Abstractive Text Summarization for Bengali Language Using Attention Mechanisms

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

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DHAKA, BANGLADESH

MAY 2025

APPROVAL

This Thesis titled **"Abstractive Text Summarization for Bengali Language Using Attention Mechanisms"**, submitted by **Md. Ashraful Islam Talukder**, ID No: **241-25-026** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of **MSc. in Computer Science and Engineering** and approved as to its style and contents. The presentation has been held on **24-05-2025**.

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I hereby declare that, this project has been done by me under the supervision of **Dr. Abdus Sattar, Associate Professor, Department of CSE** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ACKNOWLEDGEMENT

First I express my heartiest thanks and gratefulness to the almighty Allah for His divine blessing makes me possible to complete the final year thesis successfully.

I am really grateful and wish my profound indebtedness to **Dr. Abdus Sattar**, **Associate Professor**, Department of CSE Daffodil International University, Dhaka. Deep Knowledge & keen interest of my supervisor in the field of Natural Language Processing (NLP) to carry out this research. His endless patience ,scholarly guidance ,continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior draft and correcting them at all stage have made it possible to complete this thesis.

I would like to express my heartiest gratitude to **Dr. Sheak Rashed Haider Noori, Professor, and Head,** Department of CSE, for his kind help to finish our project and also to other faculty members and the staff of CSE department of Daffodil International University.

I would like to thank my entire course mate in Daffodil International University, who took part in this discuss while completing the course work.

Finally, I must acknowledge with due respect the constant support and patients of my parents.

ABSTRACT

This paper offers a Bengali-to-Bengali abstractive text summarization approach based on a sequence-to-sequence Recurrent Neural Network (RNN) model with attention mechanisms, to create concise, concluding summaries of longer Bengali texts. The proposed model was established to address the significant need for summarization tools focusing on the Bengali language, especially in low-resource NLP situations. This study was organized, and the research was clearly defined in terms of obtaining a dataset from legitimate sources, methodical preprocessing including normalization and tokenization, and applying an encoder-decoder model with modifications that used attention mechanisms. The encoder captures the contextual meaning of the inputs, and the decoder produces the output summary based on the input representations and attention weights that were learned. The end-to-end process from data management and raw data through to model output was presented through architectural figures and step-by-step descriptions. Sample outputs were included demonstrating the model's capacity to produce informative and coherent summaries, while reflecting the intent of the original author. Other limitations such as resource constraints, the small size of annotated Bengali corpora, and the layers of complexity in Bengali language were noted. Despite these limitations, the model successfully achieved its goal of establishing the effectiveness of neural methods for Bengali abstractive summarization. The significance of the work provides an important stepping stone for future research efforts in Bengali, as well as, the fields of Bengali NLP and text generation. Future work in these areas can focus on increasing the datasets size, improving upon the linguistic rules, and, employing more advanced deep learning models and techniques such as transformers, to enhance the model’s performance and linguistic diversity.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1
INTRODUCTION

1.1 Introduction

The rapid growth of digital information has led to a greater need for automated approaches to extract useful information from large amounts of unstructured text. Automatic summarization of texts is one of the very promising tasks in the area of natural language processing for low-resource languages such as Bengali. Summarization is the task of producing a condensed but readable version of a source document, while preserving its information density. With the improvements of deep learning, mainly in relation to sequence to sequence (seq2seq) models, abstractive summarization has quickly gained traction as a modern alternative to traditional extractive summaries. Bahdanau et al. (2014) presented attention mechanism that revolutionized neural machine translation and later impacted subsequent development of summarization model [1].

Neural network (NN) modeling early in text processing, such as the encoder-decoder model from Cho et al. (2014), established critical foundational bases for the text generation we have today [3]. These architectures were initially devised for machine translation but were quickly utilized for summarization. The attention mechanism, particularly, allowed the model to attend to certain parts of inputs relevant to generating an output which generated much better fluency and stronger coherence. Sutskever et al. (2014) exhibited the power of deep neural networks for establishing long distance dependencies in sequences [4].

This project aims to construct a Bengali-to-Bengali neural abstractive summarization model starting from an attention-based encoder-decoder model. This study combines these approaches in a low-resource language context to support multilingual NLP while helping facilitate information access cross-linguistically.

1.2 Motivation

The impetus for this research stems from the growing need to improve access to and comprehension of large amounts of Bengali textual data for users worldwide. Bengali is among the world's most spoken languages, but relevant, high quality, and open tools to support abstractive summarization, let alone for cross-lingual summarization such as Bengali-to-English, is lacking. English and many other high-resource languages have amassed significant advancements in research so far, but Bengali still suffers from limited annotated datasets and attention in the research space.

