Analysis of Bangla dialect translation to Standard Bangla and English using Natural Language Processing (NLP)

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Supervised by
Professor Bulbul Ahamed

Submitted in partial fulfilment of the requirements for the degree of Bachelor of Science in Computer Science and Engineering



DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
SONARGAON UNIVERSITY (SU)

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APPROVAL

The thesis titled **"Analysis of Bangla dialect translation to Standard Bangla and English using Natural Language Processing (NLP)"** submitted by **Mustafa Mohammad Nashwan Haque** (CSE2102023106), **Salman Johir Tonoy** (CSE21020203012), **Israt Jahan Archi** (CSE2102023064), **Abdullah Al Zobayer** (CSE2102023035) and **Bipasha Iasmin** (CSE2002020067) to the Department of Computer Science and Engineering, Sonargaon University (SU), has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Computer Science and Engineering and approved as to its style and contents.

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DECLARATION

We, hereby, declare that the work presented in this report is the outcome of the investigation performed by us under the supervision of **Professor Bulbul Ahamed,** Head**,** Department of Computer Science and Engineering, Sonargaon University, Dhaka, Bangladesh. We reaffirm that no part of this thesis has been or is being submitted elsewhere for the award of any degree.

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ABSTRACT

In an era of global communication and collaboration, the demand for effective language translation applications has surged. This research paper delves into the realm of machine learning (ML) to enhance the capabilities of language translation applications. The linguistic diversity of the Bangla language, marked by numerous regional dialects, presents significant challenges for automated language processing and translation systems. This study explores the application of Natural Language Processing (NLP) techniques to translate various Bangla dialects into Standard Bangla and subsequently into English. Due to the scarcity of publicly available data on Bangla dialects, the whole dataset was manually collected from different regions of Bangladesh, including Chittagong, Sylhet, Barishal and Khulna. By leveraging corpus-based analysis and dialect normalization frameworks, this research aims to bridge the gap between spoken dialects and their standard written forms. We designed and implemented a custom translation model based on Deep Learning architectures, Machine Learning architectures, incorporating domain-specific pre-training and fine-tuning strategies. Our proposed model achieved an accuracy of 95% in translating regional dialects to both Standard Bangla and English, outperforming several existing benchmarks. The study also discusses the challenges of data annotation, linguistic pre-processing, and transliteration, and assesses the impact of contextual embedding on translation quality. The results highlight the potential of NLP to support language preservation, inclusive digital communication, and the development of regionally-aware AI systems tailored to linguistically diverse communities.

Keywords

Natural Language Processing (NLP), Bengali Dialects, Machine translation, Low-Resource Languages, Regional Language Processing, Machine Learning, Deep Learning, Language Normalization

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
BanglaBERT	Bangla Bidirectional Encoder Representations from Transformers
BiLSTM	Bidirectional Long Short-Term Memory
BoW	Bag of Words
DL	Deep Learning
EDA	Exploratory Data Analysis
GPU	Graphics Processing Unit
LSTM	Long Short-Term Memory
ML	Machine Learning
MT	Machine Translation
NLG	Natural Language Generation
NLP	Natural Language Processing
NLU	Natural Language Understanding
Seq2Seq LSTM	Sequence to Sequence Long Short-Term Memory
SVM	Support Vector Machine
TF-IDF	Term Frequency-Inverse Document Frequency

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Natural Language Processing (NLP) is a technique for processing languages and transforming them into forms that the user can readily process or interpret. NLP is a method of computer programming that is based on pattern learning [1]. It consists of two parts i.e., Natural Language Understanding (NLU) and Natural Language Generation (NLG).

We can use NLU to determine the meaning of a specific word or passage of text, whether it is written or spoken. Using a representation of text or data, NLG creates meaningful sentences. NLP is the foundation of how Language Detection operates. Language is processed and identified using NLP. With the aid of NLP, different word and language types can be detected.

NLP aids in analyzing presented text and identifies language and word meaning. NLP makes it simple to recognize business writings. By identifying the datasets to which each language belongs and evaluating the text to determine its meaning and intent, NLP assists us in implementing numerous languages and detecting them.

The same can be implemented using NLP with the use of numerous datasets and libraries for assistance and a wider scope. The majority of NLP applications require data that is monolingual because they are language specific. It can be essential to perform preprocessing and filter out text that is written in languages other than the target language in order to develop an application in the target language [2]. For instance, we must declare each input's precise language. Lexical (structural) analysis, syntactic analysis, semantic analysis, discourse synthesis, and pragmatic analysis are all included in the processing processes of natural language. Voice detector, Scanner, computational linguistics, and text chats are common applications in linguistic communication. These days, we employ artificial intelligence (AI) techniques to operate tongue words by analyzing enormous samples of human-written words (conversation, keywords, and details) [3]. Training algorithms can comprehend the "context" of writing, human speech, and other forms of human communication by looking at these patterns. Algorithms for deep learning and machine learning are frequently used to build NLP frameworks and efficiently complete typical NLP tasks [1]. The application of language detection and natural language processing is expanding significantly in the current world as it develops.

1.2 Background of the Research

Bangla, the seventh most spoken language in the world, is rich in regional dialects that vary significantly in vocabulary, pronunciation, and grammar. While Standard Bangla is widely used in formal communication, literature, and education, millions of native speakers use dialects in daily life, including those from regions such as Chittagong, Sylhet, and Khulna.

These dialects often differ so much from the standard form that they pose challenges for comprehension, especially in interregional communication and digital applications. Despite the growing importance of Natural Language Processing (NLP) in bridging linguistic gaps, Bangla remains a low-resource language—particularly at the dialectal level—due to the lack of annotated datasets and language tools. This research addresses this gap by developing a custom translation model capable of converting regional Bangla dialects into Standard Bangla and English, aiming to support inclusive AI systems and better linguistic accessibility.

1.3 Objectives of the Research

- Collect and curate a diverse dataset of Bangla dialects from various regions of Bangladesh.
- Develop a parallel corpus aligning regional dialects with their corresponding Standard Bangla and English translations.
- Design and implement a custom NLP model capable of accurately translating Bangla dialects to Standard Bangla and English.
- Evaluate the performance of the proposed model using accuracy metrics and compare it with existing translation models.
- Explore the effectiveness of contextual embeddings and other deep learning techniques in handling dialectal variations.
- Contribute to the development of language resources for low-resource languages like Bangla and its dialects.
- Support language preservation and inclusivity by making dialectal Bangla more accessible in digital and formal communication contexts.

1.4 Rationale of the Research

In Bangladesh, a wide range of regional dialects—such as Sylheti, Chittagonian, Rangpuri, and Noakhali—are spoken alongside Standard Bengali, which is based primarily on the Dhaka dialect. While this diversity showcases the country's rich linguistic and cultural heritage, it also presents certain challenges. One of the main disadvantages is mutual unintelligibility; some dialects differ so greatly in pronunciation, vocabulary, and syntax that communication between speakers from different regions can be difficult without switching to Standard Bengali.

This can lead to social fragmentation and feelings of marginalization among speakers of non-standard dialects. In formal contexts such as education, media, and government, Standard Bengali is the norm, putting dialect speakers at a disadvantage. Students who grow up speaking a regional dialect at home may struggle in school, where instruction is given in Standard Bengali, potentially affecting academic performance. Similarly, in professional settings, dialect speakers may face bias or be perceived as less educated or articulate, reinforcing regional and class-based inequalities.

Our research directly addresses these challenges by exploring how NLP techniques can bridge the communication gap between dialects and standard language forms. By developing tools that can accurately translate regional dialects into Standard Bangla and English, the project aims to reduce linguistic barriers, promote inclusivity in education and digital services, and ensure better access to information for dialect speakers. This work contributes to the broader goal of linguistic equity in Bangladesh by leveraging technology to preserve dialectal diversity while enhancing mutual understanding.

1.5 Methodology and tools

We manually collected textual data, from different parts of Bangladesh and ran different analysis algorithms to identify the key differences between them. Lexical (structural) analysis, syntactic analysis, semantic analysis, discourse synthesis, and pragmatic analysis, each were conducted on each dataset to differentiate aspects of each dialect. The data contains the dialect and the translated Bengali and English counterparts. All these were preprocessed, tokenized and then fed to different AI models which are well adept for NLP to train each model. The selected models learns the patterns and the key aspects of each dialect and learns to translate each statement into the standard Bengali and English statements.

Then all the models that were selected were tested and the accuracy for the correct translation of each sets were recorded. The AI model that gave the best result was filtered and its working principal was analyzed further. The dataset and the final model was altered and optimized so that it is best fit to translate all the dialects accurately to Standard Bangla and English.

The python language was used to design the machine learning and deep learning models. Initially Google colab was used, but later when the dataset increased and more computational resource was required, we used a local external GPUs. Visual Studio Code was used as editor.

1.6 Scope of the Research

- Dialect Coverage: The research concentrates on prominent dialects from selected regions of Bangladesh, specifically Chittagong, Sylhet, and Khulna.
- Manual Data Collection: Due to the limited availability of existing datasets, the study involves the manual collection and annotation of dialectal speech and text data from native speakers.
- Corpus Development: Creation of a parallel corpus aligning dialectal expressions with their Standard Bangla and English translations.

- Model Development: Design and implementation of a custom NLP model, leveraging transformer-based architectures and contextual embeddings for improved translation accuracy.
- Translation Focus: The model is trained and tested to perform two-way translation:
    - From regional dialects to Standard Bangla
    - From regional dialects to English
- Evaluation: The model's performance is evaluated based on translation accuracy, with the proposed system achieving 95% accuracy in experimental settings.
- Limitations: The study does not cover all Bangla dialects across Bangladesh and is limited by the size and diversity of the collected dataset.

CHAPTER 2
LITERATURE REVIEW

The work on NLP truly started in the late 1940s, even though the "Turing Test," syntactic structures, and its system that was based on rules were developed in 1950 and 1957, respectively. Up until 1990, growth was sluggish because to inadequate computer power, the use of systems that relied on complex handwritten rule systems, and a narrow vocabulary. Due to the advancement of machine learning and the ongoing expansion of computer power, interest in research and applications has recently surged [5]. The recent major NLP breakthrough areas include speech recognition, dialogue systems, language processing, and the application of deep learning techniques. NLP has generated a great deal of research interest and opened up many opportunities for using its techniques in automation, robotics, and digital transformation despite the challenges it still faces (such as those related to human computer interfaces) [3].

