and Negative) for ML Algorithms

This sector has a common practice to determine positive and negative sentiments from text. The maximum number of papers worked for these two sentiments. It is clear from fig:9,fig:10 that most of studies achieved the highest accuracy using the SVM algorithm [18, 48, 60, 61, 65, 75, 97, 98]. In addition, this algorithm was evaluated by the dataset containing around a wide range of data from 1020 to 15325 Bangla texts. Nevertheless, multiple data sources

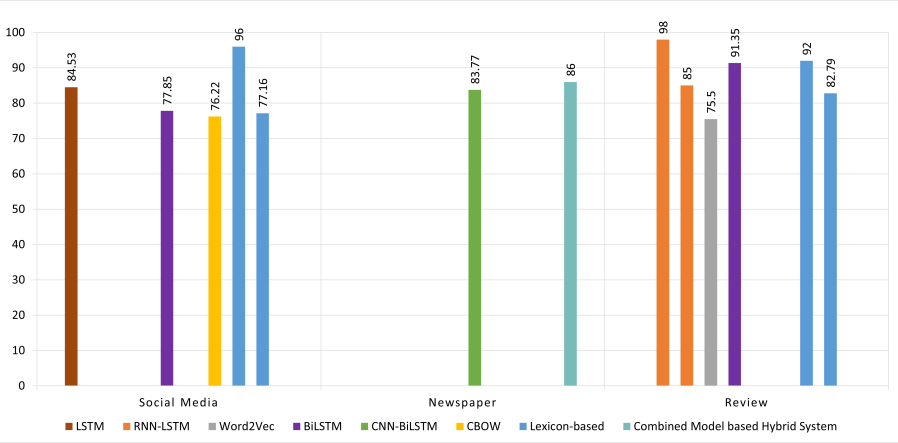

Fig. 10 Comparison Based on Two Emotions (Positive and Negative) for DL and Other Algorithms

and pre-processing techniques have been used. For example, newspaper data [48, 60, 61] has been used in several articles. Though they have used same the types of data, their pre-processing techniques and the feature extraction techniques are different. This is why these studies didn't achieve the equivalent result comparing the SVM algorithm. Similarly, public review-related data has been used in some works where SVM performs as the better-performed classifier [18, 65, 98]. But the pre-processing techniques and feature selection approaches have created inconsistency in the results though the accuracy range is almost near to each other. In a different approach, researcher have got highest accuracy using only data labeling, language mapping (translation) as pre-processing techniques [65]. Therefore, SVM performs better for properly labeled data. But when the data are not properly labeled, supervised learning is not possible. In that case SVC (Support-Vector Clustering) kernel performs better and was used for a classification problem with the highest accuracy [86].

Apart from this, few researchers have applied NB and MNB algorithms, where NB achieved the highest accuracy rate of 93% [49, 55]. Newspaper and social media data are the source of data in these articles. Some researchers claimed that NB is a probabilistic model, that's why it performs better when more pre-processing is applied to the dataset [55]. They have used stop word removal, POS tagger (noun+adjective+adverb) filtration as pre-processing techniques, and TF-IDF, Word2Vec as feature selection techniques respectively. Additionally, they mentioned that if there are multiple negative features, the algorithm produces a hostile perception even if the data is positive. Thus, ML algorithms integrate linguistic rules. On the contrary, MNB achieved an accuracy range of 80-87% in several works [14, 29, 47]. In particular, unigram features perform well with the MNB algorithm. Conversely, TF-IDF features help in producing a superior classification outcome in NB. As a result, we can observe that NB outperformed MNB.

Furthermore, the lexicon-based approach performed very well in sentence-level SA [10, 51, 65, 118]. If researchers want to maintain linguistic rules corporate with SA, the lexicon-based approach will be appropriate. The lexicon-based approach utilizes few lexical resources whereas the keyword-based approach helps to determine emotion labels. Review [51, 65] and social media [10, 118] corpora have been used to evaluate the lexicon-based model in which tokenization is the common pre-processing technique. Among the DL algorithms, BiLSTM performed better than LSTM [24, 39, 46, 71]. DL approaches performed better for Bangla text in a few cases with some effective feature selection techniques such as Word2Vec, TF-IDF, Unigram, etc. Additionally, two articles reported that a combination of RNN-LSTM performs better than only LSTM [74, 105]. Though they have collected data from distinct sources and applied similar pre-processing techniques, the probable reason for having better result from RNN-LSTM is RNN performs well in sequential input data.