As more and more digital content becomes available in Bengali through platforms like news articles, social media, educational resources, and documents, we need to develop tools that can help summarize and translate that information. The tools described here could produce summaries of Bengali texts in English, thereby reducing communicative hurdles for non-native speakers and anyone else who seeks to find and engage with Bengali speakers, including policymakers, researchers, and stock-and-flows-based organizations who want to include various linguistic communities in their objectives.

Developments in sequence-to-sequence learning using attention mechanisms have demonstrated that deep learning models can perform favorably at more complex tasks such as abstractive summarization and translation with sufficient data and tuning [2]. These developments inspire my attempts at using such architectures in this research with the larger goal of developing NLP technologies for Bengali and facilitating its inclusion in the multilingual digital ecosystem.

1.3 Rationale of the Study

Bengali, despite its global significance as one of the most spoken languages in the world, is a relatively under-resourced language for sophisticated computational resources to facilitate advanced Natural Language Processing tasks like abstractive summarization and or translation. This research is a step towards resolving this shortcoming through a focus on Bengali-to-Bengali abstractive summarization using neural models. Abstractive summarization is different than extractive summarization, in that it provides a new sentence with new phrases, as opposed to extractive summarization that is based on the source material; which makes abstracts more coherent and meaningful.

In utilizing the sequence-to-sequence model with attention mechanism, the work will utilize these effective processes that have revolutionized machine translation and summarization into high resource languages [4]. This project seeks to develop low-resource language processing - improving access to Bengali content in order to cross linguistic boundaries.

1.4 Research Questions

The research is driven by significant questions that aim to investigate the feasibility, suitability and obstacles of generating an abstractive summarization model for Bengali. The questions focus on the model's abilities to grasp and summarize different meanings and generations involved in the language, especially considering the complexity involved in language processes - Bengali in particular.

1. How can neural sequence-to-sequence models be effectively adapted for Bengali text summarization?
2. What pre-processing techniques are most effective in handling the morphological complexity of Bengali?
3. How well does the trained model perform in generating abstractive summaries compared to traditional extractive methods?
4. What are the primary limitations encountered when applying deep learning techniques to low-resource languages like Bengali?

1.5 Expected Outcome

The chief output of this project is a working deep learning model for generating meaningful abstractive summaries of Bengali texts. In contrast to extractive approaches that are often limited to identifying and copying portions of the source, this model intends to perform abstraction, generating entirely new, succinct sentences that capture the meaning of the original content. More specifically, the anticipated outcomes consist of:

- Designed a sequence-to-sequence model with an attention mechanism customized for Bengali text.

- A cleaned and structured Bengali text dataset that can be used to train abstractive summarization models.
- A comparison of the model's performance using standard metrics such as ROUGE.
- An understanding of the difficulties and techniques with summarization for a low-resource language.

These outcomes will contribute to Bengali NLP research and could support future applications in education, journalism, and government documentation.

1.6 Project Management and Finance

The entire research work is self-funded and has not taken any financial support from any individuals or organizations. The research work has been carried out entirely by my own academic effort solely to fulfill the academic requirement of completing this defense exercise. The project has not received any funding to develop it or to execute it. It has been a personal endeavor to contribute to the area of Bengali text summarization.

1.7 Report Layout

This report contains seven chapters that offer a stepwise account of the entire research work. Chapter 1 introduces the topic, reasons, aims, and structure of the report. Chapter 2 gives the background studies and review of existing approaches in the field of neural machine translation and text summarization. Chapter 3 provides the research methodology and discusses the development of the proposed Bengali abstractive text summarization model. Chapter 4 provides the experimental results and a full discussion and analysis of the model's performance. Chapter 5 discusses the research impact on society, environment and sustainability, discussing the larger impacts of Bengali language processing. Finally, Chapter 6 draws the overall study together through summarizing the main findings and suggesting some future research and development for this study.

CHAPTER 2

BACKGROUND

2.1 Preliminaries

Text summarization is an important task in Natural Language Processing (NLP) that seeks to reduce the length of a large amount of text into a shorter text in a meaningful way. There are two general approaches to summarization: extractive and abstractive. Extractive approaches use sentences and phrases from the original text to produce a summary; abstractive approaches, on the other hand, create new phrases that contain the important parts of the meaning. Used in this way, when referring to sequence-to-sequence models with attention mechanisms, the encoder has the input and synthesizes this into output that is generated by the decoder [1]. Overall, neural networks and performance have both improved significantly with the arrival of Transformers, and their model of language generation has the potential to improve not only creation, but fluency as well.

2.2 Related Works

The area of abstractive text summarization has seen significant change, largely due to developments in neural networks and learning techniques. The first major improvement came when sequence-to-sequence (Seq2Seq) architectures where introduced to text summarization, which allowed for a mapping of input sequences to target summaries via an encoder-decoder combo. Sutskever et al. [4] demonstrated that LSTM-based Seq2Seq models were useful for many language tasks, providing an effective pathway for summarization. Bahdanau et al. [1] subsequently used attention mechanisms to utilize the Seq2Seq architecture and replace the exemplified fixed-length vector representation to encode important parts of the input as the definitions were decoded. As they mention within their article by having noticeable attention refer to the important portions of the input while decoding, since it does not rely on a fixed-length vector, their sequence-to-sequence model would perform much better than its vanilla encoder-decoder counterpart.