Prior to 1990, the majority of the research on NLP concepts and machine translation was done. Deep learning, machine learning, and statistical models have been used to great effect in the most recent NLP research. Research in deep learning and artificial intelligence occasionally overlaps with research in natural language processing. Today, these techniques are commonly employed to do NLP tasks in the most efficient way possible [1].

Below are a few research papers that were studied to understand this field of research:

1. Research Paper [6]: The Author aims to create a mobile application for Indonesian and Madurese translators using RESTful API with JSON data format. In order to build a translator system that can be used by all platforms, including Android, a web service must be created. Web service is a standard and a programming method for sharing data between several applications.
2. Research Paper [7]: This paper talks about language translator where most of the population don't understand language and area unit unable to speak effectively with the deaf. Therefore, the deaf realize it tough to converse with folks on day to day basis, this issue is often solved through a smartphone application.
3. Research Paper [8]: This research work proposes a portable and 24x7 available system with support for bidirectional translation i.e. from sign language to speech and speech to sign language. The mobile application will give normal speech output as audio and text and sign language output as a 3D animated video sequence, with the help of Unity3D.
4. Research Paper [9]: According to the research results, there are some recommendation on this system to fulfil the needs and requirements of the end-users. In future, new improvements can be implemented on this application where the upgraded versions can provide the user to access more languages for translation. Moreover, online functions can be added to provide more updated information.
5. Research Paper [10]: This device basically can be used by people who do not know English and want it to be translated to their native language. e. It involves extraction of text from the image and converting the text to translated speech in the user desired language.

6. Research Paper [11]: In this paper, authors developed and introduced an Android-based framework that translates the American Sign Language to a text that can be used anywhere. The mobile camera shots the picture, and skin segmentation is achieved using YCbCr systems. Features are extracted from the image using HOG and list to recognize the symbol. Using the Support Vector Machine (SVM), the classification was completed.
7. Research Paper [12]: In this paper, author developed an English to Igbo Language Translation Natural Language Processing System in Android. The Design Word, Reference System, and Decoder were performed in Microsoft Hub.
8. Research Paper [13]: In this paper, authors developed an Android-based program that could precisely translate the sign language transmitted in written language by deaf voice. The conversion process starts with the OpenCV hand recognition and the conversion of the K-NN classification hand signals. In this program, the demonstration functions were introduced to teach users intensively the use of sign language.
9. Research Paper [14]: The new English Text to Multilingual Speech Translator using Android (T2MSTA) is designed to help people who lack the power to talk or non-native speakers and individuals who do not share a common dialectal.
10. Research Paper [15]: In this paper the author talks about Android Platform for Machine Translation -A Focus on Yorùbá Language. Which was developed on a mobile platform for easier accessibility, convenience, and portability? RST (Rough Set Theory) is the mathematical tool used in decision support and data analysis of words or phrases to be translated.

So as we can see, there are very few research papers that analyzed regional dialects of a language. And there are no papers on Bengali Dialects. So there are no prior datasets to that can be used.

CHAPTER 3

PREPARING THE DATASET

3.1 Data Collection

The first step in the implementation of any Deep Learning project is the investigation of dataset that would be used to train the pipeline as well as evaluate the pipeline. Most commonly, the datasets used for Machine Translation are from WMT (the website that is dedicated to research in statistical machine translation). But unfortunately we could not find proper dataset that has the Bangladeshi dialects of the Bengali Language.

Given the lack of publicly available datasets for Bangla dialects, especially for translation tasks, this study required a **manual data collection** process to build a reliable and linguistically diverse corpus.

1. Target Dialects and Regions

The data was collected from 14 regions of Bangladesh:

1. Barishal
2. Brahmanbaria
3. Chittagong
4. Cumilla
5. Dhaka
6. Khulna
7. Kishoreganj
8. Magura
9. Mymensingh
10. Narayanganj
11. Noakhali
12. Patuakhali
13. Rajshahi
14. Sylhet

The dataset comprises **12704 cleaned samples** across **14 regional Bengali dialects**, collected from various sources.

These regions were selected for their distinct phonological, lexical, and syntactic characteristics, which differ significantly from Standard Bangla and from one another.

2. Data Sources

Data was collected through a combination of:

- Field interviews with native speakers, recorded and transcribed.
- Community-based contributions, where participants submitted common phrases, dialogues, or stories in their dialect.
- Social media and local forums, selectively used for extracting informal dialectal expressions.

- Local literature and oral histories, where available, to enrich the cultural and idiomatic variety in the dataset.

3. Annotation and Alignment

Each dialectal entry was:

- Transcribed into text (where spoken data was used).
- Manually translated into both Standard Bangla and English by native bilingual speakers familiar with both the dialect and target language.
- Labeled with metadata such as region, speaker age/gender (when available), and linguistic notes.

A team of linguists and native speakers reviewed the translations to ensure consistency, contextual correctness, and linguistic accuracy.

4. Dataset Size

The final dataset comprised **12,704 samples**, each containing:

- A dialectal input sentence in Bengali alphabet
- Dialectal sentence in English alphabet
- A Standard Bangla in Bengali alphabet
- An English translation
- Name of the region for the dialect

This dataset was split into training, validation, and test sets for model development and evaluation.

5. Ethical Considerations

Participants were informed about the use of their contributions for academic research. Personally identifiable information was not collected, and all data was anonymized to ensure privacy and compliance with ethical research standards.

3.2 Dataset Creation

We prepared our dataset in two formats

- **JSON Format**(For structured and hierarchical processing):
  JSON (JavaScript Object Notation) is a lightweight and easy-to-read data format widely used for data interchange. One of its main advantages is its simplicity—both humans and machines can easily read and write JSON. Although it originates from JavaScript, JSON is language-independent and supported by almost all major programming languages, making it highly versatile. It enables fast data transmission between servers and clients, which is especially beneficial in web applications. JSON also supports complex data structures like arrays and nested objects, allowing flexible

and organized data representation. Its ease of parsing and widespread adoption in APIs, particularly RESTful services, make it a standard choice for modern data exchange.

- **CSV format**(For tabular inspection and modeling):
  CSV (Comma-Separated Values) is a simple and widely used file format for storing tabular data. One of its key advantages is its simplicity—CSV files are plain text, making them easy to create, read, and edit with any text editor or spreadsheet software like Microsoft Excel. They are lightweight and have small file sizes, which makes them efficient for storing and transferring large datasets. CSV is also supported by most data processing tools, programming languages, and database systems, ensuring broad compatibility. Due to its straightforward structure, CSV is ideal for data exchange between different platforms and for quick import/export of data in analytics and reporting tasks.


```
[
    {
      "bangla_speech": "তুমি কি এই কাজটা করতে পারবে",
      "banglish_speech": "tumi ki ei kajta korte parbe",
      "brahmanbaria_bangla_speech": "তুই এই কামডা করতারবে নি",
      "brahmanbaria_banglish_speech": "tumi ki ei kajta kore dite parba",
      "region_name": "brahmanbaria",
      "english_speech": "can you do this"
    },
    {
      "bangla_speech": "আমি এখনো বুঝতে পারছি না?",
      "banglish_speech": "amar boro boner ajke mon valo nei",
      "brahmanbaria_bangla_speech": " আমি অহন ও বুঝদাছি না",
      "brahmanbaria_banglish_speech": "mor boro buiner aijgo mon vala nai",
      "region_name": "brahmanbaria",
      "english_speech": "After a while it will be dark"
    },
```


Fig 3.2.1: Samples of dataset in JSON format

	bangla_speech	banglish_speech	barishal_bangla_speech	barishal_banglish_speech	region_name	english_speech
0	কেমন আছো ?	kemon acho?	আসো কোরোহম?	Aso korohom?	Barishal	How are you?
1	আজকে আমার মন ভালো নেই	ajke amr mon valo nei	আইজ মোর মনডা ভালোনা	aij mor monda valona	Barishal	I'm not feeling well today
2	তুমি কি করো ?	tumi ki koro?	ও মোনু হর কি?	o monu horo ki?	Barishal	what are you doing
3	এই গরমে আমার কিছু ভালো লাগে না	ei gorome amar kichu valo lage na	এই থাডা পরা গরমে মোর কিস্‌সু ভাল্লাগেনা	ei thada pora gorome mor kissu vallagena	Barishal	I don't like anything this summer
4	ছেলেটি সাদা রঙয়ের একটি শার্ট পরে এসেছিল	cheleti sada ronger ekti shirt pore eshechilo	পলাউগ্গা এউক্কা ধলা রং এর এউক্কা গুঞ্জি পইর্রা...	polaugga eukka dhola rong er eukka gunji poirr...	Barishal	The boy came wearing a white shirt

Fig 3.2.2: Samples of dataset in CSV format

Interpretation: The two figures above shows a few of the samples of the dataset and the format of record.

CHAPTER 4

MODEL DETAILS

4.1 Models Selected:

In this paper, we initially experimented on various machine learning and deep learning architectures such as Random Forest, SVM, Naïve bayes, LSTM.

4.1.1 Random Forest:

Random Forest is an ensemble machine learning algorithm that combines the results of multiple decision trees to improve accuracy and reduce overfitting. It is widely used for both classification and regression tasks due to its robustness, flexibility, and ability to handle large datasets with high-dimensional features.

The model works by creating many decision trees during training, each built on a random subset of the data (a technique called bagging) and a random subset of features at each split. Each tree makes its own prediction, and the final output is determined by majority voting (for classification) or averaging (for regression). This randomness helps reduce the variance and improves the model's generalization performance.

In the context of textual data, Random Forest is applied after converting text into numerical form using methods like Bag-of-Words or TF-IDF. It performs well in tasks like spam detection, sentiment analysis, and topic classification. While it does not capture word order or context, it handles sparse, high-dimensional data efficiently and provides solid baseline performance with relatively low computational cost.

