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Automated Phrasal Verb and Key-Phrase Checking with LSTM-Based Attention Mechanism

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Abstract—Text prediction and classification are crucial tasks in modern Natural Language Processing (NLP) techniques. Long short-term memory (LSTM), a type of Recurrent Neural Network (RNN), is well-known for its outstanding performance in text classification. Phrasal verbs, also known as Bagdhara in Bangla, play a vital role in making language more expressive and poetic in any language, including Bangla. These two or three-word phrases help us convey our emotions and thoughts more effectively. However, determining whether a phrase is a phrasal verb and appropriate for a given context can be challenging for writers, poets, and the general public. To address this issue, an automatic system capable of identifying and using phrasal verbs is necessary. In this study, we propose a system that can instantly and accurately predict phrasal verbs using the LSTM algorithm, a part of the RNN, and an attention mechanism. Our system achieved an overall phrasal verb prediction accuracy of 78.63%.

Keywords— Phrasal verb (Bagdhara); Natural Language Processing; LSTM; Attention Mechanism; Deep Learning.

I. Introduction

The amount of electronic text information generated daily overwhelms human ability to extract necessary information. Various approaches have been developed to automate the process, relying on automatic token inference for any document. Tokenizing data is crucial in describing documents by providing a relevant list of terms. However, identifying the listing terms can be challenging [1]. Bagdhara refers to a set of two or more words in the Bangla language that express something together, beyond the literal meaning of their individual words. Bagdhara is commonly used to make language more poetic and expressive, conveying subtle meanings or expectations, and often condenses the meaning of a sentence into a single word. However, misinterpreting Bagdhara can result in false meanings. Therefore, detecting Bagdhara in Bangla text using NLP models is crucial. This study represents the first attempt to automatically detect Bagdhara in Bangla using an NLP model NLP or Natural Language Processing enables computers to handle text or voice like humans. NLP is a popular branch in Artificial Intelligence, combining statistical, machine learning, and deep learning models with computational linguistics. Over a long time, brilliant researchers from all over the world have contributed to NLP through their hard work and innovation. Tasks like speech recognition, parts of speech tagging, word sense disambiguation, named entity recognition, and sentiment analysis have been successfully accomplished through all the years of research work.

The Attention mechanism has become a powerful technique in sequential learning and image recognition, attracting significant interest in deep learning research [2][3][4]. This study, we proposed a deep-learning model for detecting Bagdhara in Bangla text, using an attention-based LSTM network. We train and test our model on a Bangla dataset, demonstrating the effectiveness of our approach. LSTM networks including an attention mechanism provides a flexible amount of long-term memory with a much lower factorization decomposition rate. Our experimental results showing that LSTM including attention mechanism outperforms state-of-the-art methods in terms of prediction accuracy. In [5], input features and temporal attention mechanisms was proposed to capture influence of exogenous series on the target series, extracting temporal information from historical observations to the present. This work has inspired our study of attention mechanisms in LSTM-based Bagdhara detection.

This paper presents a deep-learning model for detecting Bagdhara in Bangla text using an attention-based LSTM network. The paper is divided into five parts: a literature review, methodology, experimental results, discussion, and conclusions. In the literature review (part 2), we discuss previous work on NLP and attention mechanisms, and highlight the relevance of our approach. In part 3, we describe our methodology, including data preprocessing, model architecture, and training details. Experimental results and discussions are presented in part 4, where we evaluate the performance of our model on a Bangla dataset, compare it with state-of-the-art methods, and analyze the impact of different parameters on its accuracy. Lastly, in part 5, we provide our conclusion and discuss the potential applications and future directions of our research.