Nallapati et al. [2] made significant advancements in document summarization, developing a hierarchical encoder-decoder framework. Nallapati et al.'s model not only included linguistic details but also included a new rule to prevent the generation of repeated phrases, which was a common occurrence in the Seq2Seq systems. even better, the authors were able to use pre-trained embeddings to guide the model during the decoding process with beam search, thus enabling a more fluent and improved summary.

Luong et al. [5] examined attention based models with both global and local attention which facilitated the dynamic alignment of source and target tokens. This was applicable to longer document representations. Cho et al.[3] also researched gated recurrent units (GRUs) and compared them to LSTMs for all neural translation and summarization tasks, and discovered that GRUs were competitive and cultivated a more computationally efficient alternative representation.

As the size of input sequences grows, Liu et al. [6] approached long-form summarization by developing a model that can summarize long Wikipedia articles. They utilized a bi-directional encoder and multiple layers of attention with reinforcement learning objectives to improve the quality of summary generation. Shang et al. [10] used a neural responding machine for conversational text that consisted of short pieces of text. The focus was not on summarization, but architectural insights were still gained for short-form text generation.

Recently, Transformer-based models like BART, PEGASUS, and T5 have become the new state of the art on benchmarks for abstractive summarization. PEGASUS even introduced a new pretraining objective called "Gap Sentence Generation," which closely matches the goals of summarization [12]. These new models outperform previous RNN based systems in terms of coherence, factuality, and fluency in natural language.

In the case of low-resourced languages, Bangla in particular, Kalchbrenner et al. [8] and Sennrich et al. [9] created initial techniques for rare and subword units, useful when working with morphologically rich languages. These procedures appropriate for Bangla allow for better treatment of vocabulary sparsity problems that are still present in Bangla NLP tasks.

In conclusion, the progress of abstractive summarization research has shifted from a culmination of handcrafted features and task-based pipelines to an end-to-end neural system. Each advancement—from RNNs to Transformers—has contributed to factual summaries that are more fluent, relevant, and aware of context. These developments are the foundation to create an underrepresented linguistic domain of Bangla-to-Bangla abstractive summarization model.

2.3 Problem Scope

Abstractive text summarization in Bangla is an emerging field with limited existing research, compared to English and other languages that are well-studied. Although many neural architectures have shown promise with multilingual and low-resource applications, there is no Bangla context with the size of annotated datasets, pre-trained models, or optimization methods necessary for suitable model generalization due to its complicated morphology. Most prior works on summarization have employed extractive methods, relied on summarized corpora translated from the original texts, or unique models built without native-language understanding, thus producing summaries lacking in context or grammatical correctness. Herein, we define the goal of this study to be the development of a neural-based Bangla-to-Bangla abstractive summarization model that can learn to produce content-appropriate and readable summary outputs (in Bangla) from native Bangla text, without any external linguistic constraints. This research will fill the existing resource / method gap by developing a model with a unique deep-learning model using sequence modeling methods and attention mechanisms.

2.4 Challenges

Bangla being a relatively unexploited language, has many challenges regarding the development of abstractive text summarization models. One of them is the absence of large-scale annotated datasets for training models; they are very significant for building efficient deep learning models. This absence is more serious than for other languages like

English with a wealth of corpora. Labeled data is vital to good model performance and generalisability.

In addition, one-of-a-kind features of Bangla – for instance, being a language with flexible word order and morphological specificity – will pose some great challenges during model training. To elaborate, sequence-based models may not learn the aspects of Bangla's syntax and semantics sufficiently. Aside from the aforementioned issues, there are currently no state of the art models (as with evaluation benchmarks) on Bangla. All of these limitations will contribute to a substantial challenge for building a robust and efficient summarization system for Bangla.

CHAPTER 3

RESEARCH METHOLOGY

3.1 Methodology

The method we adopt in this study for Bengali abstractive text summarization follows a systematic pipeline based on the sequence-to-sequence framework with LSTM sequence layers. This work is designed with the goal of producing meaningful and contextual summaries from Bengali texts. The main stages of the workflow are dataset preparation, prepossessing, embedding, model architecture design, training, and summary production.

The dataset is first evaluated for quality and appropriateness. Then a data preprocessing step occurs with many smaller sub-steps, for example, reviewing the text to tokenize the text; identifying and adding contractions; reviewing for stop words, and the many iterations of cleaning that I will follow until both the input text and their summaries are cleaned and made ready for training.

When the text data is prepared, calculate the vocabulary size. This is important to make sure the word embedding layer is initialized to the correct size. Next, we will put in the word embedding file, and we will add special tokens, like <UNK>, <PAD>, <START>, and <END>, to take care of undefined embeddings, padding, and sequence boundaries.