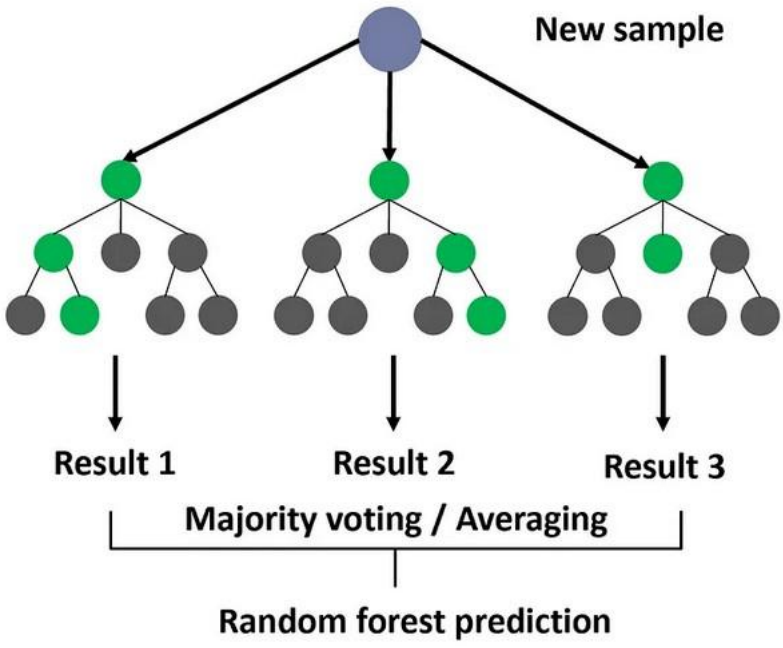


Fig 4.1.1: Random Forest working principle

4.1.2 Support Vector Machine (SVM):

Support Vector Machine (SVM) is a powerful supervised learning algorithm used for classification and regression tasks. It works by identifying the optimal hyperplane that separates data points of different classes with the maximum margin. The data points closest to the hyper plane are called support vectors, and they play a key role in defining the decision boundary.

SVM is highly effective in high-dimensional spaces and is especially useful when the number of features exceeds the number of samples, as is common in text data. For non-linearly separable data, SVM uses kernel functions (such as polynomial, radial basis function, or sigmoid) to transform the input space into a higher dimension where a linear separator can be found.

In Natural Language Processing (NLP), SVM is commonly used for tasks like text classification, sentiment analysis, and spam detection. Text data is first converted into numerical form using techniques like Bag of Words or TF-IDF, making it suitable for SVM to process. Its ability to handle sparse and high-dimensional data makes it a strong choice for many NLP problems.

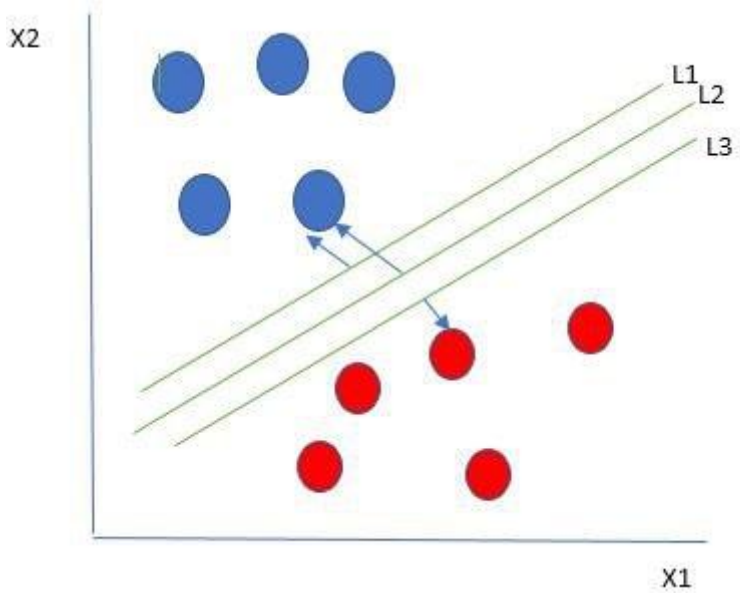


Fig 4.1.2: SVM working principle

4.1.3 Naïve Bayes:

Naive Bayes is a family of simple yet effective probabilistic classifiers based on Bayes' Theorem. It assumes that features are conditionally independent given the class label, which is why it is called "naive."

The algorithm works by calculating the probability of a class given a set of features (e.g., words in a document) and choosing the class with the highest probability. Despite its simplicity and the unrealistic independence assumption, Naive Bayes often performs well in real-world applications, especially in Natural Language Processing (NLP).

In NLP, Naive Bayes is widely used for tasks like spam filtering, sentiment analysis, and text classification. Text data is typically converted into feature vectors using methods like Bag of Words or TF-IDF. Naive Bayes is particularly effective when working with large datasets and is known for its speed and efficiency.

There are several types of Naive Bayes classifiers, including:

- **Multinomial Naive Bayes**: Best suited for discrete data like word counts.
- **Bernoulli Naive Bayes**: Works with binary/boolean features.
- **Gaussian Naive Bayes**: Assumes features follow a normal distribution; used for continuous data.

Naive Bayes is easy to implement, requires little training data, and provides solid baseline performance for many classification problems.

4.1.4 LSTM:

LSTM (Long Short-Term Memory) is a type of Recurrent Neural Network (RNN) designed to model sequential data and overcome the limitations of traditional RNNs, such as the vanishing gradient problem. It was introduced by Hochreiter and Schmidhuber in 1997.

LSTMs are capable of learning long-range dependencies in sequence data through a special architecture that includes memory cells and gates:

- **Forget gate**: Decides what information to discard from the cell state.
- **Input gate**: Determines what new information to store.
- **Output gate**: Controls what information is output from the cell.

This gated structure allows LSTMs to retain relevant information over long time steps, making them well-suited for tasks involving sequential or time-series data.

In Natural Language Processing (NLP), LSTMs are commonly used for tasks such as language modeling, text generation, machine translation, speech recognition, and sentiment analysis. They are especially effective when context and word order are important for understanding meaning.

Despite the rise of transformer-based models like BERT and GPT, LSTMs remain useful for many real-time and resource-constrained applications due to their relatively lower complexity and ability to handle sequential input naturally.

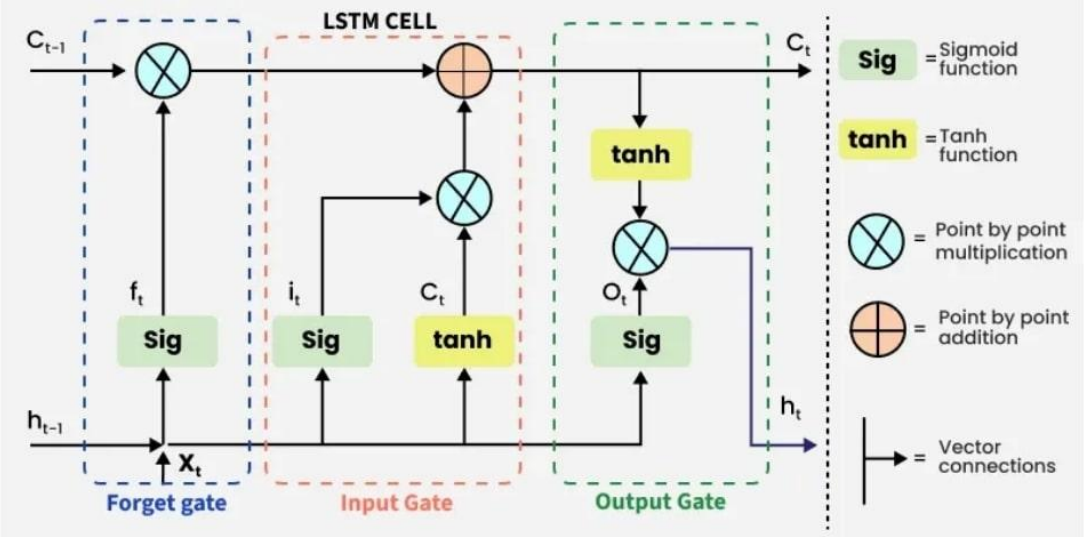


Fig 4.1.4: Basic principle of LSTM

4.1.5 BanglaBERT:

BanglaBERT is a pre-trained transformer-based language model designed specifically for the Bengali language. It is an adaptation of BERT (Bidirectional Encoder Representations from Transformers), which was originally developed for English. BanglaBERT is fine-tuned for various natural language processing (NLP) tasks in Bengali, such as text classification, sentiment analysis, named entity recognition (NER), and machine translation.

Built on the transformer architecture, BanglaBERT uses self-attention mechanisms to process text and capture contextual relationships between words. Unlike traditional models, it is bidirectional, meaning it analyzes both the left and right context of each word, improving the accuracy of its language understanding.

BanglaBERT is trained on a large corpus of Bengali text from diverse sources like books, news articles, and social media, making it capable of handling various NLP tasks. It performs well in text classification, NER, question answering, and even translation tasks, especially for Bengali-to-other languages and vice versa.

One of the key advantages of BanglaBERT is its high accuracy, which is driven by its ability to leverage pre-trained transformer models. Its bidirectional nature ensures better context comprehension, and it can be easily fine-tuned for specific tasks, making it versatile. However, challenges include the scarcity of high-quality, domain-specific Bengali text data and the significant computational resources required for training and fine-tuning.

Overall, BanglaBERT is an important advancement in Bengali NLP, offering improved accuracy and more efficient tools for tasks such as sentiment analysis, machine translation, and text understanding, which can greatly benefit various applications in fields like business, healthcare, and education.

CHAPTER 5

RESEARCH METHODOLOGY

5.1 Machine Translator Block Diagram:

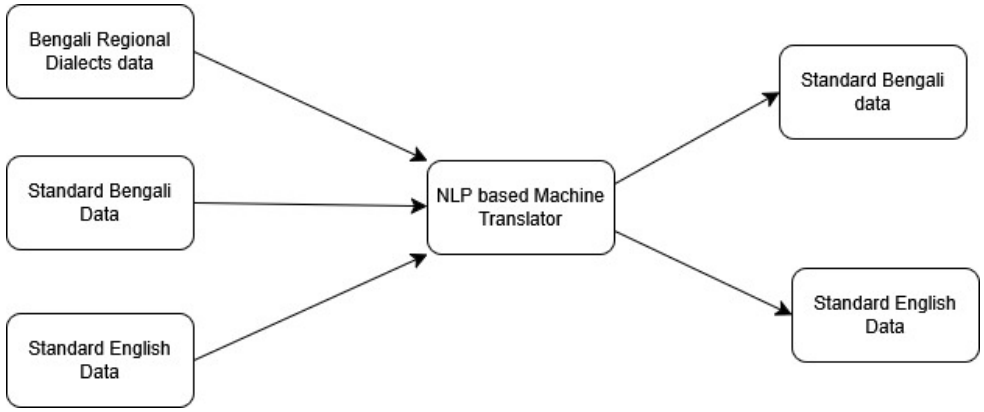


Fig 5.1: Machine translator

The block diagram above shows how our Machine translator works. It can take any of three inputs (Regional dialect or Bengali or English statement), and can produce one or both of the subsequent output (Standard Bengali or English statement).

