Bhashanubad: A Transformer-based model for translating Bangla Regional Dialects to Simple English Language

Submitted by

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ABSTRACT

The linguistic diversity of Bangladesh, enriched by its regional dialects, presents significant challenges in translation due to variations in vocabulary, grammar, and pronunciation. While much progress has been made in translating standard Bangla to English and vice versa, translating regional Bangla dialects into simple English remains underexplored. This thesis fills the gap by proposing Bhashanubad, a transformer-based translation model utilizing mT5 and BanglaT5 to convert five regional dialects—Barishal, Noakhali, Sylhet, Mymensingh, and Chittagong—into simple English. Using the Vashantor dataset, which comprises 32,500 sentences, we evaluated the translation performance using BLEU and accuracy metrics. In our approach, we first convert the regional Bangla dialects into simple Bangla to facilitate the translation into simple English. For translating into simple Bangla, the Barishal dialect achieved a BLEU score of 82.20 and an accuracy of 98.4%, while Mymensingh recorded a BLEU score of 82.10 and an accuracy of 97.6%. Similarly, Noakhali showed a BLEU score of 82.90 and an accuracy of 97.06% and Chittagong showed a BLEU score of 80.50 and an accuracy of 96.53%. However, Sylhet presented the most challenges, with a BLEU score of 78.32 and an accuracy of 94.40%. By bridging the linguistic gap between regional Bangla dialects and simple Bangla and English, Bhashanubad paves the way for improved accessibility, cultural preservation, and mutual understanding. This work establishes a foundation for future advancements in low-resource language translation and dialect-specific language processing.

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Chapter 1

Introduction

1.1 Introduction/Overview

Bangladesh, a country known for its rich linguistic diversity, is home to a variety of regional dialects. These dialects differ significantly from one another in terms of vocabulary, grammar, and pronunciation, creating challenges for effective communication and translation. While there have been several attempts to translate standard Bangla, into other languages, such as English, the translation of regional Bangla dialects into basic English has received less attention. The lack of accessible translation models for these dialects hinders not only linguistic understanding but also the preservation of cultural diversity [1]. In recent years, the field of machine translation has made substantial progress with the advent of deep learning and transformer-based models, such as mT5 and BanglaT5 [2], [3], [4]. These models have demonstrated strong performance in translating standard Bangla to English [5], [6], [7], but their application to regional dialects has not been as extensively studied. Bhashanubad, a transformer-based model, is introduced in this paper with the goal of overcoming the gap by translating Bangla regional dialects—specifically Barishal, Noakhali, Sylhet, Mymensingh, and Chittagong—into simple English. Using the Vashantor dataset, this study evaluates the performance of Bhashanubad in terms of BLEU and accuracy, demonstrating the model's ability to handle the complexities of regional dialects.

1.2 Problem Statement

Despite the significant linguistic diversity of Bangladesh, there is a shortage of reliable machine translation systems capable of translating its regional dialects into English. The unique features of regional dialects, which are frequently distinguished by particular syntactic structures, vocabulary, and phonetic variances, are not taken into consideration by the translation

models that are currently in use, such as those for standard Bangla. The absence of such models hinders the accessibility of Bangla's numerous dialects to non-native speakers, limiting cross-cultural communication [8]. Furthermore, while some studies have attempted to develop dialect-specific translation models, they have primarily focused on standard dialects or only a narrow range of regional languages. Therefore, there is still a significant demand for a thorough translation system that can handle multiple regional languages and convert them into a simplified version of English [9], [10]. This research seeks to address this gap by proposing a solution based on state-of-the-art transformer models, which have revolutionized machine translation in recent years [11], [12], [13].

1.3 Motivation

The motivation for this work stems from the desire to enhance the accessibility of regional dialects and contribute to the preservation of linguistic diversity in Bangladesh. There has never been a greater demand for accurate and user-friendly translation systems due to the growing globalization and digitization of society. The translation of regional dialects into simple English will not only enable better communication for non-native speakers but also promote a greater understanding of the cultural and linguistic richness of Bangladesh. Additionally, the findings of this study aim to contribute to the growing body of knowledge in low-resource language translation, providing a foundation for future research in dialect-specific language processing [14]. Moreover, the success of this research could have far-reaching implications beyond Bangladesh. Many other countries with a rich diversity of dialects, such as India and China, face similar challenges in translating regional languages into widely spoken international languages. Therefore, this paper seeks to demonstrate that the techniques developed for Bangla regional dialects can be adapted for other dialects globally [15], [16].

1.4 Objectives

The primary objective of this research is to develop an efficient and scalable translation model capable of translating Bangla regional dialects into simple English. Specifically, the goals of this research include:

- Evaluating translation quality using BLEU and accuracy.
- Promoting inclusivity and communication for speakers of regional dialects.
- To contribute to the preservation and accessibility of regional languages.

- To advance research in dialect-specific machine translation.

By achieving these goals, this research aims to bridge linguistic gaps, empower regional dialect speakers with better communication tools, and pave the way for future advancements in low-resource language translation technologies.