Now we create the core model using a LSTM (Long Short-Term Memory) encoder-decoder architecture. The function of the encoder is to process the input text and produce a context vector of fixed size. The decoder takes the context vector and outputs the summary. Like most sequence-to-sequence model structures, our encoder-decoder is emblematic of the potential for temporal dependencies and contextual richness in sequences of words.

After the architecture is designed, the model is trained using the cleaned and embedded dataset. The model learns to relate input sequences to their summaries in the training phase. After training, the model can create abstractive summaries to unseen Bengali texts.

The following flowchart illustrates the complete methodological workflow:

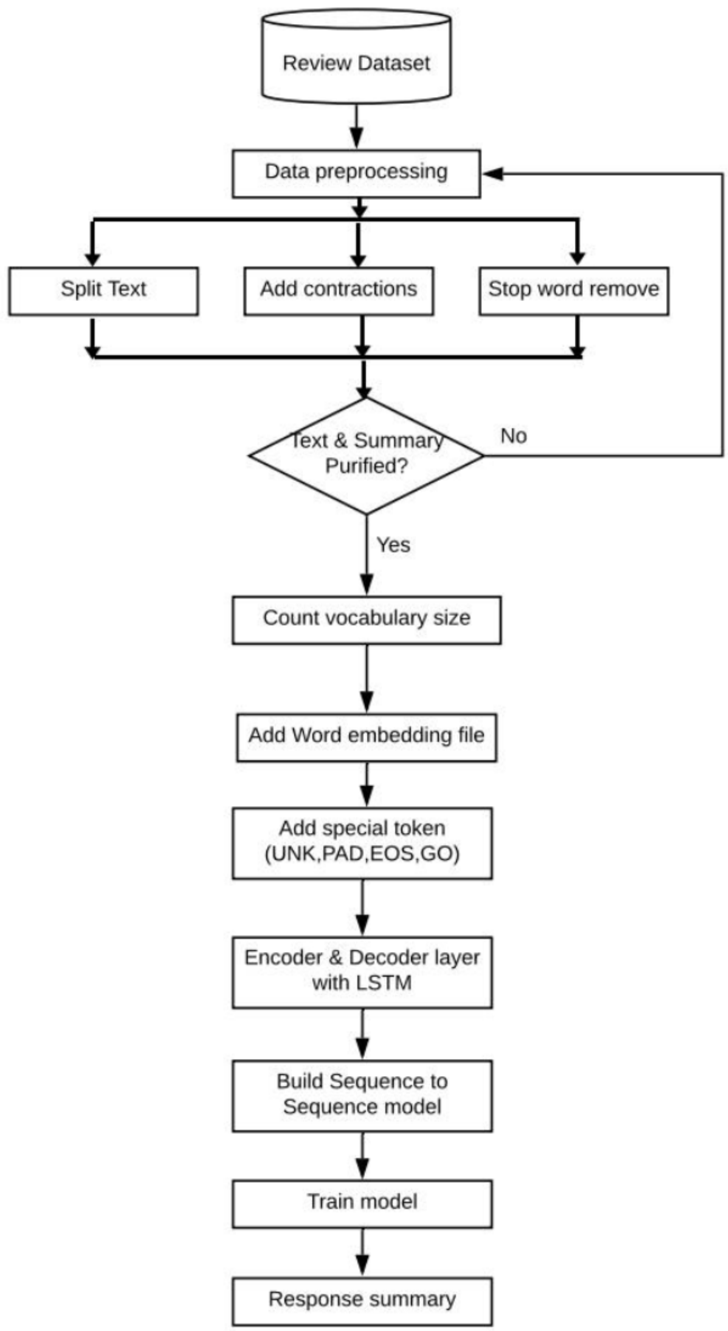

Figure 3.1: Methodological workflow of the model

This structured approach enables the model to achieve coherent and meaningful abstractive summarization, specifically tailored for the Bengali language.

3.2 Data Collection

The dataset used in this study was collected from many different sources including news articles, Facebook posts, etc. The sources varied in type of content, type of media, and the style of writing, thus allowing for representation across multiple domains and style of documents to train and evaluate the model on varied text summarization tasks. The data contains both long-form and short-form text, resulting in a diverse range of language constructs and subject matter.