5.2 Methodology Pipeline:

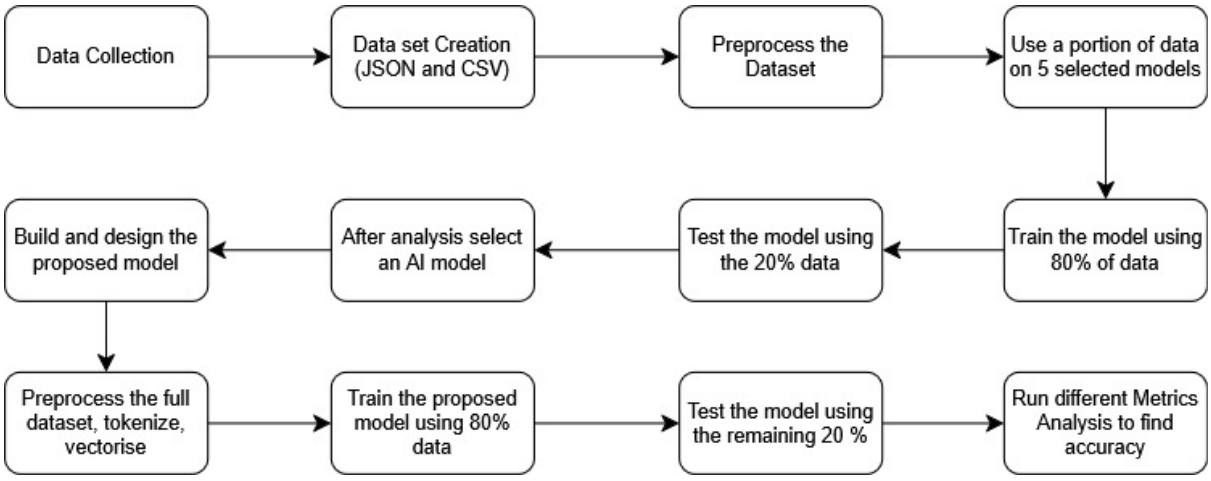


Fig 5.2: Sequential steps of research.

A methodology pipeline is a structured, step-by-step process that outlines the sequence of methods and procedures used to carry out a research study, data analysis, or system development. It ensures a logical flow from data acquisition to final results or deployment, promoting reproducibility, clarity, and efficiency in the execution of a project.

5.3 Initializing the Libraries/Frameworks:

Libraries/Frameworks:

- *pandas, matplotlib, seaborn* — data handling and visualization
- *scikit-learn* — ML models and metrics
- *TensorFlow, Keras* — Deep learning (LSTM, Seq2Seq LSTM)
- *Hugging Face Transformers* — Fine-tuning BanglaBERT
- *NLTK* — Text processing
- *PyTorch* — For future extension or model experimentation

5.4 Dataset Loading:

- The system starts by loading all JSON files from directories representing different regions.
- Each file contains localized speech phrases (<region>_bangla_speech), standard Bangla, and English translations.
- It stores this data in memory for processing.
- Loop through all regions.
- For each region, find .json files inside the corresponding directory.
- Parse the data into a unified format: {local, standard, english}.

5.5 Data Preprocessing:

Preprocessing a textual dataset is an essential step in Natural Language Processing (NLP), as raw text data often contains noise, inconsistencies, and irrelevant information that can hinder model performance. The goal of preprocessing is to clean and transform text into a structured, standardized format so that algorithms can interpret them effectively. The main steps involved are:

1. **Text Cleaning:** This involves removing unnecessary elements such as HTML tags, URLs, emojis, and special characters that do not contribute to meaningful language analysis. For example, texts scraped from the web often include HTML markup or symbols that must be stripped out.

2. **Lowercasing:** Converting all text to lowercase ensures uniformity. For instance, "Apple" and "apple" would be treated as the same word, preventing duplication of vocabulary and improving model efficiency.

3. **Tokenization:** This is the process of splitting the text into individual units, typically words or subwords. Tokenization helps break down large chunks of text into manageable parts for analysis. For example, the sentence "I love NLP" becomes ["I", "love", "NLP"]. Each character and word is assigned a number, conventionally called character IDs and word IDs, respectively. A word level model used word ids that generate text predictions for every word. This has lower complexity compared to character level model. Keras has a utility class known as Tokenizer.

4. **Stop Word Removal:** Stop words are common words such as "is", "the", "in", and "and" that usually carry little meaning and are removed to focus on the more informative terms. However, in some tasks (like sentiment analysis), stop words might be important and should be retained.

5. **Stemming and Lemmatization:** These techniques reduce words to their base or root forms. *Stemming* involves chopping off word endings (e.g., "playing", "played", and "plays" become "play"), often with less concern for proper grammar. *Lemmatization*, on the other hand, uses linguistic rules to convert words to their dictionary form (e.g., "better" becomes "good").

6. **Removing Numbers and Special Characters:** Depending on the use case, numbers, punctuations, and symbols may be irrelevant and are often removed to reduce noise.

7. **Handling Spelling Errors and Typos:** Correcting misspelled words ensures consistent vocabulary and helps avoid confusion in vectorization or word embedding stages.

8. **Text Normalization:** This includes removing accents, expanding contractions (e.g., “don’t” to “do not”), and standardizing slang or abbreviations.

9. **Vectorization:** Since machine learning models work with numbers, the final step is to convert text into numerical form. Common techniques include:

    - Bag-of-Words (BoW**):** Represents text by the frequency of each word.
    - TF-IDF (Term Frequency–Inverse Document Frequency**):** Weighs words by their importance across documents.
    - Word Embeddings**:** Converts words into dense vectors that capture semantic meaning (e.g., Word2Vec, GloVe, or BERT embeddings).

10. **Padding:** When batching the sequence of word ids together, each sequence needs to be the same length. Since the sentences are dynamic in length, padding is done at the end of sentences to make them the same length. The function used to perform padding is present in Keras as pad_sequences. It takes three parameters which is x- List of sequences, length-Length to pad to and return padded numpy array of sequences. The output of padding is given below.

```
Sequence 1 in x
  Input:  [1 2 4 5 6 7 1 8 9]
  Output: [1 2 4 5 6 7 1 8 9 0]
Sequence 2 in x
  Input:  [10 11 12  2 13 14 15 16  3 17]
  Output: [10 11 12  2 13 14 15 16  3 17]
Sequence 3 in x
  Input:  [18 19  3 20 21]
  Output: [18 19  3 20 21  0  0  0  0  0]
```

Fig 5.5: Padding example

Effective preprocessing not only improves the accuracy and efficiency of NLP models but also ensures that the input data is clean, consistent, and meaningful. The choice of techniques often depends on the nature of the dataset and the specific NLP task (e.g., sentiment analysis, machine translation, or text classification).

5.5.1 Exploratory Data Analysis (EDA):

Exploratory Data Analysis (EDA) was performed to understand the structure, diversity, and characteristics of the collected dataset before training the Seq2Seq LSTM model. EDA helped identify potential issues, guided preprocessing decisions, and informed model architecture and hyper parameter tuning.

1. Dialectal Distribution Analysis

- The dataset was analyzed to determine the number of samples per region
- This ensured a balanced representation of dialects and helped detect regional biases that could affect model performance.
- If imbalances were found, data augmentation or weighting strategies were considered.

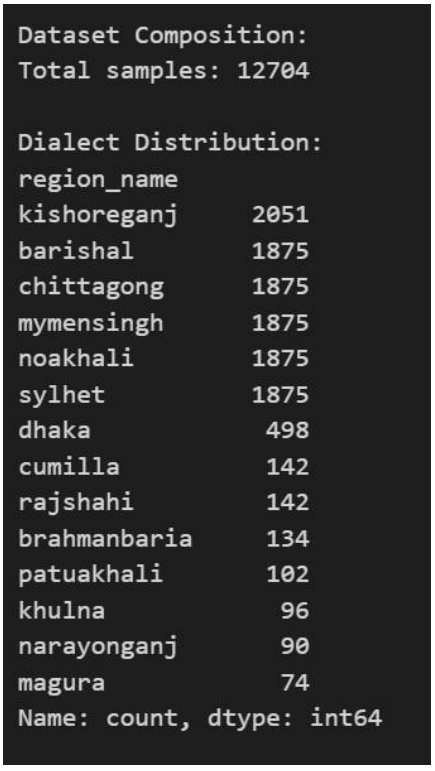


Fig 5.5.1.1: Number of samples for each region

Interpretation: This figure shows the number of dialect samples for each of the regions. This is a screenshot from the terminal of the progarm. It also shows the total data collected.