II. LITERATURE REVIEW

Language processing, especially text processing and word processing, has been the subject of significant research in recent years. Various approaches have been proposed to improve the accuracy of text detection and classification. Meng et al. [6] proposes an encoder-decoder based deep learning model for predicting key phrases which can generate words from a lexicon. According to Meng et al. [6], their model is good in identifying key phrase from various datasets, offering a direct comparison with a key phrase extractor that uses a single neural model to predict the likelihood of words being key phrases. However, as their focus was on a complex abstractive extractive task rather than a simple extractive task, direct comparison with other works is difficult. Medelyan et al. [7] used a bagged decision tree, while Lopez et al. [8] used an MLP and SVM for binary classification. Liu et al. [9] used lexical features to extract a list of candidate key phrases showing specific patterns, and a ranking model was used to select a key phrase from the candidates. A rule-based technique is proposed by Yang et al. [10], that can process unlabeled text and extract expected phrases as responses also can use a question generation mode which can be pre-trained.

Gupta et al. [11] have presented a testing system for weakly supervised phrase recognition. They have used BERT [12], a speech representation model, to test negatives that maintain the phrase context. However, this approach has some limitations, such as the requirement for state-establishing datasets to be annotated with a specific context, and the reliance on noisy external language datasets such as WordNet [13] to identify incorrect negatives. Donut et al. [14] have suggested an overall plan for selecting the most suitable algorithm for syntax deduction under various conditions. Cheng et al. [15] researched on phrase identification classifier with spatial relevance within tweet content. Their proposed model has the prediction capability the top k locations of the user with a city-level accuracy and identifies more than half of users within 100 miles of their actual location based on the content. Chen et al. model compares with gazetteer-based systems because gazetteers may miss some spatial vocabulary, and tweets.

They aim to identify local words with a high local concentration that quickly diminishes as the Twitter user's location deviates from the focus. However, this method does not use the probabilistic approach, it requires manually selecting and calculation of local words in classifier training. to train the classifier, it indicates the central focus. Serdyukov et al. [16] have predicted the location of Flickr photos based on their labels using a probabilistic technique and the Bayesian hypothesis. They have used the Geo-names gazetteer to identify partial labels, but they may miss phrases with spatial relevance. Because of the noisy nature of tweets, creating a comprehensive manually selected dataset can be time-consuming.

Additionally, some words have more than one location. To address these issues, Chang et al. [17] have used a separate approach based on GMM. Hecht et al. [18] have worked with an MNB model [19] to identify user locations as accurately as the state in a content-driven approach. Although the models discussed in this section have demonstrated efficient and more accurate performance in text detection and classification, no algorithms have been developed for Bangla phrasal words or Bagdara detection. Into this paper, we used a machine learning (LSTM) algorithm to predict phrasal words in the Bangla language. Our approach aims to overcome some of the limitations of existing models, such as the need for annotated state-establishing datasets and the reliance on external language datasets. By developing a model specifically for Bangla phrasal words, we can improve the accuracy of text detection and classification for Bangla language content. Our results demonstrate the effectiveness of our model in identifying Bangla phrasal words, indicating its potential for use in various application, for example sentiment analysis, text summarization, and machine translation.

III. PROPOSED METHODOLOGY

This research has addressed the gap by proposing a machine learning (LSTM) algorithm for predicting Bangla phrasal words, demonstrating its effectiveness in improving the accuracy of text detection and classification in Bangla language content. This approach has been demonstrated with available datasets as explained in the following sections.

3.1. DATA SET

To achieve better performance in deep learning, a sufficient number of datasets are necessary. However, for the task of Bangla Phrase (Bagdhara) recognition, no Bangla dataset was readily available. Collecting a suitable dataset can be a daunting and challenging task. In our study, we obtained data from various online sources as well as a Bangla grammar book. By reviewing different phrases from the book, we created contexts and rewrote sentences to incorporate the meaning of each phrase. These sentences were then split into separate columns for "Context", "Text", and "Phrase". The dataset was thus divided into three distinct categories to facilitate analysis.