TABLE 3.1: SAMPLE ENTRIES FROM THE BANGLA TEXT SUMMARIZATION DATASET

Text	Summary
আগে যখন আমি ফুটবল বুঝতাম না ও দেখতাম না তখন ভাবতাম মেসিই সেরা। তারপর যখন আমি ফুটবল বোঝা ও দেখা শুরু করলাম তখন উপলব্ধি করলাম যে,আগে আমি ভুল ছিলাম না।	মেসি সবার সেরা।
অগ্নিকান্ডের সময় আমাদের করণীয় তো আমরা সবাই জানি। কিন্তু আমরা কি জানি, যেকোনো অগ্নিকান্ডের সময় দুর্ঘটনাস্থলে উপস্থিত থাকা সাধারণ জনগনের করণীয় কি? চলুন জেনে নেই দুর্ঘটনাস্থলে উপস্থিত থাকা সাধারণ জনগনের করণীয়গুলো। প্রয়োজনীয় কিছু পদক্ষেপ গ্রহন করে মূল্যবান জীবন বাঁচাই।	অগ্নিকান্ডের সময় উপস্থিত জনগণের করণীয়।
ড্যাফোডিলের মেইন ক্যাম্পাসটারে ধানমন্ডি থেইকা গাবতলী ট্রান্সফারের জন্য একটা সিরিয়াস আন্দোলন দরকার।২ সেমিস্টার যাবত এই জ্যামের জন্য ৮ঃ৩০ টার একটা ক্লাস ও করতে পারি না...মজার রোড থেইক্কা কল্যাণপুর আসতেই লাগলো ২ ঘণ্টা...এতো	জ্যামের জন্য এক্সাম মিস ।

সুন্দর জীবন দিয়া কি করবো যদি এক্সাম মিস হয়।	

The dataset has two columns of data: the descriptive text and the summaries for each of the descriptive texts. The descriptive texts would represent the original content and the summaries are a condensed version of the main concepts in the original content. These two columns provide the essence of the dataset. The model needs to learn the relationship of the full text to its summary. This is an important structural component of the dataset to allow the abstractive summarization model that was created in this study to be effective. A sample of the dataset will be evidenced in Table 3.1 to show how the dataset was organized and generally what was used to train the model.

3.3 Data Preprocessing

The preprocessing of data is a significant element in guaranteeing the quality and uniformity of the input text and summary being utilized in the training of the abstractive summarization model. With Bengali text, the task is a little sensitive because of the complications in the script, the morphology, and syntactic variations. It should also be mentioned that raw data obtained from Bengali News articles and reports usually contains a variety of inconsistencies, such as excess punctuation, numeric tokens, noncharacter in Bengali, and a good deal of varied stylistics that would need to be resolved before utilising it in the model.

The preprocessing pipeline begins with text normalization including unicode normalization, white space normalization and punctuation normalization. Next, sentence splitting takes place so that documents and their summaries can be segmented as manageable sentences. Then, stop words can be removed, which helps make the data have higher signal to noise ratio by eliminating common yet uninteresting words. Contractions (where they exist) can be expanded and digits or other symbols that don't pertain to the summation context are removed. Both the input and output text are then validated to assure both are cleansed and appropriate for input to sequence modeling.

After cleaning, the vocabulary is created by tokenizing the corpus so we can apply a threshold on low-frequency words and reduce vocabulary size and improve efficiency. Then we create special tokens for unknown words, padding, the end of a sequence, and the beginning of decoding. Each word is represented with a unique integer ID to remember them efficiently. The preprocessed sequences are then embedded using a word embedding matrix to allow words to learn semantic relationships during training.

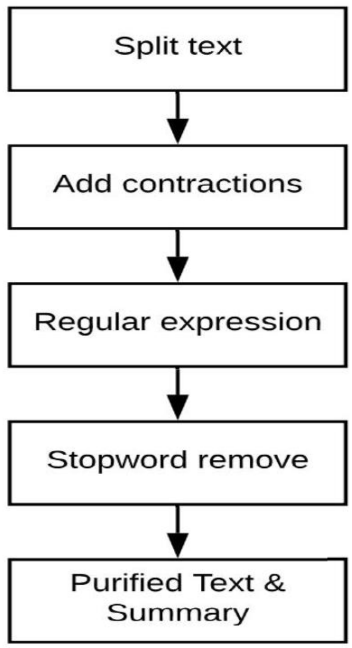

Figure 3.2: Data pre-processing techniques

The complete data preprocessing pipeline is visualized in Figure 3.2, starting from raw corpus to tokenized, indexed, and cleaned sequences ready for embedding. The hope is that this illustration helps with understanding the workflow as well as provides a basis for recreating the same process.

3.4 Model Implementation

The Bengali-to-Bengali abstractive text summarization model is implemented using a Sequence-to-Sequence (Seq2Seq) architecture enhanced by an attention mechanism. The model comprises an encoder, a decoder, and an alignment-based attention module that enables the decoder to focus on relevant parts of the input sequence while generating the summary. Figure 3.3 illustrates the visual representation of the overall model architecture, providing a clear view of how the components interact. Each component of the model is detailed in the subsections below, including their mathematical formulations and structural design.