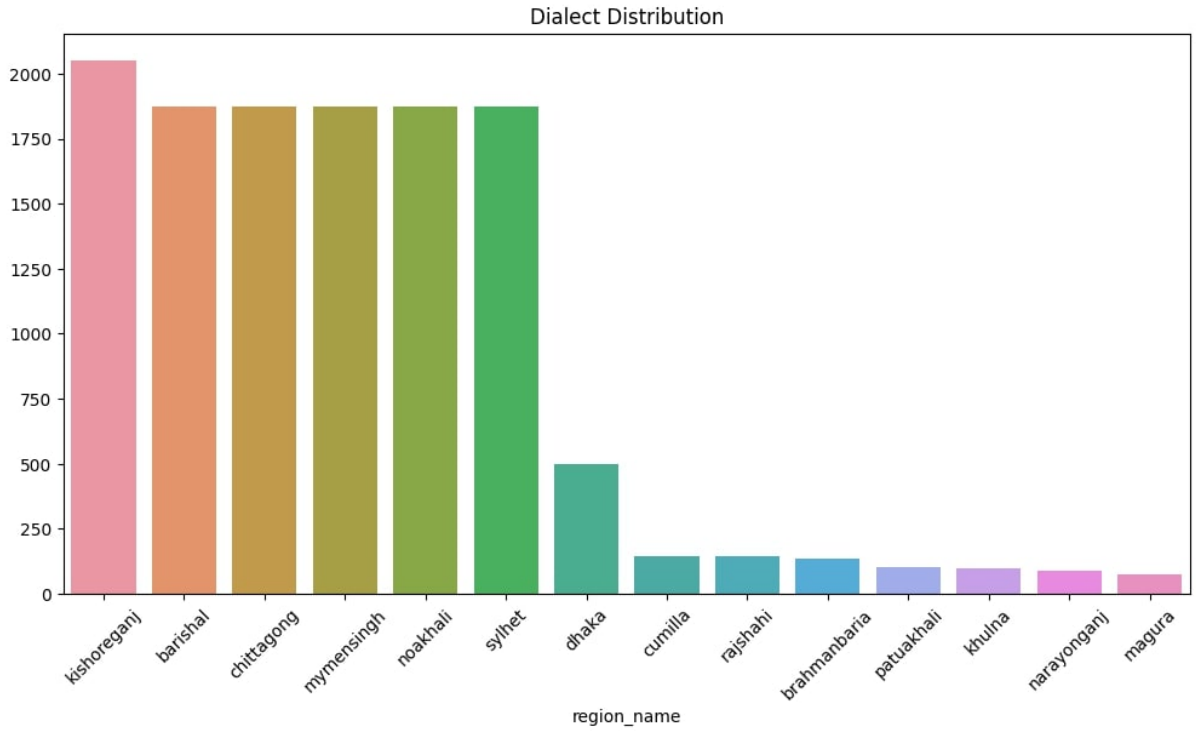
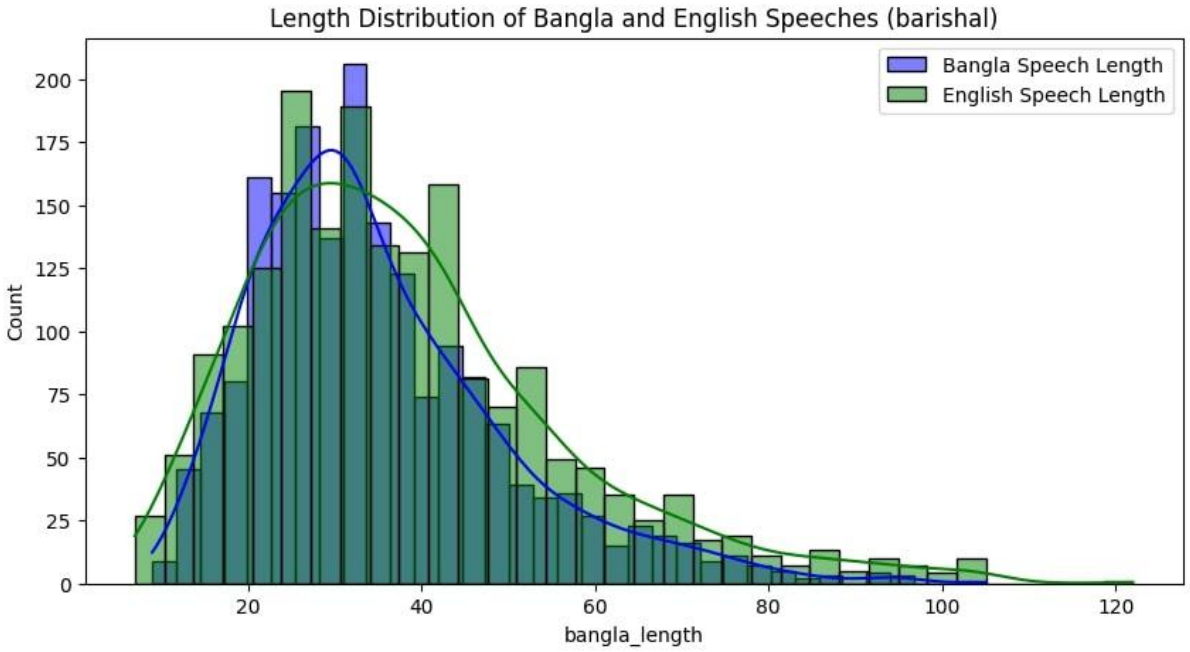


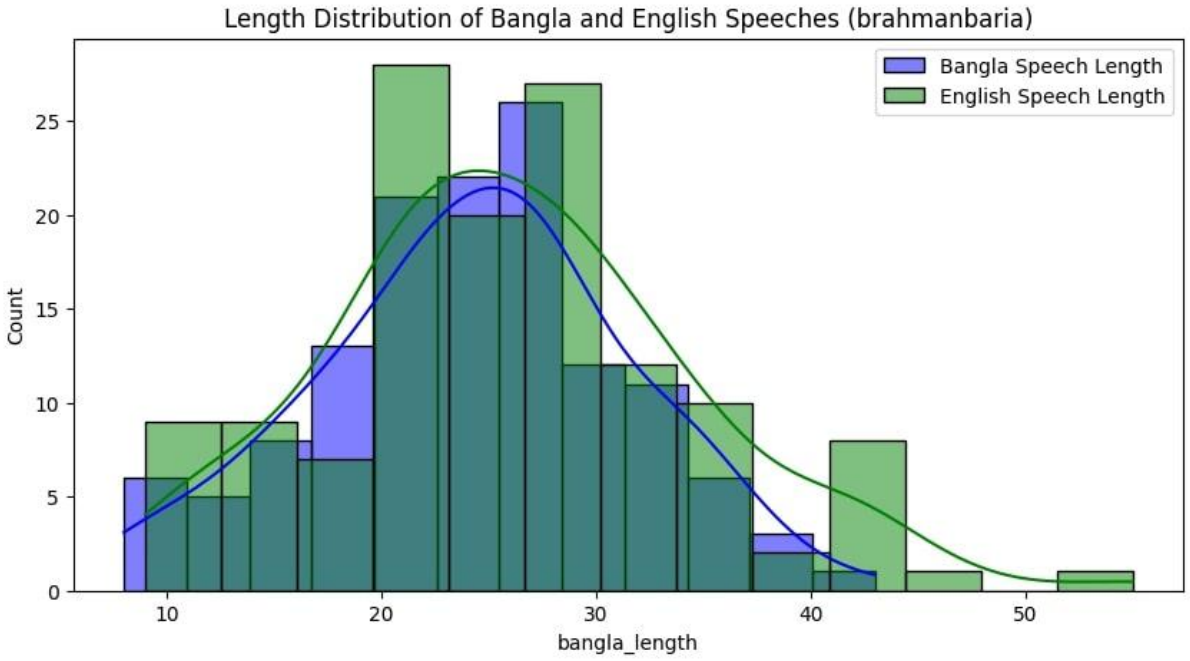
Fig 5.5.1.2: Dialect Distribution across all regions.

Interpretation: The figure above show the dialect distribution in a bar chart format. Each bar represents the number of samples for each region, with Kishoreganj being the highest and Magura being the lowest. The y-axis represents the number of samples.

2. Sentence Length Analysis

- Histograms of input and output sentence lengths (in tokens) were generated for:
    - Dialectal input
    - Standard Bangla output
    - English translation
- This analysis helped in:
    - Determining optimal sequence lengths for padding
    - Preventing loss of information or unnecessary padding
    - Understanding linguistic complexity across dialects


Length Distribution of Bangla and English Speeches (barishal)
Bangla Speech Length
English Speech Length
Count
bangla_length
0
25
50
75
100
125
150
175
200
20
40
60
80
100
120


Length Distribution of Bangla and English Speeches (brahmanbaria)
Bangla Speech Length
English Speech Length
Count
bangla_length
0
5
10
15
20
25
10
20
30
40
50

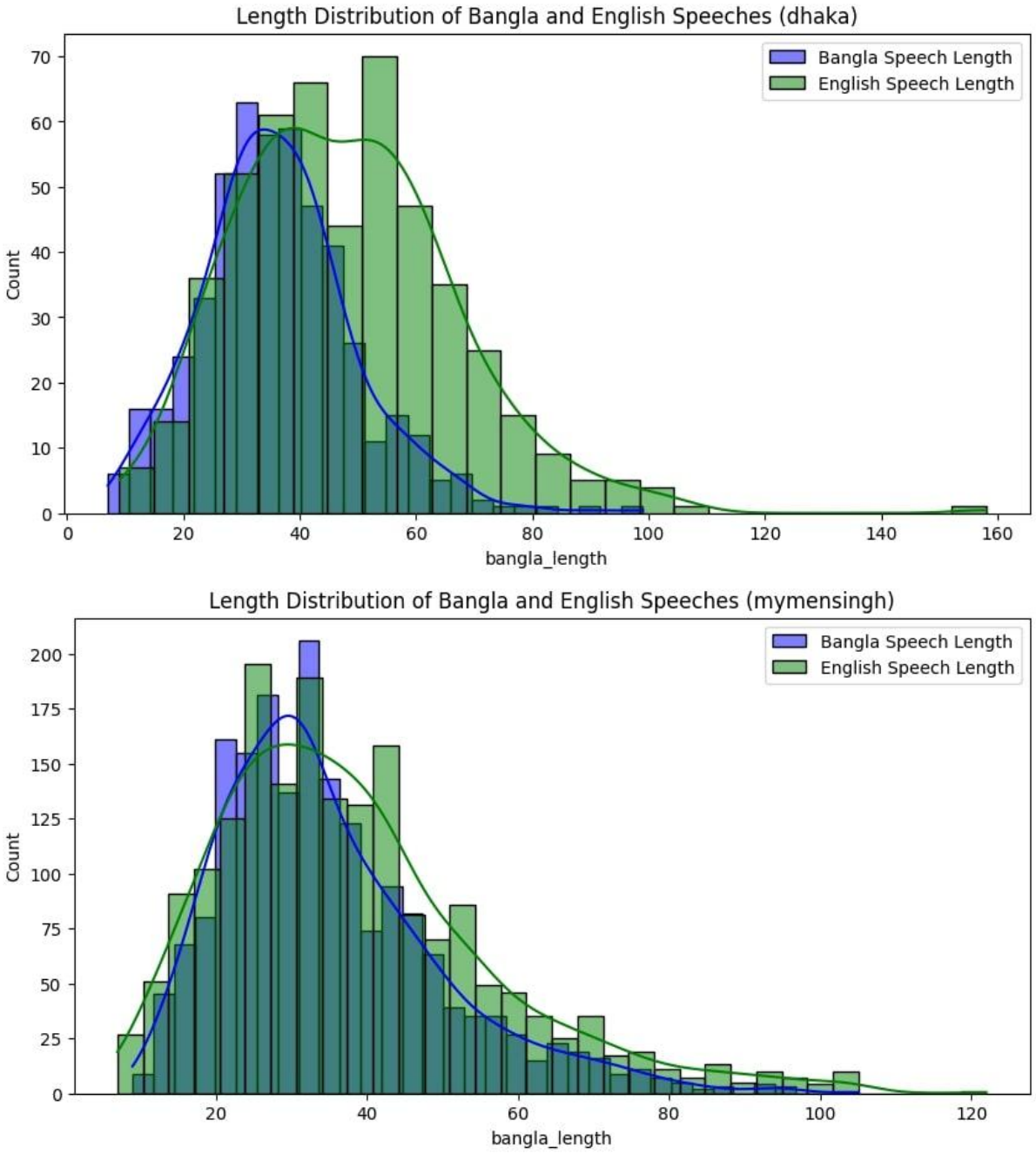


Fig 5.5.1.3: Length Distribution for individual regions

Interpretation: The above four graphs give the difference in the speech length for the Bangla statement and its contemporary English (translated) statement. Only 4 regions have been selected as an example. This gives the generic idea about the number of vocabulary used to express something in each respective dialect.