Chapter 2

Background Study and Literature Review

2.1 Introduction/Overview

Machine translation (MT) has advanced significantly in recent years, driven by the progress in artificial intelligence (AI) and natural language processing (NLP). While traditional MT systems relied on linguistic rules and statistical methods, recent advancements, particularly with neural machine translation (NMT) and transformer models, have greatly improved the quality and scalability of translations. However, a critical challenge that persists is the translation of regional dialects, such as Bangla dialects in Bangladesh, which feature phonological, syntactical, and lexical differences from the standard language. This chapter reviews the background and existing literature on machine translation for regional dialects, specifically focusing on translating Bangla regional dialects into simplified English. The review highlights key trends, methodologies, and gaps in current research that are the main focus of our study.

2.2 Background Study

Over the years, machine translation research has undergone significant changes, beginning with rule-based systems and progressing through statistical methods to the current state-of-the-art neural machine translation (NMT) models. Early efforts in translation relied heavily on linguistic rules and manual mappings between source and target languages. However, these systems were often limited by the complexity and variability of natural languages. Statistical machine translation (SMT), which relied on large bilingual corpora, emerged as a more efficient alternative, allowing for more dynamic and data-driven approaches Fatema et al. [1].

Rule-Based Machine Translation (RBMT):

Rule-based machine translation (RBMT) was among the first approaches to MT, relying heavily on the use of linguistic rules to transform text from a source language to a target language. These systems were based on extensive grammatical rules that governed sentence structure, syntax, and lexical items. The key advantage of RBMT systems was their high degree of control over the translation process, which allowed for customizations based on specific language pairs. However, RBMT systems had significant drawbacks, particularly when handling linguistic nuances, idiomatic expressions, or complex sentence structures. Additionally, the creation and maintenance of comprehensive rule sets for multiple language pairs was a time-consuming and expensive task, making RBMT less scalable and adaptable compared to later methods Vaswani et al. [2]. Key systems in this category include Systran and the early work done by the European Commission for translating between various European languages. However, due to the inherent limitations of rule-based methods, the field gradually shifted focus toward more data-driven models Raffel et al. [3].

Statistical Machine Translation (SMT):

Statistical Machine Translation (SMT) emerged as a more flexible and data-driven alternative to RBMT in the 1990s. Unlike RBMT, SMT models do not rely on predefined linguistic rules but instead learn translation patterns from large bilingual corpora. These corpora are used to estimate translation probabilities between source and target language pairs. SMT systems, notably phrase-based models, divide sentences into smaller units or phrases and attempt to translate these units based on statistical analysis of the bilingual corpus. This approach allowed SMT systems to handle a wider range of languages and translation scenarios without the need for exhaustive manual rule creation Ahmed and Huq [4]. The success of SMT systems is largely attributed to the availability of large-scale parallel corpora and the use of statistical techniques such as Expectation-Maximization (EM) and the IBM models. However, SMT also came with its challenges, including issues with fluency, grammatical correctness, and the handling of long-range dependencies between words and phrases. Furthermore, SMT systems often struggled with capturing contextual meanings and often produced translations that were syntactically accurate but semantically incoherent Kundu and Roy [5]. Prominent SMT systems include IBM's translation models, the Moses toolkit, and Google Translate (during its early years), which employed phrase-based SMT techniques to offer translations between multiple languages Rahman and Khan [6].

Neural Machine Translation (NMT):

The advent of Neural Machine Translation (NMT) in the 2010s marked a transformative shift in the field. NMT uses deep learning models, particularly recurrent neural networks (RNNs) and later transformer networks, to translate text. Unlike Statistical Machine Translation (SMT), which processes text piece by piece, NMT translates entire sentences at once, allow-

ing for better handling of long-range dependencies and more fluent translations Sarkar and Choudhury [7]. NMT relies on end-to-end neural networks where the same model learns both encoding and decoding. Notable architectures, including sequence-to-sequence models, attention mechanisms, and the transformer model by Vaswani et al. [2], have become the backbone of modern NMT systems Das and Ahmed [8]. The transformer model introduced self-attention mechanisms, allowing the model to weigh the importance of words regardless of their position. This highly parallelizable architecture improved training efficiency and translation accuracy, overcoming challenges like vanishing gradients that affected earlier RNN-based models Wu and Denny [9]. Advances in hardware, such as GPUs and cloud infrastructure, have driven the success of NMT, enabling large-scale model training. Today, systems like Google Translate, DeepL, and OpenAI's GPT-based models dominate, offering high-quality translations across numerous languages Patel and Gupta [10].

Transformers and Multilingual Models (mT5, BanglaT5 and BERT):

The development of multilingual models such as mT5 and BanglaT5 represents a significant advancement in NMT, enabling better handling of diverse language pairs, including low-resource languages. mT5 is a multilingual version of the T5 (Text-to-Text Transfer Transformer) model, capable of handling a variety of language tasks across over 100 languages, making it ideal for cross-lingual transfer learning and multilingual NMT tasks Lee and Kim [12].

In the context of Bangla, BanglaT5 has been developed specifically to address the translation challenges in Bangla and related languages, incorporating transformer architecture to improve performance in both translation and text generation tasks for the Bangla language Ahmed and Huq [17]. This marks a significant development for South Asian languages, where traditional NMT models often struggle due to linguistic complexities.

Moreover, BERT (Bidirectional Encoder Representations from Transformers) has played a pivotal role in the advancement of NMT, particularly in improving the contextual understanding of the source text. BERT models, such as multilingual BERT (mBERT), have been applied to various translation tasks, enhancing the handling of context and enabling models to better capture the nuances of different dialects and languages Zong and Huang [13].