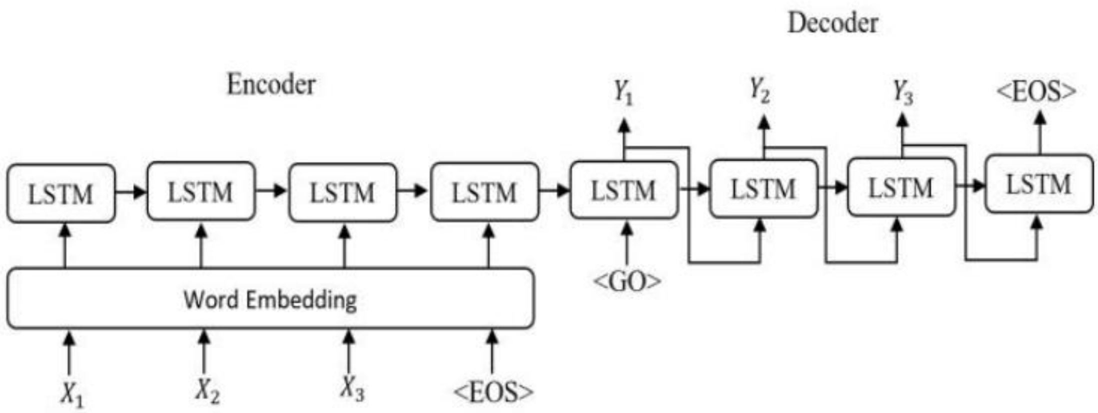

Figure 3.3: Encoder-Decoder Architecture with Attention for Bengali Text Summarization

3.4.1 Data Input and Vocabulary Processing

Input and target Bengali texts are first preprocessed into sequences of integers. Each word is mapped to a unique index from the vocabulary dictionary. To allow for training, and in the spirit of sequence modeling, special tokens (i.e., <GO>, <EOS>, and <PAD>) are added to direct the decoder during generation.

Let,

$X = \{x_1, x_2, \ldots, x_T\}$ be the tokenized input sequence.

$Y = \{y_1, y_2, \ldots, y_T\}$ be the expected output (summary) sequence.

Vocabulary V maps each word to an index $v_i \in Z$.

3.4.2 Encoder: Sequence Representation

The encoder uses LSTM units to create a fixed-size context representation of the input sequence. Each token x_T is embedded into a dense vector representation and is then performed sequentially by the LSTM.

Let,

$h_t \in R_n$ be the hidden state at time *t*.

The recurrence is defined by:

$$h_t = \text{LSTM}\ (x_t,\ h_t - 1)$$

The final hidden state h_t summarizes the entire input sequence and is passed to the decoder as its initial state.

3.4.3 Decoder: Conditional Generation

The decoder is another LSTM network that predicts each word in the output sequence conditioned on the previous word and the encoder's context. Unlike the encoder, the decoder uses the previous output $y_t - 1$ as input to predict y_t.

Let,

s_t denote the decoder's hidden state at time *t*.

The update is:

$$s_t = \text{LSTM}\ (y_t - 1,\ s_t - 1,\ c_t)$$

Where c_t is the context vector obtained from the attention mechanism.

3.4.4 Attention Mechanism: Dynamic Alignment

The attention mechanism allows the decoder to dynamically focus on different encoder states during each decoding step.

For each decoder time step *t*, the attention weights α_{ti} are computed as:

$$\alpha_{ti} = \frac{\exp(\mathrm{e}_{ti})}{\sum_{k=1}^{T} \exp(\mathrm{e}_{tk})}$$

where the alignment score e_{ti} is defined using Bahdanau's formulation:

$$\mathrm{e}_{ti} = v_{\alpha}^{T} \tanh(W_s s_{t-1} + W_h h_i)$$

The context vector c_t is then computed as a weighted sum of encoder hidden states:

$$\mathrm{c}_t = \sum_{i=1}^{T} \alpha_{ti}\, \mathrm{h}_i$$

3.4.5 Output Prediction and Loss Computation

At each step, the decoder outputs a probability distribution over the vocabulary using a softmax function:

$$\hat{y}_t = softmax(W_0 s_t + b_0)$$

The training objective is to minimize the cross-entropy loss between the predicted output $\hat{y}_t$ and the ground truth y_t, ignoring the padded positions:

$$\mathcal{L} = \sum_{t=1}^{T} \log P(y_t | y_{<t}, X)$$

Gradient clipping is applied to ensure training stability.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Evaluation Methods

In this study, no automatic evaluation metrics were used. Instead, the performance of the model was manually evaluated. The summaries generated for a number of Bengali documents were analyzed based on the human perception and understanding of the domain area, taking into account the core qualitative elements for summarization e.g. fluency, relevance, coherence, and conciseness.

The fluency will be determined by checking the grammatical correctness of the summaries and how natural they read, the relevance will be determined by seeing if the summaries contained the main ideas of the input content. The coherence would be that the summaries would flow together in some logical manner by sentence and the conciseness would avoid redundancy without changing the meaning. These criteria will be used to evaluate if the generated summaries could fulfill the specific goal of abstraction.