3. Word Frequency Distribution

- Word frequency histograms and word clouds were generated to identify:
    - High-frequency common words (e.g., function words, region-specific terms)

- Rare or potentially noisy tokens (which might be candidates for filtering or OOV handling)

- Separate analyses were done for dialectal inputs and both target outputs.

```
Most Common Words in Bangla Speech (barishal):
[('আমার', 368), ('আমি', 330), ('না', 240), ('অনেক', 150), ('করে', 139), ('কথা', 110), ('সে', 108), ('কি', 104), ('ভালো', 101), ('সাথে', 91)]

Most Common Words in English Speech (barishal):
[('I', 623), ('to', 507), ('the', 463), ('is', 330), ('a', 316), ('you', 245), ('in', 241), ('of', 201), ('my', 169), ('me', 145)]
```

```
Most Common Words in Bangla Speech (brahmanbaria):
[('কি', 33), ('তুমি', 23), ('আমি', 23), ('তোমার', 17), ('এই', 16), ('খুব', 14), ('আমার', 13), ('না', 11), ('আজকে', 10), ('আজ', 10)]

Most Common Words in English Speech (brahmanbaria):
[('you', 37), ('I', 37), ('to', 24), ('is', 21), ('a', 19), ('very', 17), ('are', 13), ('the', 12), ('this', 11), ('have', 9)]
```

```
Most Common Words in Bangla Speech (dhaka):
[('না', 96), ('কি', 47), ('করে', 41), ('আমার', 39), ('আমি', 30), ('কথা', 28), ('এই', 26), ('আর', 26), ('থেকে', 21), ('অনেক', 21)]

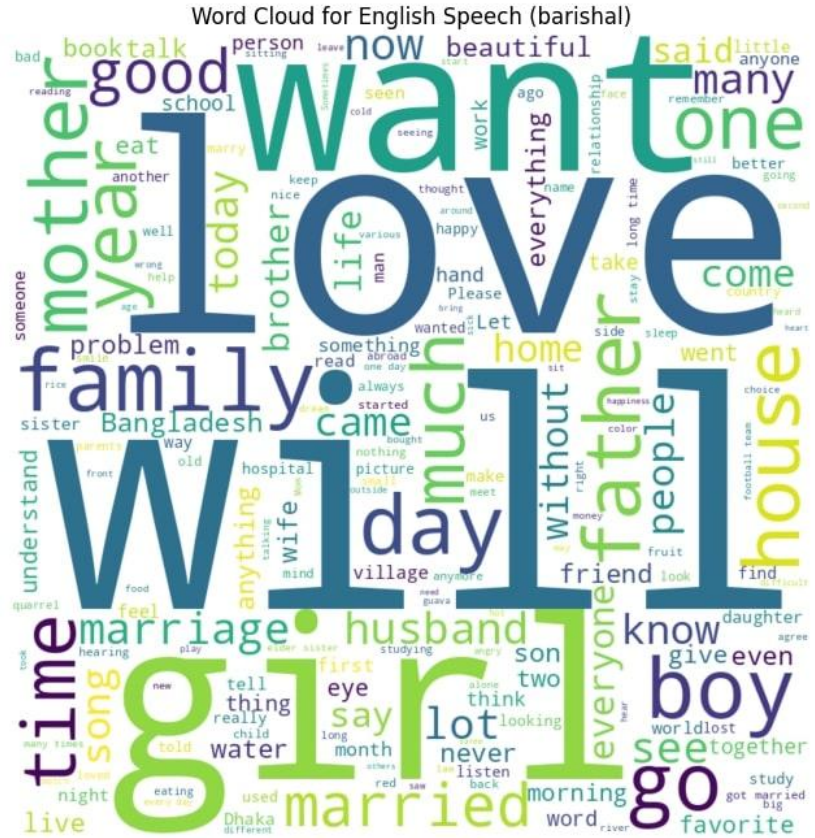
Most Common Words in English Speech (dhaka):
[('the', 238), ('I', 126), ('you', 108), ('to', 96), ('is', 84), ('a', 83), ('of', 79), ('and', 75), ('in', 73), ('will', 54)]
```

```
Most Common Words in Bangla Speech (mymensingh):
[('আমার', 368), ('আমি', 330), ('না', 240), ('অনেক', 150), ('করে', 139), ('কথা', 110), ('সে', 108), ('কি', 104), ('ভালো', 101), ('সাথে', 91)]

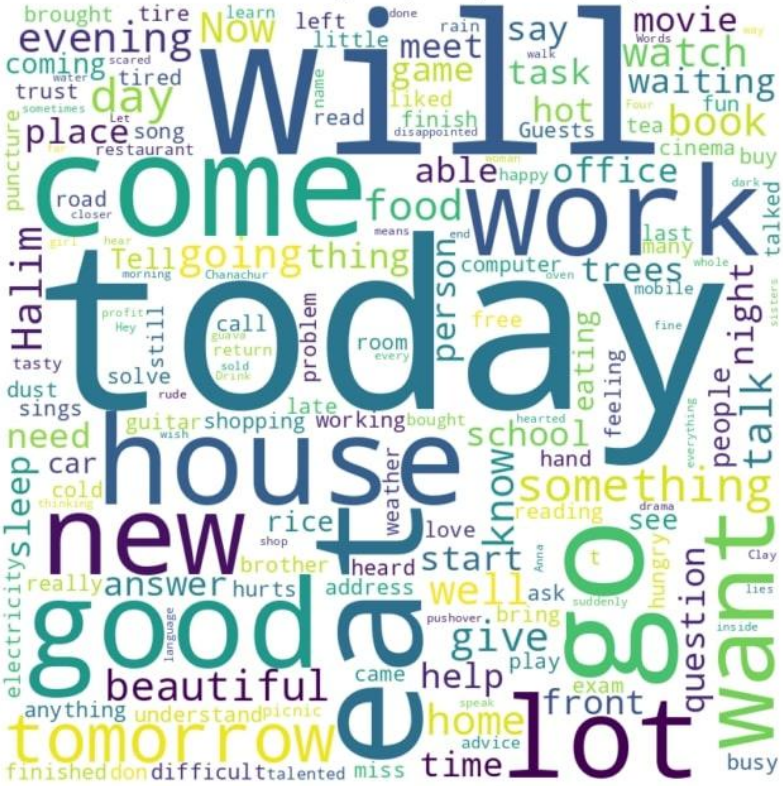
Most Common Words in English Speech (mymensingh):
[('I', 623), ('to', 507), ('the', 463), ('is', 330), ('a', 316), ('you', 245), ('in', 241), ('of', 201), ('my', 169), ('me', 145)]
```

Fig 5.5.1.4: Most Common words for a particular region

Interpretation: The figure above show the most common words used in the samples of the regional dialect. The words in each dialect differ. Even the translated English words used in each dialect differ. This shows that the people of each regions are culturally different.



Word Cloud for English Speech (brahmanbaria)



Word Cloud for English Speech (dhaka)

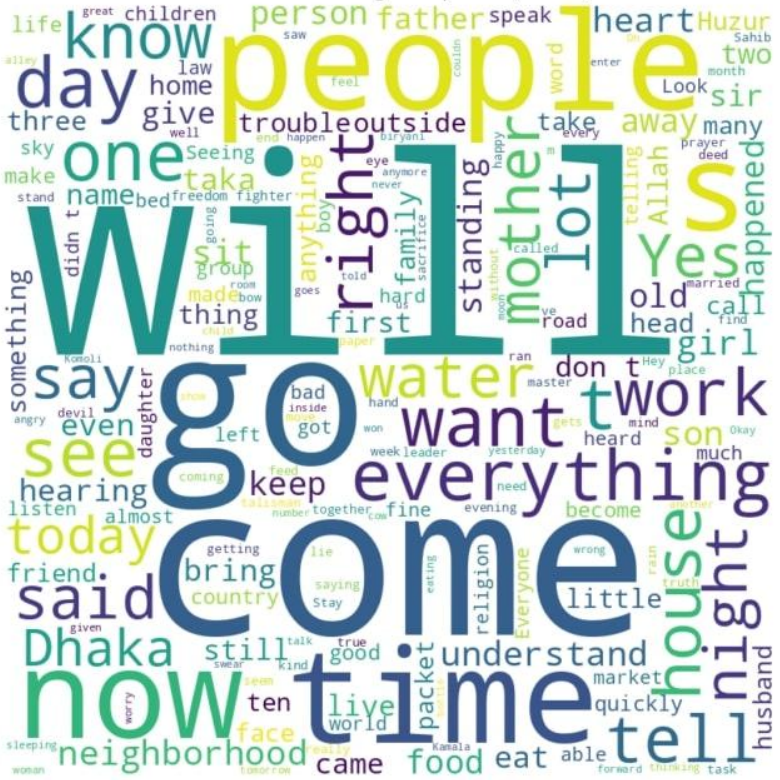




Fig 5.5.1.5: Word Cloud generated for a specific region

Interpretation: The word cloud visually highlights the most frequently occurring words in the dataset for the English statements. Larger words indicate higher frequency, providing a quick insight into the dominant vocabulary used in the corpus. The word clouds display words like love, family, will and want, likely corresponding to translated equivalents or recurring terms in target sentences. This visualization helps identify key themes, lexical repetition, and potential translation patterns across the dataset. Additionally, it can assist in preprocessing decisions, such as the removal of stop words or identifying domain-specific vocabulary relevant to dialect-to-standard language translation.