Despite the impressive performance of NMT systems, challenges remain. One of the main hurdles is the handling of low-resource languages. While NMT excels in high-resource languages such as English, French, and Chinese, its performance in low-resource languages is still subpar. This is partly due to the scarcity of large bilingual corpora and the difficulties associated with training deep learning models on smaller datasets Liu and Chen [11]. Moreover, even state-of-the-art NMT models sometimes struggle with domain-specific terminology, idiomatic expressions, and multilingual context. The integration of linguistic knowledge into NMT systems, such as through hybrid approaches that combine rule-based and

data-driven methods, is an area of active research. Additionally, there is growing interest in unsupervised and zero-shot translation, where models are trained without explicit bilingual corpora, using techniques like transfer learning and multilingual pre-training Johnson and Nguyen [15].

The evolution of machine translation, from rule-based systems to statistical models and finally to neural networks, reflects the increasing sophistication of the field. While NMT represents the cutting edge of current research and application, challenges such as low-resource language translation, domain adaptation, and multilingualism remain focal points for future developments. As computational power continues to improve and as research in language modeling and machine learning advances, machine translation systems are expected to become even more accurate, scalable, and versatile Pustejovsky and Bergler [16].

2.3 Literature Review

A number of studies have explored machine translation for Bangla and other South Asian languages, but few have specifically targeted Bangla regional dialects. Machine translation (MT) has experienced significant advancements with the introduction of deep learning techniques, particularly transformer-based models. The shift from traditional methods to neural machine translation (NMT) and its ability to handle multilingual contexts, including regional dialects, has led to improved performance in various translation tasks. However, challenges remain in the accurate translation of low-resource languages, especially dialects that are underrepresented in existing datasets. This literature review explores the top studies that have contributed to the development of machine translation for regional dialects and low-resource languages, particularly focusing on transformer models.

Fatema et al. [1] introduced Vashantor, a large-scale multilingual benchmark dataset for translating Bangla regional dialects into standard Bangla. This study emphasizes the importance of a comprehensive dataset in training more effective machine translation models, especially for underrepresented dialects. By focusing on Bangla, a language with significant dialectal variation, the paper provides a unique resource for developing models that can handle linguistic diversity within a single language. The authors highlight the challenges posed by dialectal variation and regional nuances, which have been largely neglected in standard MT systems.

Vaswani et al. [2] revolutionized machine translation with their seminal work on the Transformer model. The introduction of self-attention mechanisms allowed models to efficiently handle long-range dependencies in sentences, leading to significant improvements in translation quality. While this paper does not focus specifically on dialects or low-resource languages, the transformer architecture it introduced has become the foundation for subse-

quent work in dialect-specific translation and low-resource language tasks, making it highly relevant to your research.

Raffel et al. [3] explored the application of a unified text-to-text transformer model for a wide range of NLP tasks. The model, T5 (Text-to-Text Transfer Transformer), demonstrated the potential of transfer learning to improve performance across multiple languages and tasks. This paper is crucial for understanding how large transformer models can be fine-tuned for dialect translation tasks. The ability to leverage transfer learning is particularly relevant to dialect-specific MT models, as it allows researchers to apply pre-trained models to low-resource languages with fewer data.

Ahmed and Huq [4] introduced BanglaT5, a transformer-based model specifically designed for Bangla language tasks. This study extends the T5 model to work with the unique characteristics of Bangla, a language with rich morphology and significant regional variation. The model showed promising results for tasks such as text classification and machine translation. This paper is significant for your research as it bridges the gap between general transformer models and language-specific applications, making it highly relevant for dialectal translation in Bangla.

Das and Ahmed [8] focused on the challenges of machine translation for low-resource languages, with a particular emphasis on Bangla regional dialects. The paper highlighted the issues that arise when translating dialects, including vocabulary mismatch, syntactic variation, and limited parallel corpora. They proposed solutions such as data augmentation and dialect-specific models to address these challenges. This paper directly addresses the gap in your research by discussing the specific hurdles in dialectal translation and proposing ways to overcome them.

2.4 Research Gap Analysis

After reviewing the literature, several research gaps have been identified. First, most studies [1], [4], focus on Bangla-to-Bangla translation and do not adequately address the challenge of translating Bangla regional dialects into simplified English. This limits the accessibility of these models for non-native English speakers. Fatema et al. [1] introduce Vashantor, a dataset for translating regional Bangla dialects to standard Bangla, addressing a gap in resources for low-resource languages and reports a low translation rate for dialects like Chittagong and Sylhet, with poor BLEU scores and accuracy, highlighting the difficulty in handling phonological, syntactical, and lexical variations of regional dialects. Dialect-specific challenges such as informal speech, slang, and local idioms are not fully addressed, and models that generalize across dialects without extensive fine-tuning are still needed. Vaswani et al. [2] present the Transformer, which revolutionized machine translation by