TABLE I. The Summary of the dataset

Context	Text	Phrase
লোকটা গুলি খেয়ে অক্কা পেল	লোকটা গুলি খেয়ে মারা গেল	অক্কা পাওয়া
এ অগ্নিপরীক্ষায় সাফল্য লাভ করা আমার পক্ষে অসম্ভব	কঠিন পরীক্ষায় সাফল্য লাভ করা আমার পক্ষে অসম্ভব	অগ্নিপরীক্ষা
তার মতো অগাধ জলের মাছকে তুমি বুদ্ধিতে হারাতে পারবে না	তার মতো চালাককে তুমি বুদ্ধিতে হারাতে পারবে না	অগাধ জলের মাছ
Total = 1000		

The specific dataset is constructed as shown in Table-1. We have collected 1000 Bangla data from a different platform.

TABLE II. The Summary of the Parameter

Parameters	Values
Hidden Units	256
Embed Hidden Units	100

Dropout	0.3
Epoch	35
Batch Size	32
Verbose	1
Validation Split	0.15

In table 2, different parameters and their assigned values are displayed. The hidden units allude to the parts involving the layers of processors among input as well as output units in a connectionist framework. The dropout is used to slow down the overfitting of data. Epoch is the numbers of occasion that the learning computation will work through the entire preparation of the dataset. Sets the training progress verbose to 1 for each epoch. To determine the validation dataset when accommodating a model that can be evaluated similarly utilizing similar misfortune as well as measurements, the values of the validation split are set as 0.15.

3.2. Preprocessing:

Preprocessing is important, before using the data. After completing the dataset collection, we prepare our dataset for preprocessing. For splitting the dataset, we used the encoder layer. Then we applied a tokenizer for tokenizing the data. It can tokenize the data into separate word fragments. To ensure the successive comparable index of the length pad sequence and Keras function is applied. We consider the pad sequence like ([['লোকটা','অক্কা',' পেল'], ['অক্কা',' পাওয়া']]).

Here, the first queue is contemplated as [1,2,3] and the second queue is contemplated as [1,2]. As pad sequence is considered as a 2D array and for starting all the sequence padding 0 is performed in the embedded layer to as a prolonged sequence to all sequences for a similar length. In the example, 0 is used to match the similar length of the first array such as [0,1,2] where the first queue is considered as the prolonged sequence.

TABLE III. Data Shape

Context		Text		Bagdhara	
Tokens	Max Length	Tokens	Max Length	Tokens	Max Length
3585	19	3083	22	1513	6

As we applied encoder and decoder in context, text, and Bagdhara, we found different lengths and tokens for them. In table 3 various tokens and max length for context, text, and Bagdhara is shown. We consider context and text as input tokens while Bagdhara is used as an output token.

Context and Text are used as encoder input, and Bagdhara is used as decoder input. In the above table, we can see that the max length of the context is quite larger than others and the number of tokens for text is greater than the other number of tokens because they vary in the sentence's length.

3.3. Attention-based LSTM

Attention-based models have a place with a class of models generally known as arrangement-to-grouping models. The focus of these models, as the name proposes, is to deliver a result succession given an info grouping which is, as a rule, of various lengths. This model has recently thrived in image characterization [20], neural machine interpretation [21], mixed media proposal [22], and numerous different undertakings since it can focus on the compelling parts of highlights adaptively.

A significant element of human discernment is that it doesn't promptly manage all inputs from the outside world. All things considered; people will initially focus on the significant parts to get the data they need. Comparably, the significance of detecting phrases in Bangla is additionally unique, some data is excess [23], and others might be analytical [24][25][26].

To improve phrase detection in Bagdhara, it is necessary to focus on key elements and eliminate repetitive information. This allows successful data from various time frames to a financial forecast will be used to create the model, which can guide decision making. To optimize the input feature sequence, we propose an attention-based LSTM model, which belongs to the class of sequence-to-sequence models. This model is widely used in various applications such as image classification, neural machine translation, and multimedia recommendation due to its ability to adaptively focus on important features. The model plans a context and a set of key-value pairs to produce a result, where all four elements are represented as vectors.