4. Vocabulary Size Estimation

- The size of the vocabulary was calculated for each language variant (Dialect, Standard Bangla and English).
- This helped optimize:
    - Embedding dimensions
    - Memory usage
    - Model efficiency and complexity

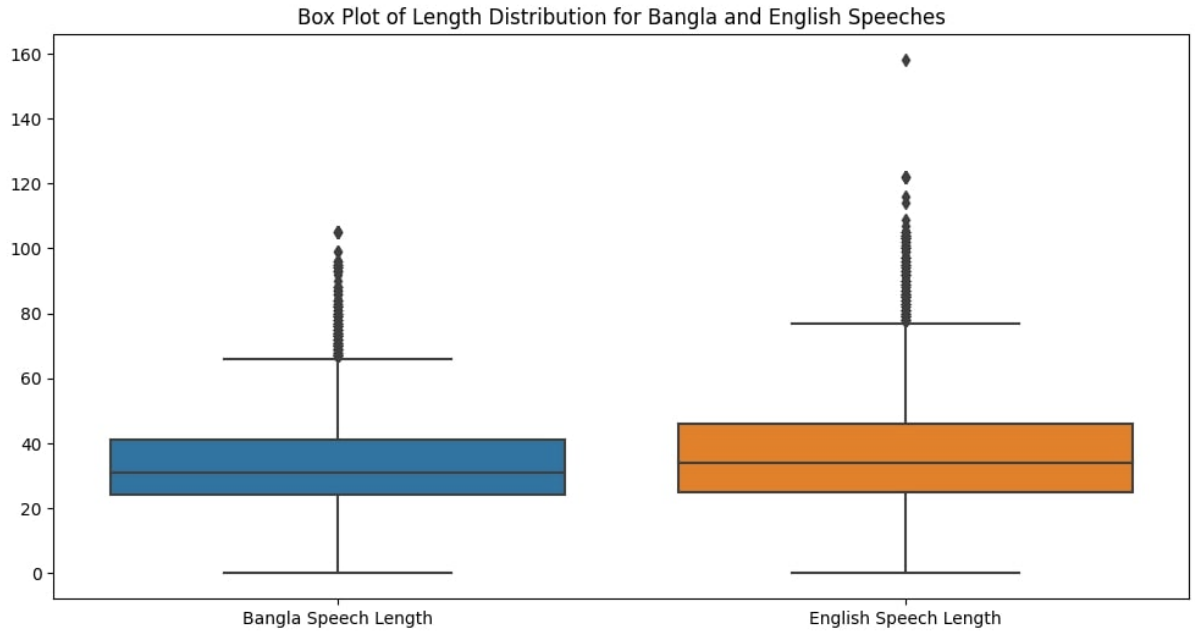


Fig 5.5.1.6: Box plot for the English and Bengali statements

Interpretation: The box plot illustrates the length distribution of Bangla and English statements in terms of the number of tokens or words. From the plot, it is evident that the median length of Bangla statements is slightly shorter compared to English statements. The interquartile range (IQR), which represents the middle 50% of the data, indicates that Bangla statements show less variability in length than their English counterparts. Additionally, the presence of outliers suggests that there are some unusually long or short statements in one or both languages. This difference in length distribution may reflect linguistic structure differences, such as word formation, sentence construction, or translation techniques. Understanding these variations is crucial for designing NLP models that handle both Bangla dialects and their translations effectively.

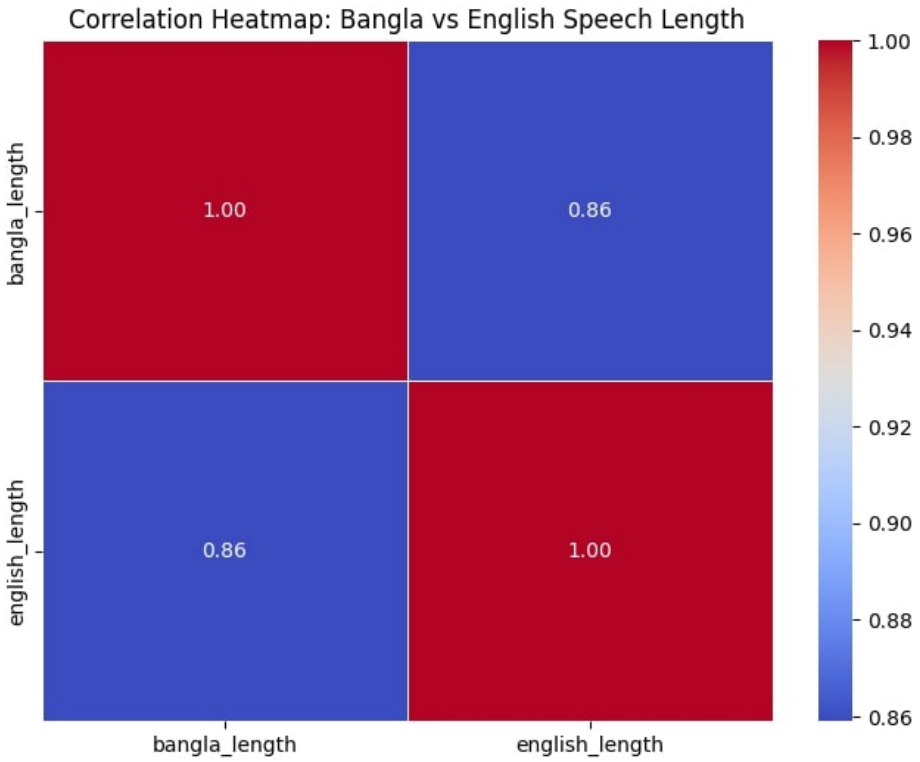


Fig 5.5.1.7: Heat map for the English and Bengali statements

Interpretation: The heat map illustrates the relationship between the lengths of Bangla statements and their corresponding English translations. Each cell represents the frequency or density of occurrences for a specific pair of Bangla and English statement lengths, with color intensity indicating the concentration of such pairs. Darker regions suggest that many statements fall within those specific length combinations, while lighter areas indicate fewer occurrences.

5. Linguistic Variation Mapping

- A comparative analysis was done between dialectal words and their corresponding Standard Bangla forms.
- Examples of phonological and lexical variation were documented, helping to inform model training on expected transformation patterns.

6. Translation Quality Review

- A small subset of the dataset was manually reviewed to assess the quality and consistency of human-generated translations.
- Feedback from this review helped refine annotation guidelines and identify ambiguous or context-sensitive expressions.

5.6 Initial Analysis of the Selected Models:

A small amount of processed data **(One Fifth to be precise)** is then fed into all the selected models to run a comparative analysis. 80% of the data was used to train the model and 20% data was used for testing the model. The analysis is below.

5.6.1 Random Forest analysis

Random Forest Accuracy: 0.11

Classification Report:

	precision	recall	f1-score	support
barishal	0.00	0.00	0.00	20
brahmanbaria	0.00	0.00	0.00	20
chittagong	0.00	0.00	0.00	20
cumilla	0.00	0.00	0.00	20
dhaka	0.71	0.25	0.37	20
khulna	0.00	0.00	0.00	19
kishoreganj	0.42	0.25	0.31	20
magura	0.31	0.53	0.39	15
mymensingh	0.00	0.00	0.00	20
narayonganj	0.00	0.00	0.00	18
noakhali	0.00	0.00	0.00	20
patuakhali	0.58	0.55	0.56	20
rajshahi	0.00	0.00	0.00	20
sylhet	0.00	0.00	0.00	20
accuracy			0.11	272
macro avg	0.14	0.11	0.12	272
weighted avg	0.14	0.11	0.11	272