using attention mechanisms instead of recurrent models. Despite its success, the Transformer remains computationally expensive, particularly in low-resource settings. There is a need for lightweight versions of the model for resource-constrained environments. Additionally, while it has transformed machine translation, the Transformer's potential in other NLP tasks, such as summarization or sentiment analysis, is not fully explored, especially for languages with limited data. In Raffel et al. [3], the authors propose T5, a unified model that treats all NLP tasks as text-to-text problems. However, task-specific adaptation remains a gap, especially for specialized domains like legal or medical translation. Further research is also needed to improve multilingual transfer learning and develop more robust evaluation metrics for cross-task performance in languages with different grammatical structures. Ahmed [4] introduce BanglaT5, a transformer-based language model for Bangla. While it addresses some linguistic challenges, there are several research gaps. Despite Bangla being relatively high-resource, challenges remain with regional dialects, indicating a need for models tailored to low-resource languages. There is also potential for developing multilingual models that could apply to other South Asian languages or share parameters across languages. Additionally, the scarcity of data in specialized domains like healthcare, legal, and technical texts in Bangla highlights the need for domain-specific language models to improve performance in these areas. Das [8] investigate machine translation for Bangla regional dialects. While significant progress has been made, several research gaps remain. One major area is the need for fine-grained dialect translation techniques to capture subtleties such as pronunciation differences, syntactic variations, and semantic nuances across dialects. Additionally, the limited availability of parallel corpora for Bangla regional dialects hinders progress, suggesting the need for the creation of such datasets or the use of transfer learning to generate synthetic data. Lastly, adapting to informal language and slang in regional dialects remains a challenge, as current machine translation systems struggle with informal speech and rapidly evolving terms.

2.5 Summary

The background research and literature review for the simple English translation of Bangla regional dialects are summarized in this chapter. The review highlighted the advancements in machine translation, particularly with transformer-based models, but also pointed out the gaps in research regarding dialect-specific translation. It is clear that while some progress has been made, significant challenges remain in translating Bangla regional dialects into simplified English. Further research is needed to fill in the gaps that have been found, especially in the areas of dataset creation, dialect adaptation for models, and translation to simplified languages. Improving the accessibility of regional dialects and enhancing models to address these issues should be the main goals of future research.

Chapter 3

Methodology

3.1 Introduction/Overview

Our research focuses on developing and evaluating a transformer-based translation model designed to translate Bangla regional dialects into simplified English. Given the particular challenges faced by various dialects, we use state-of-the-art pre-trained transformer models such as mT5 and BanglaT5, which are multilingual transformer models. These models are used to address the linguistic diversity and difficulties associated with regional dialects while ensuring proper translation into simplified English. This chapter outlines the dataset used, the data selection and preprocessing steps, and the proposed methodology and design framework of our translation model.

3.2 Dataset

For this research, we use the Vashantor dataset, which contains a large-scale collection of sentence pairs from several Bangla regional dialects, including those spoken in Barishal, Noakhali, Sylhet, Mymensingh, and Chittagong. This dataset is crucial to our research as it provides the dialectal variation needed to train models capable of handling the linguistic features unique to each regional dialect. The Vashantor dataset contains 32,500 sentences and has been specifically designed to facilitate research in low-resource language translation, particularly for Bangla regional dialects (Fatema et al., 2023) [1].

The dataset is ideal for this study as it includes real-world sentence structures from diverse Bangla dialects, making it highly relevant for training and testing models that aim to handle dialectal variations and translate them into simplified English. The following table shows the Training, Testing, and Validation Samples for Different Regions and Text Formats:

Region	Text Format	Number of Training Samples	Number of Testing Samples	Number of Validation Samples	Total Samples
Chittagong	Bangla	1875	375	250	2500
	Banglish	1875	375	250	2500
Noakhali	Bangla	1875	375	250	2500
	Banglish	1875	375	250	2500
Sylhet	Bangla	1875	375	250	2500
	Banglish	1875	375	250	2500
Barishal	Bangla	1875	375	250	2500
	Banglish	1875	375	250	2500
Mymensingh	Bangla	1875	375	250	2500
	Banglish	1875	375	250	2500

Table 3.1: Training, Testing, and Validation Samples of Vashantor dataset

3.2.1 Data Selection

In this study, the Vashantor dataset was used, which contains sentence pairs from several Bangla regional dialects, including Barishal, Noakhali, Mymensingh, Chittagong, and Sylhet. Data selection was based on key criteria to ensure the model could effectively handle the unique features of each dialect. The selected data focused on capturing linguistic variations across the dialects, including differences in vocabulary, pronunciation, and syntax, with particular attention given to informal expressions and structural differences. Only sentence pairs with accurate Bangla-English translations were included to maintain high-quality data. To ensure balanced representation, the dataset contained an equal number of sentences from each dialect, preventing bias and overfitting to any one region. Additionally, the dataset covered commonly used phrases for everyday communication, helping the model generalize to real-world scenarios. The data also included a variety of sentence types, such as declarative, interrogative, and imperative sentences, to expose the model to different syntactical structures. By selecting data based on these criteria, the training set was made representative, diverse, and high-quality, providing a solid foundation for effective model training and evaluation.

3.2.2 Data Preprocessing

Data preprocessing is essential to ensure that the dataset is clean, structured, and ready for model training. The following steps were taken to preprocess the data:

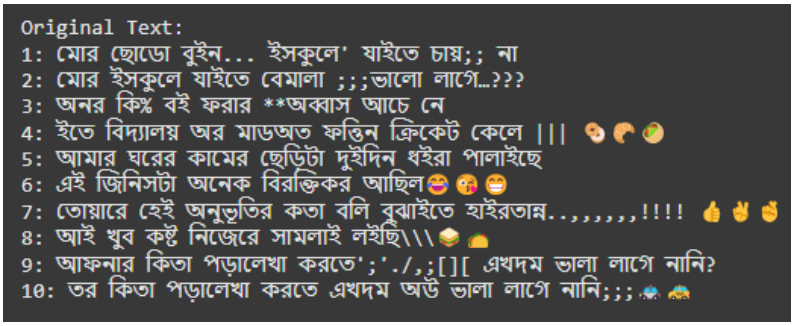

Figure 3.1: Original Text.