Besides this, some specialized approaches such as word embedding methods [59, 73], hybrid system, and KNN-SVM [63] combination have been proposed. Word2Vec and CBoW have performed adequately in word-level SA. Combined model-based systems played a more vital role than other hybrid models in a study [84], where a variety of different ML algorithms and rule-based post-processing have been implemented. And also the combination of KNN and SVM is found to perform with a good precision [63], thus it can be said that the combined algorithms generated better results than not combined.

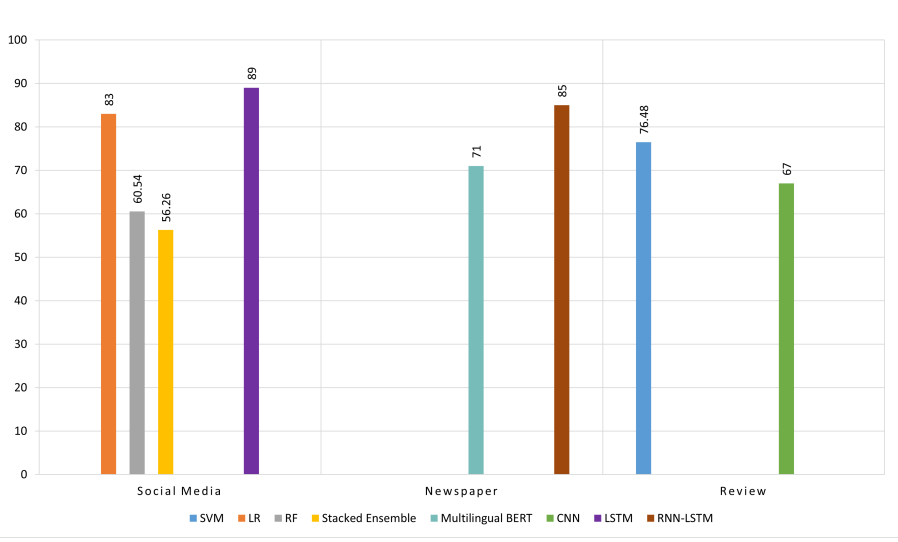

Fig. 11 Comparison Based on Three Emotions (Positive, Negative, and Neutral)

A comparative landscape has been presented in Figure 11 for the works detected three categories of sentiments (positive, negative, neutral). According

to the findings, RNN-LSTM showed the most accurate performance [15, 64]. Researchers have used ABSA corpora to classify the sentiments where stop word removal, text process, name process, tokenization, and word embedding have been applied before evaluating the model [15]. On the other hand, an accuracy level of 85% achieved using newspaper data and n-gram, word embedding, and context encoder to process the data [64]. Authors depicted that RNN performs effectively for sequential input data such as text, audio, and music. That's why they have used RNN [15, 64]. But there is a drawback of RNN that it cannot recall input data for a long duration. This is why researchers prefer to combine RNN with LSTM so that the input data can be remembered for a longer duration [15, 64].

However, SVM [62], LR [41], RF [100] have been applied from the ML approach. Accordingly, most of the research articles among them have collected data from social media. Though their corpus category is identical, these approaches didn't perform a noteworthy result in identifying three types of emotion. Furthermore, NB provided superior accuracy despite the accuracy not being sufficient, authors claimed that NB uses the numeric linguistic feature that's why it gives the most incredible accuracy [100]. In some CNN and adaptive neural fuzzy inference system based studies, the exact accuracy were not mentioned [72, 109]. Therefore, it might not be wrong to deduce that, the DL-based approaches accomplished the highest consequence comparing with other approaches [15, 43, 64, 72, 99].