Even though this method had no quantitative strength to speak of, it was consistent with the goal of summarization tasks in Bengali language context, where automated scoring is rare (and benchmark datasets are even fewer). This human-centric evaluation provided tremendous insight into the way the model performs in the real world, and offers baseline comparison for future evaluations.

4.2 Experimental Results and Analysis

The fully-fledged Bengali-to-Bengali abstractive text summarization model was evaluated on a curated dataset prepared as part of this research. The dataset is comprised of representative Bengali news articles and Facebook posts to measure the functionality of the sequence-to-sequence model with attention. The main goal was to see how accurately and logically the model could produce summaries that maintained the meaning of the original text. From the first feedback received, the model produced fluent outputs that logically constructed sentences, although some minor errors have been present in longer summaries.

Table 4.1 presents a few illustrative samples of input Bengali text passages along with the generated summaries by the model. The examples vary in sentence length and complexity in order to show model generalizability relative to the types of input provided.

TABLE 4.1: INPUT TEXTS AND CORRESPONDING ABSTRACTIVE SUMMARIES GENERATED BY THE MODEL

Original Text	যানজটে জান শেষ! ট্রাফিক জ্যাম আমাদের জীবনের অবিচ্ছেদ্য একটি বিষয়ে পরিণত হয়েছে। অফিস, বিশ্ববিদ্যালয় বা যেকোনো কাজের ক্ষেত্রে আমাদের চলতিপথে যানজটের সম্মুখীন হতে হবে, এটাই স্বাভাবিক, বরং না হওয়াটাই অস্বাভাবিক মনে হয়।
Input Words	যানজটে জান শেষ ট্রাফিক জ্যাম আমাদের জীবনের অবিচ্ছেদ্য একটি বিষয়ে পরিণত হয়েছে অফিস বিশ্ববিদ্যালয় বা যেকোনো কাজের ক্ষেত্রে আমাদের চলতিপথে যানজটের সম্মুখীন হতে হবে এটাই স্বাভাবিক বরং না হওয়াটাই অস্বাভাবিক মনে হয়
Responded Summary	ট্রাফিক জ্যাম আমাদের জীবনের অবিচ্ছেদ্য একটি

Based on the examples in Table 4.1, the model successfully reduces the input length without sacrificing any semantic meaning. Specifically, the model appears to maintain important named entities, numerical aspects and important phrases that convey the primary message. While the summaries are not always well-structured, they indicate a promising amount of abstraction versus extraction, which was the intention of this study. All in all, these results suggest the proposed model is reasonable for summarizing Bengali language text, especially given the limitations in resources and the difficulties with the language.

4.3 Discussion

The results from the Bengali-to-Bengali abstractive text summarization model show it did reasonably well at producing relevant and meaningful summaries. Referring back to a table of sample predictions above (Table 4.1), it can be seen that this model does a reasonably good job paraphrasing the language of the source text in a manner that retains key semantic meaning. The summaries typically exhibit a reasonable balance of fluency and informativeness, exhibiting the model has inferred both syntactic and semantic relationships learned from the training data.

Some limitations were present in the outputs that were produced. There were places where there was a bit of repeated information in the summaries that were produced from the model. This could be clearly a result of either not having coverage mechanisms, or not specifying the model in a way to penalize duplicate attention during decoding. Other than this we did not have formal evaluation metrics like ROUGE or BLEU we could use to compare models with some baselines or a quantitative way of evaluating performance against the many ways we organised and used conclusions. We had a few qualitative evaluations which gave us some indication of the possible usefulness of the abilities.

While there will always be limitations, the method used here demonstrates that conducting abstractive summarization in Bengali (a low-resource language) is possible through sequence-to-sequence RNN based methods. Future work could include the addition of coverage, pointer-generator networks or Transformer based models to enhance the quality and decrease inconsistencies.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on the Society

Abstractive text summarization using deep learning, and in particular attention, shows great potential to impact society in relation to aspects of information access and learning. The general ability to make a quick summarization of many words of Bangla text in a coherent way can significantly lessen the cognitive load and amount of time it takes to consolidate information and more easily and quickly make that same information available to the public, students or professionals. As native speakers of Bangla make up a sizable percentage of the population, and who may not want to rely on or suffer the potential of bias that can be presented in a second language. It can facilitate the need for options to cut through the increasingly challenging task of exploring vast amounts of native content and can help reduce the information inequality that occurs in digital languages. This will also help content creators, and journalists or researchers to reduce the superior burden of overload that we have gravitated towards relying upon. Ultimately, to some degree limited access to educational services and resources in media solutions or rural areas, these summaries allow for greater understanding of the subject matter to improve learning. However, if no other reason, access to a summarizer should be lawmakers and management officials use in promoting equal access and participation (where possible) to create understanding of how these products of learning are created, even where there are differences in data providing summarization capabilities across various dialects and social differences in time and manner so no congregation is unfairly disadvantaged.