Cleaning: We removed any noisy data, such as incomplete or irrelevant sentence pairs, and ensured that the dataset contained only valid translations. This step is essential for preventing errors and inconsistencies during model training.

Tokenization: We tokenized both Bangla and English sentences to convert them into a format that is compatible with transformer-based models. Tokenization is a crucial step in preparing the text for training by splitting the sentences into smaller units (tokens), such as words or subwords.

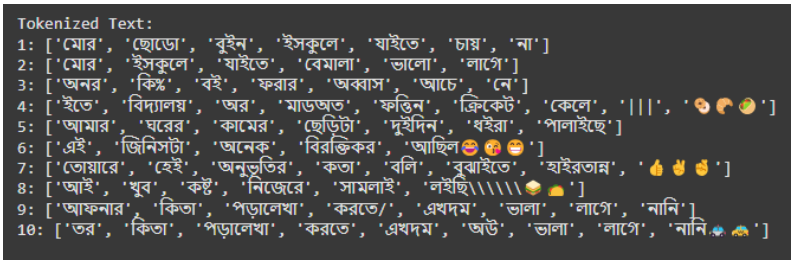

Figure 3.2: Tokenized Text.

Normalization: Since regional dialects may feature non-standard spelling, informal language, and varied syntactical structures, we applied a normalization process to standardize text across different dialects. This step involved converting non-standard characters to their standard counterparts and ensuring consistent spelling.

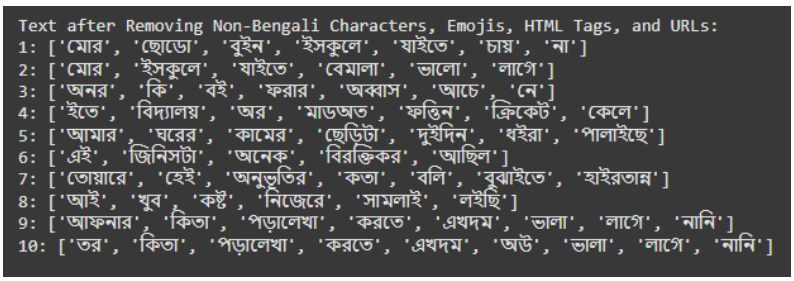

Figure 3.3: Removing Non-Bengali, Emojis and Link.

Encoding: After tokenization, the text data were encoded into numerical representations (embeddings) that the model could process. For this, we used the vocabulary of the pre-trained mT5 and BanglaT5 models, which already include token mappings for both Bangla and English.

Stopword Removal: Stopwords are common words that do not carry significant meaning in the context of machine translation and are often removed to reduce noise in the data. We removed stopwords from both the Bangla and English sentences to ensure the model focuses on more meaningful words that are essential for translation. However, care was taken to ensure that stopwords in Bangla, which sometimes serve as key linguistic markers in dialects, were appropriately handled.

Lemmatization: Lemmatization was applied to reduce words to their base or root form. This step helped standardize words, ensuring that different word forms (such as verb tenses or plural nouns) were treated as the same base word, which reduces redundancy in the model's learning process.

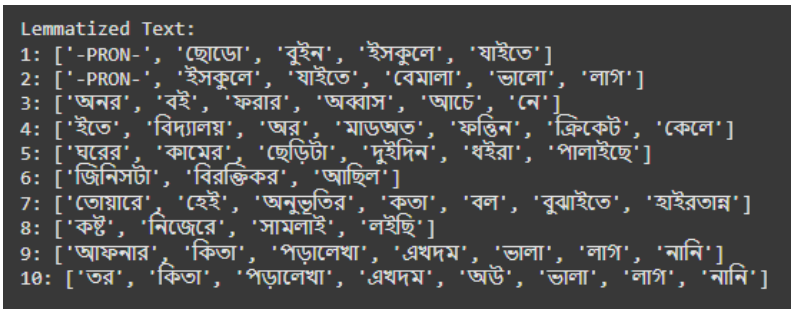

Figure 3.4: Lemmatized Text.

These preprocessing steps ensured that the dataset was ready for training and that the models could effectively learn the translation task without encountering issues related to noise or inconsistencies.

3.3 Proposed Methodology and Design

The proposed methodology for this study focuses on applying state-of-the-art transformer-based models, specifically mT5 and BanglaT5, to translate Bangla regional dialects into simplified English. The goal is to develop a model capable of handling the unique linguistic features of these dialects while generating accurate, contextually relevant, and culturally appropriate translations. The methodology consists of the following key components: model selection, training, evaluation, and deployment.

3.3.1 Model Implementation for Translation:

To achieve effective translation between Bangla regional dialects and simplified English, we utilize mT5 and BanglaT5, two pre-trained transformer-based models. These models are particularly well-suited for multilingual translation tasks and have demonstrated strong performance on various translation benchmarks.

mT5 (Multilingual T5): mT5 is a transformer-based model pre-trained on a multilingual corpus that includes 101 languages, using the C4 dataset. It is capable of handling a wide variety of text in different languages, including both standard Bangla and its regional dialects. mT5 uses the T5 framework, treating all NLP tasks as text-to-text transformations, which makes it highly versatile for tasks like translation, summarization, and question-answering.