The result is computed as a weighted sum of the values, with the weight assigned to each value determined by a similarity function between the context and its corresponding key. LSTM model gradually control flow of data through the use of gates, which helps to deal with the long-term dependencies in the recurrent neural network (RNN). During the training of this model an embedded layer is learned. We can calculate the position weight of the attention-based LSTM from this matrix. By transposing P, we can compute the position weight for p. The attention mechanism can be put before the LSTM layer or at the back of the LSTM layer.

$$P = \begin{bmatrix} p_1^1 & \cdots & p_1^n \\ \vdots & \ddots & \vdots \\ p_m^1 & \cdots & p_m^n \end{bmatrix}$$

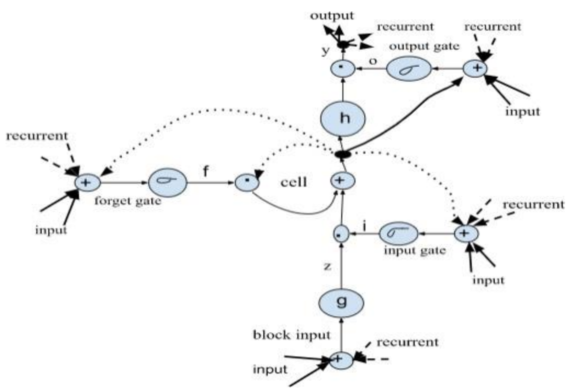

Fig. 1. LSTM model

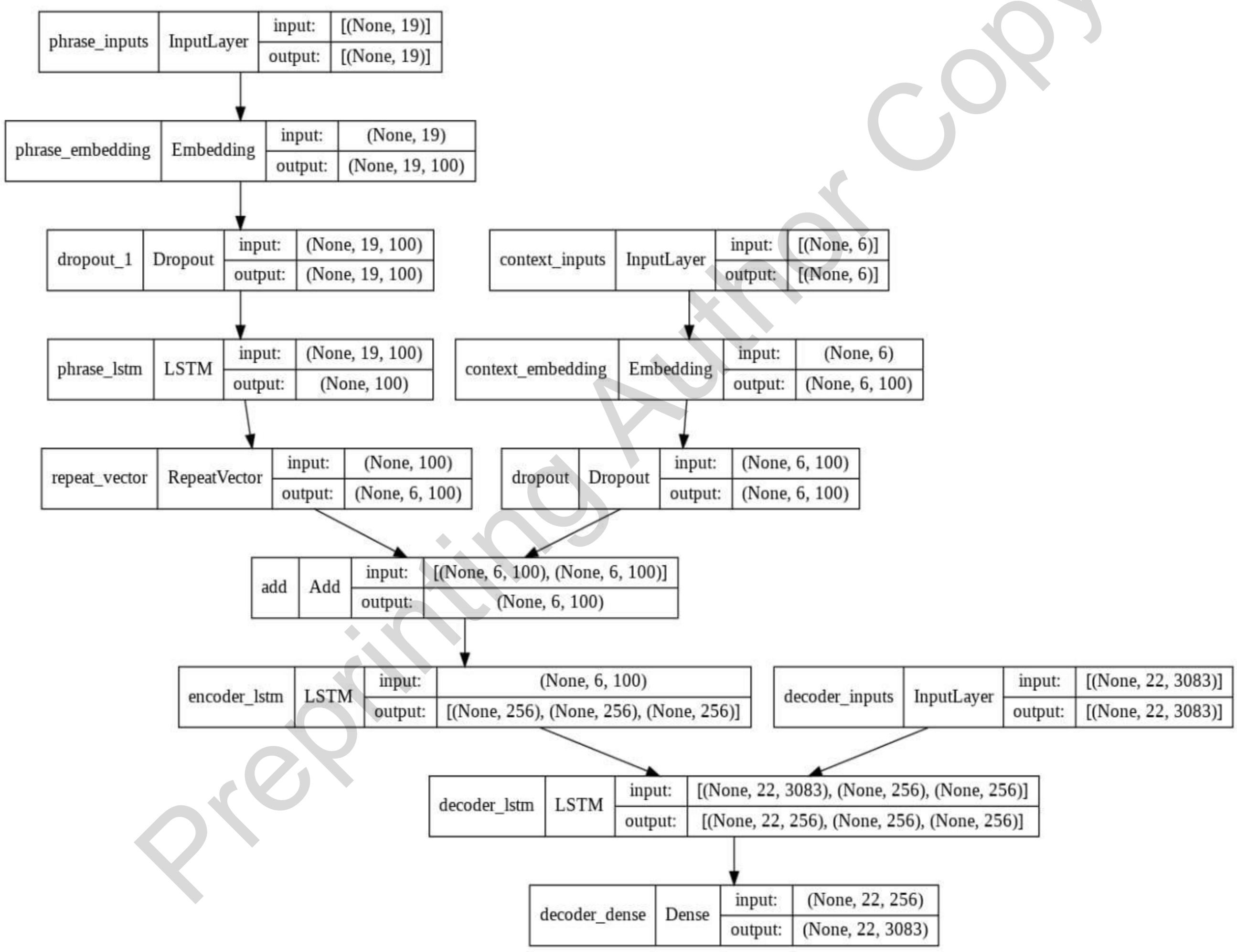

Fig. 2. Internal Structure of LSTM model

3.4. Attention Gate:

The attention gate base LSTM model empowers cells to screen the past cell state and the current input each time (Fig.1.). Attention LSTM model utilizes a gate system like that utilized by LSTM. This model also utilizes a consideration gate rather than a forgetting gate or an input gate [18]. In the first LSTM proposed by Hochreiter, the updated calculation of the cell state relates to the hidden layer yield at the former seconds and the contribution at the current second. Besides, they added a peephole association and took the cell condition of the past second as a parameter to refresh the present status. Internal Structure of LSTM model is shows in Fig.2.

IV. Result and Discussion

4.1. Loss Function:

Whenever the model is prepared, the loss is determined by the loss function as well as afterward BP is utilized to modify the parameter accommodating. We used Categorical Cross entropy as the loss function of the model, in this paper. It processes the cross-entropy loss among the genuine classes and anticipated classes. But there are other possible values such as sparse categorical cross-entropy, binary cross-entropy, mean absolute error cross-entropy, mean squared error cross-entropy, etc. A loss function also quantifies the error between the output of the model and the given target value.

$$L(x_i, y_i) = -\sum_{j=1}^{c} y_{ij} * log(P_{ij})$$

4.2. Activation Function:

To find the probabilities of P, we used SoftMax as an activation function. SoftMax is executed through a neural ij organization layer not long before the result layer. It converts the real value into probabilities. We can consider the higher probability as actual output. This function not only maps our output function but also maps each output in such a way that the summation is equal to 1. A high value will have a higher probability than others. It classifies the input into multiple categories. The activation function for the final layer is the SoftMax activation function which results in a multiclass probability distribution of our target classes.

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

4.3. Statistical Analysis:

Our dataset is consisted of using overall 1000 data and our proposed model used 35 epochs. Initially, the accuracy was very low, and loss was very high, and with the increase of epochs, the accuracy showed an increasing pattern. At the very first epoch accuracy was 56.42% and loss was 5.23. We found that at epoch 8 the accuracy was 60% but the loss was 2.78 and after epoch number 25 accuracy was 65% and the loss was 1.89. Then with the increase of epoch, the accuracy was also rising and loss was decreasing, and in epoch 30 the accuracy was 75.72% and loss was 1.72. At the final epoch 35, the accuracy was 78.63% and the loss was 1.43. So it is clear that if we increase our epoch more, then the accuracy of the model will be increased and loss will be decreased.