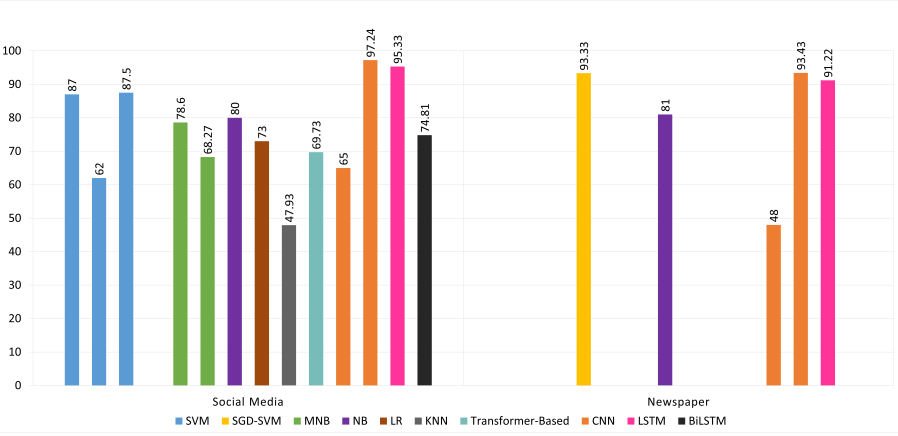

Fig. 12 Comparison Based on More than Three Emotions and Ekman's Emotion

As ER helps to identify the exact emotion of a particular text, we have described the correlation of the works that have been done for ER. In Figure 12, only these articles [16, 17, 25, 27, 30, 31, 42, 69, 70, 87, 101, 108] used the Bangla corpus to detect more than three categories of emotion that indicates the constraints to work with Bangla language. Most of the articles proposed SVM and CNN-based techniques in this area [27, 30, 31, 69, 108]. But CNN

provides much better result than SVM because CNN performs better for multi-class text detection. Some of them have applied a combination of CNN-LSTM [17, 40]. Correspondingly, CNN-BiLSTM has also applied in several studies but the corpus holds the English data. Additionally, SVM delivers decent results on several articles that make use of social media and the ABSA dataset. Tokenization and the removal of various unnecessary items have been used in several works that provides the same outcomes [69, 87]. So, it can be said that for detecting more than three kinds of emotions, SVM and CNN has been utilized widely. However, the authors who applied CNN, claimed that it has a strong ability to learn relevant features and is frequently used in NLP tasks, that is the fact of using it [30, 108]. Additionally, SVM also performs good for multi-class text classification and it is the common phenomenon in the majority of articles for using SVM [27, 31, 69]. In spite of that, there are some limitations as well. For instance, small volume of data (3000) results in an unsatisfactory accuracy level [27]. Besides, due to the small amount of data, they were unable to use CNN or RNN as they perform well on large dataset.

Similarly, several articles discuss the purpose of LSTM: LSTM alleviates the gradient problem associated with RNNs. And LSTM can memorize data for an extended period of time [25, 108]. Besides this, for the topical approach, researchers state that lack of smooth data and the complexity of the Bangla language are responsible to provide efficient result, despite the fact that their accuracy level is not significantly lower than that of other approaches [42].

Thus, this article made this comparison in order to gain a better understanding of the selection criteria for particular approaches of the Bangla corpora and other corpora. Categorizing two or three types of sentiments is common, that determines why some approaches are already available. But there is a severe shortage of approaches for more than three emotions. As illustrated in Figure 12, CNN-BiLSTM [50, 122], SGD-SVM [92], NB [28, 89], BiLSTM [117], MLP [85], KNN [86], and lexicon-based approaches [118] have been implemented on many languages excluding Bangla. This refers the inability of detecting a variety of sentiments. Therefore, combined DL-based approaches are suitable for determining positive, negative and neutral emotions. Accordingly, recognition of positive and negative sentiments is easier if the combination of DL approaches is applied. But SVM shows more reliable performance with unnecessary characters removal, data labeling, unigram, bigram, and trigram features.

6 CONCLUSION

This article has summarized the existing works done on SA and ER in the Bangla language and deduced a generalized work procedure to pursue this domain. The several types of corpora in the Bangla text are explained, such as social media corpora, multi-sourced corpora, code-mixing corpora, and regional language corpora. The applied SA procedures in the Bangla language, including primarily used data pre-processing methods, feature extraction techniques,

and algorithms, are also discussed in this study. Besides, this article also compiles a generalized framework from the articles evaluated and illustrates the simplified views of SA and ER from various perspectives. For instance, choosing the feature selection techniques after locating a corpus, an effective methodology for a specific corpus along with algorithm selection from a specific source. Eventually, a complete roadmap is presented, demonstrating the journey from dataset selection to algorithm identification. The outline is also described using both as a simplified view and an expanded view for a better understanding of the Bangla SA and ER. The main objective of compiling this framework is to present a holistic overview of this domain, specifically a low-resourced language and also guide the aspirants to choose appropriate research methods in this particular research domain.

However, some limitations exist in this work. Though this article presented a roadmap from the existing research, this outline is not tested yet. Evaluation of this outline is considered for further research work. Accordingly, text-based SA or ER plays a vital role in this domain. Therefore, the new research direction will address this aspect. Besides this, comprehensive corpus building for multiple emotion classification can be a new research study as Bangla is a low-resourced language. Since Bangla has its own complex structure and multiple dialects, data extension, incorporation and annotation are needed to reveal the unfolded understanding of this versatile language. For this, understanding data structure and systematically processing it is indispensable for further research work. In the end, efficient framework building needs to be addressed to enrich the field of NLP using Bangla text.

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