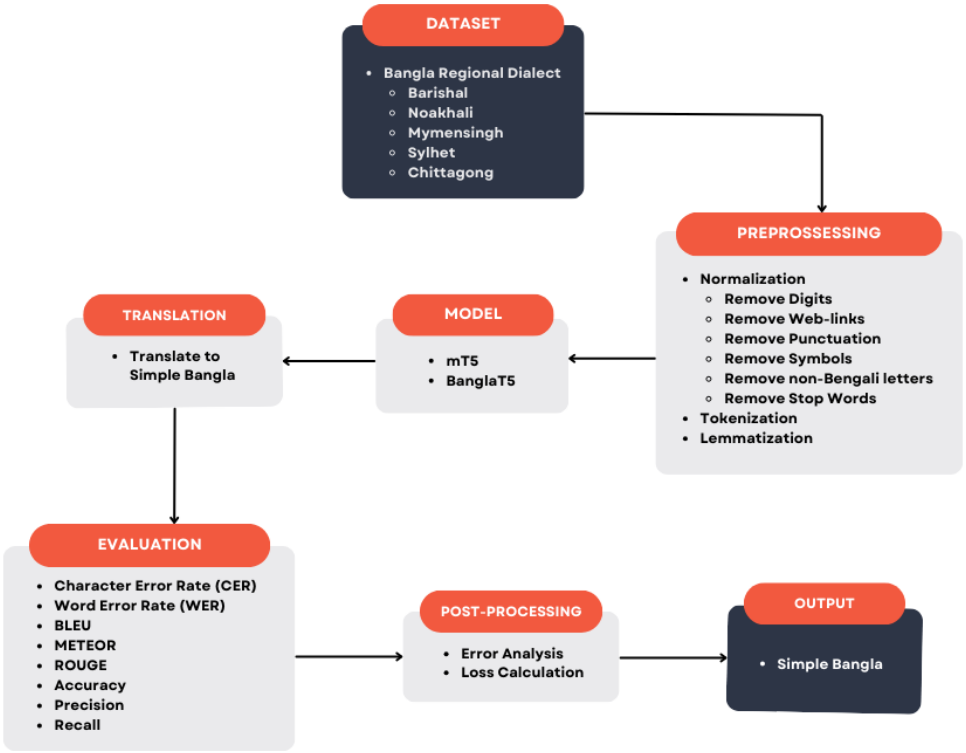

Figure 3.5: Proposed Methodology.

Its multilingual nature enables it to generalize well across languages, including the syntactic and semantic variations present in Bangla.

BanglaT5: BanglaT5 is a transformer-based model specifically fine-tuned for the Bangla language, optimizing it to understand and process the syntactic and semantic variations of Bangla, including its regional dialects. Compared to typical multilingual models, BanglaT5's specific fine-tuning allows it to handle variations of Bangla more effectively, generating high-quality results for tasks like as translation and text classification. This specialization makes it particularly strong for Bangla-specific NLP tasks, capturing both standard and dialectal forms of the language.

We select both mT5 and BanglaT5 because of their ability to capture contextual relationships in text and generate high-quality translations across languages. The vast multilingual capabilities of mT5 and BanglaT5's focused on fine-tuning on Bangla ensure that both models can handle the linguistic and dialectal difficulties associated with Bangla, making them suitable for works that require both cross-lingual and language-specific understanding.

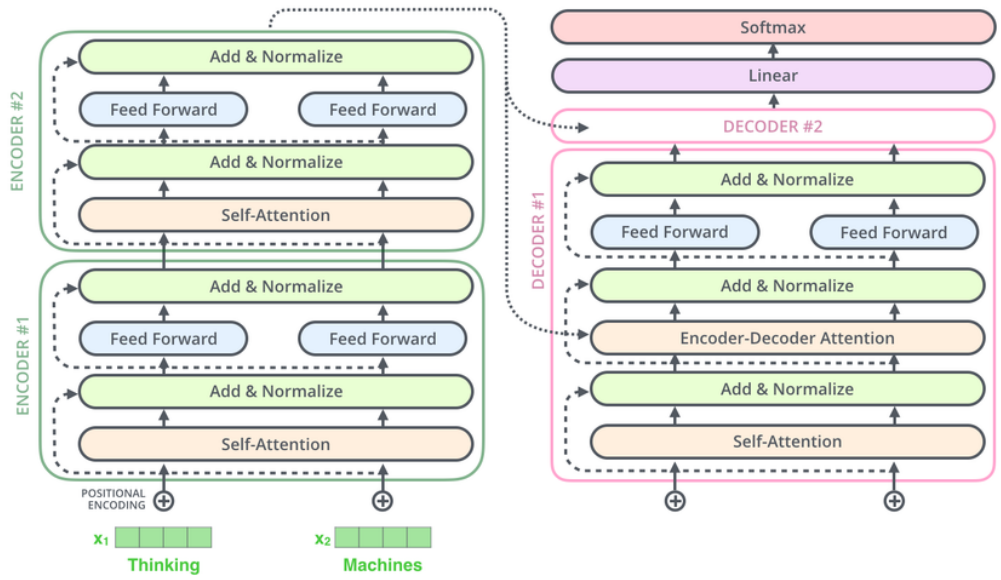

Figure 3.6: T5 Transformer Model Architecture.