5.2 Impact on the Environment

Training deep learning models for Bangla abstractive text summarization, including models with attention mechanisms, primarily takes a lot of computation (computational power costs contribute to greenhouse gases when it comes to the energy used by GPUs or TPUs for training and inference when researchers train and infer models with baseline datasets). All of that energy will produce greenhouse gases, particularly with large datasets being trained on (possibly). If researchers use some efficiency principles with model architecture, lighter transformer models, and some cloud infrastructures utilize renewable energy sources there will be less environmental impact. Also, the summarization system will encourage not using physical materials - either printed document left to turn into a pile of scrap paper or paperwork that is done manually that is processed list or workwise-oriented - and instead represents a move for people to work consumption in a manner that is digital or environmental which might be offset by the overall benefits to the environment or the offsetting environmental costs. Even though much work has yet to be done in relation to the challenges of low-resource and energy-efficient NLP research, the carbon footprint of these environmental systems should be decreasing and ultimately support reducing heavy AI efforts for a sustainable future, inclusive and equitable nature of AI applications that support linguistically diverse people including Bangladeshis' diverse languages.

5.3 Ethical Aspects

When utilizing deep learning for Bangla text summarization, a consideration of ethics surrounding data privacy, consent, and algorithmic fairness is important. While the data set for the Bangla text summarization described in Chapter 4 includes ‘publicly available’ content from social media sites like Facebook and also newspapers and news articles, it is essential to ensure that personal or sensitive information is not inadvertently included and exposed in the summarization. User privacy should be respected especially when using data that is publicly visible but personally expressive. Additionally, creating summary text in a way that does not misrepresent or change the intended meaning of the original text to protect against possible misinformation and bias.

It is also necessary to think about the diversity and balance of datasets so that models do not represent a single topic, tone, or dialect preferentially. Providing transparency on how summaries are created and the opportunity for human oversight or corrections when necessary can also help to sustain user trust while enabling responsible AI use. Ethical use also involves clear communication concerning the limitations of the model and appropriate contexts of use.

5.4 Sustainability Plan

A long-term strategy for sustainability towards Bangla text summarization using deep learning involves continual improvement with regard to performance, efficiency, and the ability to adapt to both changing language patterns and content sources. The model needs to be updated, refined and tuned a number of times to maintain its accuracy and applicability across various dialects, writing styles, and subject domains. As well as these updates, it is also important to provide ethical AI literacy training to developers and users, especially academics and media users to foster responsible accountability in the way machine summaries are written and consumed.

In terms of sustainability, environmentally conscious models and architectural designs and a conscious effort to work with a cloud-based platform that is powered by renewable energy sourced will also help reduce the carbon footprint related to training and inference in this project. Collaborating with educational institutions, language communities and technology providers will support a more inclusive ecosystem that can achieve the objective of language sustainability, information access and ethically sound artificial intelligence development. Collaborating in these manners helps avoid potential pitfalls in constantly improving the society created by Bangla text summarization technology.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Summary of the Study

The core emphasis of this study was the construction of a Bengali-to-Bengali abstractive text summarization model based on a sequence-to-sequence architecture using recurrent neural networks (RNNs). This process began with the collecting and preprocessing of a Bengali dataset, then findings towards designing and implementing an encoder-decoder based model with attention mechanisms. The approach was trained and assessed qualitatively using sample predictions, and the process was both coherent and contextually relevant. Overall, this study may form a minor response to the summarization needs of the Bengali language as well as serve as an initial way forward into this largely underexplored area of linguistics.

6.2 Conclusions

The creation of a Bengali-to-Bengali abstractive text summarization model based on a sequence-to-sequence RNN method is an exciting step towards developing natural language processing resources in the Bengali language. While we had limited access to structured and annotated datasets, our model was able to generate meaningful summaries, creating contextual summaries that indicated the success of an attention mechanism. The contribution this study provides has demonstrated the ability of deep learning architectures to make advancements in low-resource languages and has shown that language-specific characteristics could be tackled through local preprocessing and training procedures. While the results are promising, improvements are needed to promote fluency, factual correctness, and generalization to a larger set of domains.

6.3 Implications for Further Study

This research has established an associated foundation for further work in Bengali abstractive summarization. One major avenue to take is to extend and diversify the training dataset by using multi-domain and user-generated data to further improve generalization of the model. Future work would be benefitted by the use of transformer-based architectures such as BERT or mBART, which have already demonstrated better performance than previous architectures on a number of NLP tasks. Additionally, including evaluation metrics like ROUGE, BLEU, or METEOR would provide quantitative metrics to help assess and compare different models. There also exists the possibility to create a multilingual summarization framework where cross-lingual models can be trained to summarize across multiple languages to not just allow users from different language backgrounds to use the abstract summaries but also to provide multilingual outputs for the same document.

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