4.4. Accuracy Graph:

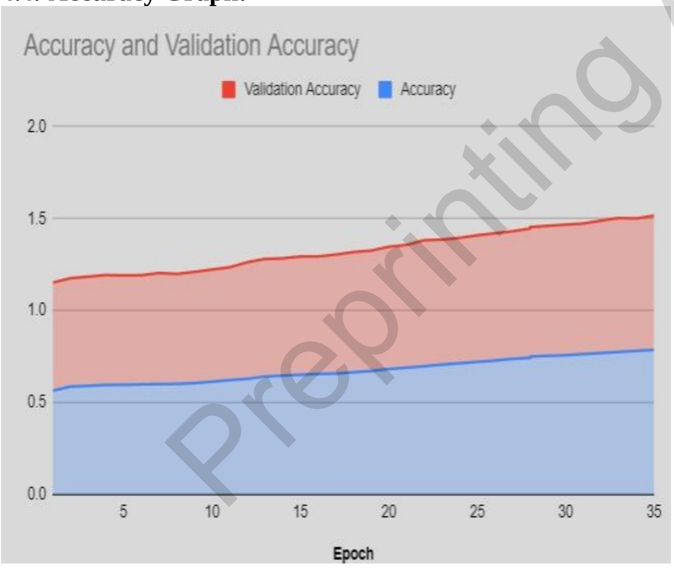

Fig. 3. Epoch vs Accuracy and Validation Accuracy

The accuracy graph (Fig.3.) is constructed using three factor for instance epoch vs accuracy and epoch vs validation accuracy. The data set we used here is completely pure and raw data. This data is not completely noise free. That is why it impact our accuracy sharply. However, from our accuracy graph pink color graph represent validation accuracy and the blue color graph present the accuracy. It is clear that with the increase of number of epochs, the accuracy is increased. Our model overall accuracy is 78.63%.

Table IV. Sample of the Prediction

Examples	এ অগ্নিপরীক্ষায় সাফল্য লাভ করা আমার পক্ষে অসম্ভব
Phrase	অগ্নিপরীক্ষা
Prediction	অগ্নিপরীক্ষা
Examples	হিংসে করে সবাই হুঁকো নাপিত বন্ধ করেছে
Phrase	হুঁকো নাপিত বন্ধ করা
Prediction	হুঁকো নাপিত বন্ধ করা

We use several examples to test our model which included Bagdhara. Our model can determine the Bagdhara's keyword and provide the meaning of the Bagdhara based on the examples provided. In Table 4. The demonstration of our model testing is shown.

V. Conclusion and Future Work

Bagdhara, which are phrasal words, are powerful and useful tools in the Bangla language, as they can make speech more attractive and poetic. Various language processing approaches, particularly text processing and phrasal word processing have been proposed to improve the accuracy of text detection and classification, with different strengths and limitations. However, there is a lack of models specifically developed for certain languages, such as Bangla. Our research has addressed this gap by proposing a machine learning (LSTM) algorithm for predicting Bangla phrasal words, demonstrating its effectiveness in improving the accuracy of text detection and classification in Bangla language content. However, accurately selecting the appropriate Bagdhara is a difficult task. To address this issue, we propose an automatic system that can instantly and accurately detect Bagdhara. We employ an LSTM model based on attention in our study to detect Bagdhara. Our model achieved an accuracy of 78.63%. We tested our model by providing input sentences, and it successfully detected Bagdhara in each sentence. Our dataset consisted of only 1000 data, and not all of the data was completely free of noise. Additionally, we only used 35 epochs, which is why our accuracy was limited to 78.63%.

This approach has the potential to be applied to various applications and could pave the way for further research in the field of language processing. In the future, we will increase the size of our dataset and publish it online as it is the first work that uses a Bangla dataset. We will also evaluate different deep-learning models in our proposed study.

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