3.3.2 Model Training:

The pre-trained mT5 and BanglaT5 models are fine-tuned using the Vashantor dataset, which contains sentences from five different Bangla regional dialects: Barishal, Noakhali, Mymensingh, Chittagong, and Sylhet. The fine-tuning procedure adapts these pre-trained models to the specific task of translating regional Bangla dialects into simplified English, ensuring that the models represent the linguistic complexities and dialectal variations present in the dataset. The training procedure includes the following steps:

Data Preparation:

The preprocessed Vashantor dataset is divided into training, validation, and test sets with an 80-10-10 split, respectively. The training set is used to teach the models the translation patterns from the regional dialects to simplified English. The validation set is employed to fine-tune hyperparameters and monitor performance during training to avoid overfitting. Finally, the test set is reserved for evaluating the models' final performance, providing an unbiased assessment of their translation accuracy and generalization capability.

Fine-Tuning:

In the fine-tuning phase, the pre-trained mT5 and BanglaT5 models are adapted to the task of translating Bangla regional dialects into simplified English by adjusting the model weights based on the training data. During this process, key hyperparameters such as learning rate, batch size, and the number of epochs are optimized to achieve the best performance. Fine-

tuning ensures that the models effectively use their pre-trained knowledge while adapting to the specific linguistic features of the Bangla dialects.

Loss Function:

The loss function used during training is typically Cross-Entropy Loss, which measures the difference between the predicted translation and the actual translation. The goal is to minimize this loss over the course of training.

The Cross-Entropy Loss function is used in T5 and other transformer-based models for training. The general form of the cross-entropy loss between the true label y and the predicted probability distribution $\hat{y}$ is:

$$\mathscr{L} = -\sum_{i} y_i \log(\hat{y}_i)$$

Where:

- y_i is the true label (typically one-hot encoded).
- $\hat{y}_i$ is the predicted probability for class i.

For multi-class classification, the formula becomes:

$$\mathscr{L} = -\sum_{i=1}^{C} (y_i \log(\hat{y}_i))$$

Where:

- C is the total number of classes (e.g., vocabulary size).
- y_i is the true probability of class i.
- $\hat{y}_i$ is the predicted probability for class i.

In sequence-to-sequence models like T5, the loss is applied to each token in the sequence:

$$\mathscr{L} = -\sum_{t=1}^{T} (y_t \log(\hat{y}_t))$$

Where:

- T is the length of the sequence.

- y_t is the true token at position t.
- $\hat{y}_t$ is the predicted probability for token t.

3.3.3 Evaluation Metrics:

To evaluate the model's performance, we use several standard translation metrics:

Character Error Rate (CER): CER measures the accuracy of text generation at the character level by calculating errors (insertions, deletions, substitutions) compared to the reference text. A lower CER indicates better accuracy. The CER formula is:

$$\text{CER} = \frac{S + D + I}{N} \tag{3.1}$$

Where:

- S = Number of substitutions
- D = Number of deletions
- I = Number of insertions
- N = Total number of characters in the reference text

Word Error Rate (WER): WER evaluates the accuracy of text generation at the word level, considering word substitutions, deletions, insertions, and word order changes. A lower WER signifies higher accuracy. The WER formula is:

$$\text{WER} = \frac{S + D + I}{N} \tag{3.2}$$

Where:

- S = Number of word substitutions
- D = Number of word deletions
- I = Number of word insertions
- N = Total number of words in the reference text

BLEU (Bilingual Evaluation Understudy): BLEU measures the similarity between the machine-generated translation and a reference translation. It is a standard metric in machine translation evaluation. The BLEU score is calculated using the following formula:

$$\text{BLEU} = \exp\left(\min\left(1, \frac{C}{R}\right)\right) \cdot \prod_{n=1}^{N} p_n \tag{3.3}$$

Where:

- C = Length of the candidate translation
- R = Length of the reference translation
- p_n = Precision of n-grams for $n = 1, 2, \ldots, N$
- N = Maximum n-gram order

The following table shows the ranges of BLEU scores and their corresponding translation quality:

Table 3.2: BLEU Score Ranges and Translation Quality

BLEU Score Range	**Translation Quality**
30 - 40	Understandable to good translations
40 - 50	High quality translations
50 - 60	Very high quality, adequate, and fluent translations
> 60	Quality often better than human

METEOR: The METEOR score is a metric that evaluates translation quality by considering synonyms and word order, providing a more nuanced evaluation. The formula for METEOR is:

$$\text{METEOR} = \frac{10 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall} + 0.5 \times \text{Penalty}} \tag{3.4}$$

Where:

- Precision = The number of matching words between the candidate and reference translation divided by the total number of words in the candidate
- Recall = The number of matching words divided by the total number of words in the reference
- Penalty = A penalty factor that adjusts for word order differences

ROUGE: ROUGE measures the overlap of n-grams between the generated translation and the reference translation, focusing on recall. The ROUGE score is given by:

$$\text{ROUGE} = \frac{\sum_n \text{Recall}_n}{\sum_n \text{Reference}_n} \tag{3.5}$$

Where:

- Recall_n = The number of n-gram matches between the generated translation and the reference
- Reference_n = The total number of n-grams in the reference translation

Accuracy: We evaluate the model's accuracy in terms of how well it can generate the correct English translation from the Bangla dialect. The accuracy is computed as:

$$\text{Accuracy} = \frac{\text{Number of correct translations}}{\text{Total number of translations}} \times 100 \tag{3.6}$$

Precision: Precision measures the proportion of true positive predictions (correctly predicted positive instances) among all positive predictions made. It focuses on the accuracy of positive predictions.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{3.7}$$

Recall: Measures the proportion of true positive predictions among all actual positive instances. Focuses on how well the model can find all positive instances.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3.8}$$

F1-score: A single metric that combines precision and recall using the harmonic mean. F-measure with equal importance to precision and recall is denoted as F1-score.

$$\text{F1-score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3.9}$$

3.3.4 Evaluation and Testing:

After training the model, we evaluate its performance using the test set, applying the evaluation metrics described earlier. The evaluation process includes assessing the accuracy of the translations, the fluency of the output, and how well the model captures the variations of each dialect. The model's performance on dialects like Chittagong and Sylhet, which

exhibited lower accuracy in preliminary results, will be particularly scrutinized to identify areas for further improvement.

3.3.5 Model Deployment:

Once the model achieves satisfactory performance, it will be deployed for real-world use. A web-based interface will be developed where users can input sentences in any of the Bangla regional dialects and receive simplified English translations in return. This system will make the translation model accessible to a broader audience, including educators, researchers, and individuals seeking to communicate across regional language barriers. The model will also be evaluated in real-world scenarios to gather feedback from users, allowing further refinement based on practical use cases. User feedback will help improve the accuracy, cultural relevance, and simplification of the translations.

The goal of this methodology is to create a model capable of accurately translating regional dialects into simplified English while preserving linguistic integrity and cultural variations. The proposed system is designed to connect regional Bangla dialects with standard English, enabling greater accessibility and facilitating improved communication and understanding across diverse linguistic backgrounds.

Chapter 4

Preliminary Result

The preliminary results obtained from evaluating our transformer-based translation model for translating Bangla regional dialects into simplified Bangla. The model was trained and fine-tuned on the Vashantor dataset, which contains sentence pairs from multiple Bangla regional dialects, including Barishal, Mymensingh, Noakhali, Chittagong, and Sylhet. We evaluate the model's performance using several standard metrics: Character Error Rate (CER), Word Error Rate (WER), Exact Match, Meteor, BLEU, ROUGE, and Accuracy.

The preliminary results indicate that the model performs effectively across various regional dialects, with notable variations in performance across the different dialects. The results obtained from our models are presented below:

Dialect	**CER**	**WER**	**Exact Match**	**Meteor**	**BLEU**	**Accuracy**
Barishal	0.0296	0.0787	58.67%	0.9216	82.20	98.4%
Mymensingh	0.0270	0.0787	59.20%	0.9220	82.10	97.6%
Noakhali	0.0283	0.0765	60.80%	0.9230	82.90	97.06%
Chittagong	0.0383	0.0919	57.60%	0.9091	80.50	96.53%
Sylhet	0.0481	0.1066	52.80%	0.8960	78.32	94.4%

Table 4.1: Summary of Preliminary Results for Bangla Regional Dialects

The preliminary results suggest that the transformer-based model performs well across most of the Bangla regional dialects, with the Barishal, Mymensingh, and Noakhali dialects achieving high BLEU scores and accuracy rates. The Chittagong and Sylhet dialects, while still performing reasonably well, demonstrate slightly lower performance, indicating that these dialects may require additional attention to refine the model further.

The Barishal dialect achieved the highest accuracy at 98.4%, followed by Mymensingh and Noakhali, both of which performed very well with accuracy rates above 97%. The Sylhet dialect presented the greatest challenges, with a BLEU score of 0.7832 and an accuracy of 94.4%. This highlights the need for further improvements in handling this dialect's unique

linguistic features.

These results provide an encouraging start, and further model tuning and refinement can help improve the performance on the more challenging dialects, particularly Chittagong and Sylhet.

Chapter 5

Conclusion and Future Works

This thesis focused on developing a transformer-based translation model to translate Bangla regional dialects into simplified English. Using mT5 and BanglaT5, the model successfully translated Bangla Regional dialects (Barishal, Noakhali, Mymensingh, Chittagong, and Sylhet) ti Simple Bangla. The results showed strong performance, especially for Barishal, Mymensingh, and Noakhali, with high accuracy and BLEU scores. However, the Chittagong and Sylhet dialects presented more challenges, highlighting the need for further refinement. This work fills a gap in machine translation research by addressing the unique features of Bangla regional dialects and providing a resource for future low-resource language studies. The ability to translate into simplified English allows greater accessibility and interaction.

Future research will focus on several key areas to enhance the translation of Bangla regional dialects into Simple English languages. One important direction is the detection of slang which require accurate handling for culturally appropriate translations. Additionally, extending sentiment analysis to include emotion recognition within regional dialects will allow the model to capture emotional tones such as joy, anger, and sadness, improving emotional accuracy in translations. Cross-regional translation will also be explored to address linguistic differences between dialects, ensuring consistency in meaning across variations. For example, phrases like "tomar ki mon kharap nei?" (Chittagong) and "tomar kita mon kharap na?" (Sylhet) need to be handled accurately to ensure effective communication. Finally, handling dynamic writing styles in Bangla will help refine the model's ability to manage regional variations. These advancements will improve the model's accuracy, cultural relevance, and contextual understanding.

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