Fig 5.6.1.1: Classification report of Random Forest

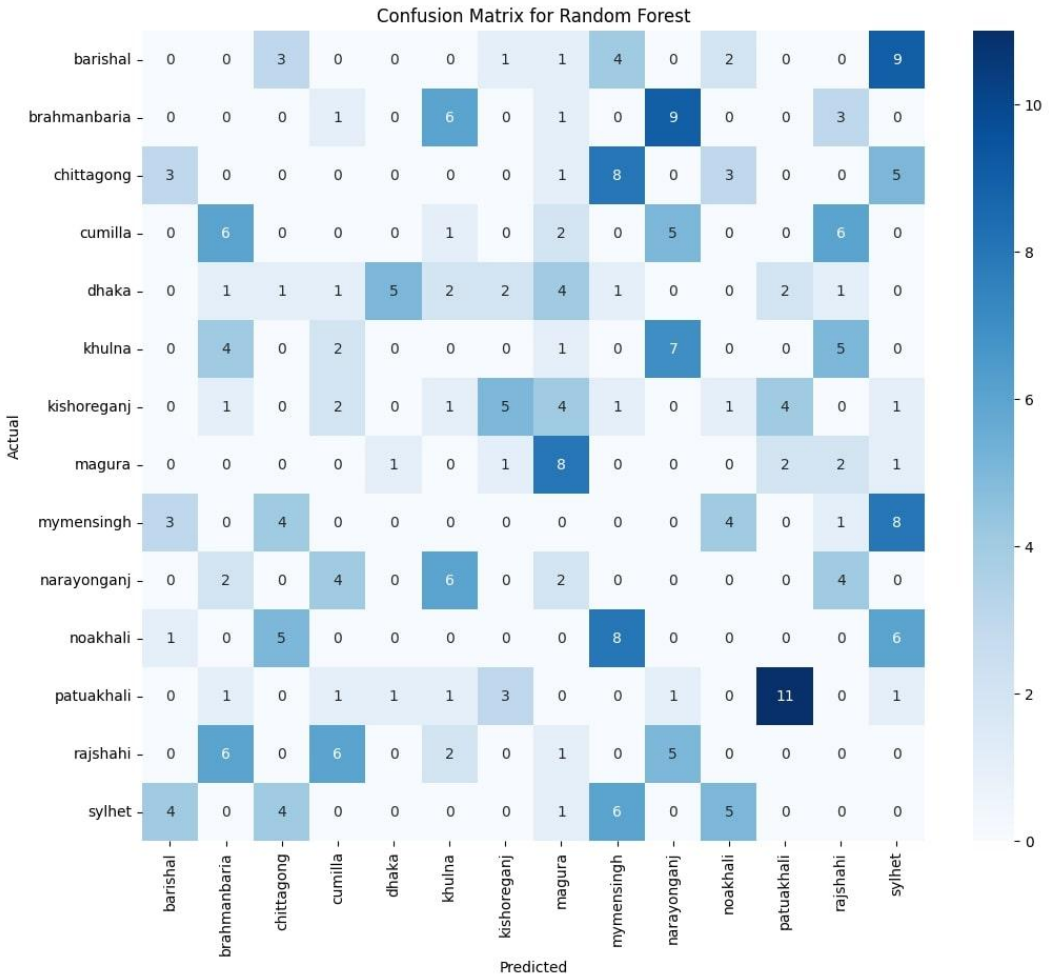


Fig 5.6.1.2: Confusion Matrix for the output of Random Forest

Interpretation: The confusion matrix and classification report for the Random Forest model indicate poor performance in classifying Bangla dialects. The overall accuracy is only 11%, showing that the model struggles to correctly identify the dialects. The confusion matrix reveals significant misclassification across nearly all dialects, with predictions widely dispersed rather than focused along the diagonal. A few dialects like Patuakhali show relatively better performance, while others like Cumilla, Khulna, Rajshahi, and Narayanganj are almost never correctly predicted. The low precision, recall, and F1-scores in the classification report confirm the model's limited ability to distinguish between dialects, likely due to overlapping linguistic features, small dataset size, and limitations of Random Forest in handling complex language data.

5.6.2 SVM (Support Vector Machine) analysis

SVM Accuracy: 0.09

Classification Report:

	precision	recall	f1-score	support
barishal	0.00	0.00	0.00	20
brahmanbaria	0.00	0.00	0.00	20
chittagong	0.00	0.00	0.00	20
cumilla	0.00	0.00	0.00	20
dhaka	0.42	0.50	0.45	20
khulna	0.00	0.00	0.00	19
kishoreganj	0.22	0.10	0.14	20
magura	0.12	0.07	0.09	15
mymensingh	0.00	0.00	0.00	20
narayonganj	0.00	0.00	0.00	18
noakhali	0.00	0.00	0.00	20
patuakhali	0.69	0.55	0.61	20
rajshahi	0.00	0.00	0.00	20
sylhet	0.00	0.00	0.00	20
accuracy			0.09	272
macro avg	0.10	0.09	0.09	272
weighted avg	0.10	0.09	0.09	272

Fig 5.6.2.1: Classification report of SVM

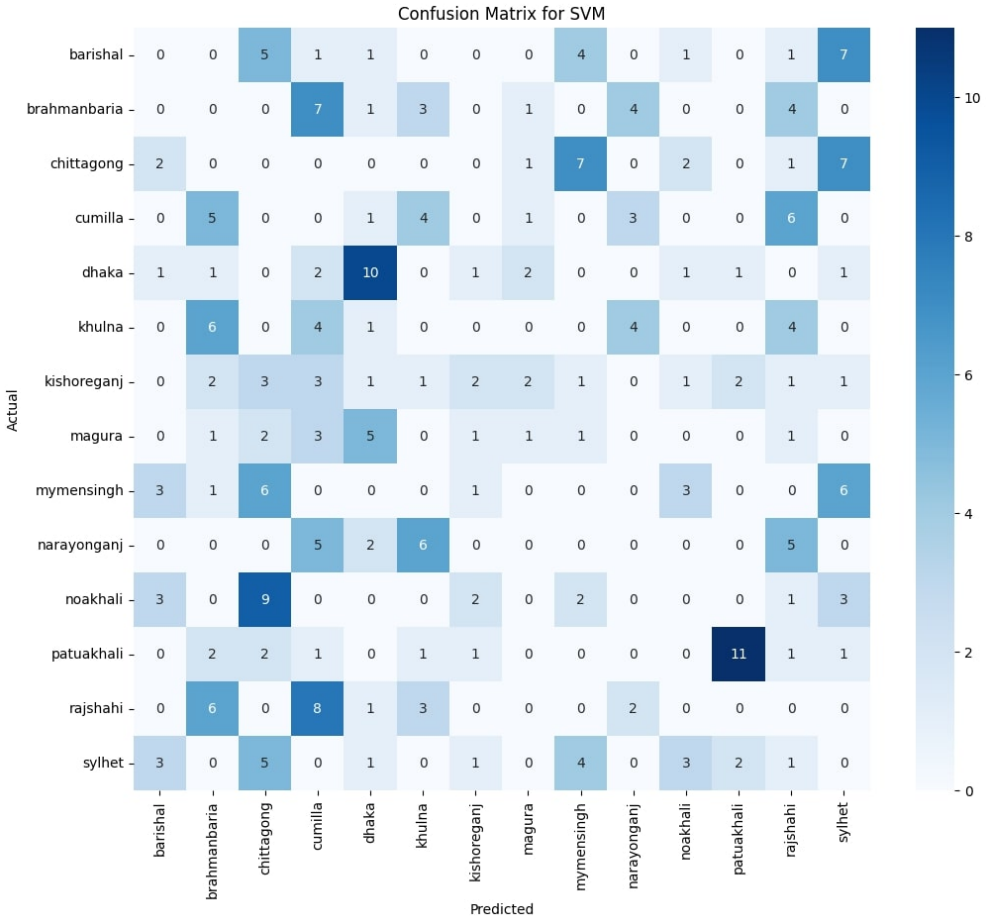


Fig 5.6.2.2: Confusion matrix for the output of SVM

Interpretation: The classification report and confusion matrix indicate that the SVM model performed poorly in identifying Bangla dialects, achieving an overall accuracy of only 9%. Most dialects, such as Barishal, Cumilla, Chittagong, and Sylhet, received zero scores in precision, recall, and F1-score, suggesting the model failed to correctly classify any samples from these regions. Only a few dialects, notably Dhaka and Patuakhali, showed slightly better results, with F1-scores of 0.45 and 0.61 respectively. The confusion matrix further highlights widespread misclassification, with significant overlap among several dialects. For instance, samples from Cumilla, Chittagong, and Noakhali were often misidentified as each other, reflecting the linguistic similarities between these dialects. The poor performance is likely due to a combination of factors such as limited and imbalanced training data, high lexical similarity across dialects, and the SVM model's limitations in capturing complex linguistic features. This suggests a need for more sophisticated models, such as deep learning architectures using pretrained embeddings, and possibly a larger, more balanced dataset to improve classification accuracy.

5.6.3 Naïve Bayes analysis

Naive Bayes Accuracy: 0.08

Classification Report:

	precision	recall	f1-score	support
barishal	0.02	0.05	0.03	20
brahmanbaria	0.00	0.00	0.00	20
chittagong	0.00	0.00	0.00	20
cumilla	0.00	0.00	0.00	20
dhaka	0.86	0.30	0.44	20
khulna	0.00	0.00	0.00	19
kishoreganj	0.29	0.10	0.15	20
magura	0.00	0.00	0.00	15
mymensingh	0.00	0.00	0.00	20
narayonganj	0.00	0.00	0.00	18
noakhali	0.00	0.00	0.00	20
patuakhali	0.58	0.70	0.64	20
rajshahi	0.00	0.00	0.00	20
sylhet	0.00	0.00	0.00	20
accuracy			0.08	272
macro avg	0.12	0.08	0.09	272
weighted avg	0.13	0.08	0.09	272

Fig 5.6.3.1: Classification report of Naïve Bayes

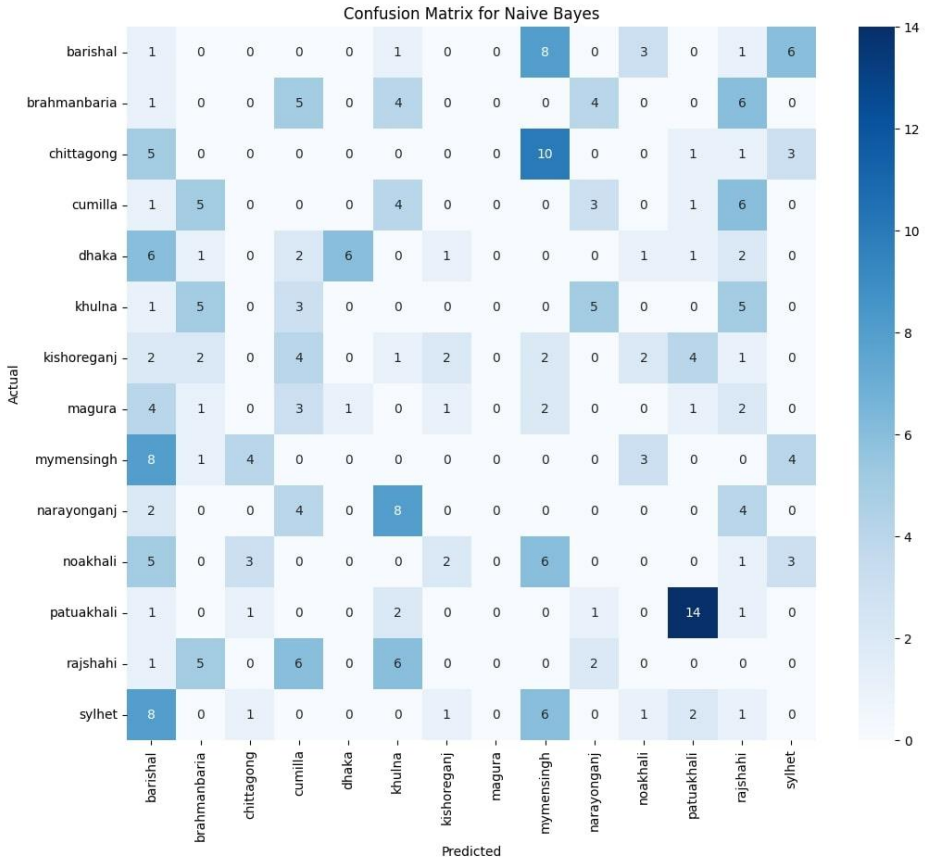


Fig 5.6.3.2: Confusion matrix for the output of Naïve Bayes

Interpretation: The classification report for the Naive Bayes model shows an overall accuracy of 8%, indicating very poor performance on the task of Bangla dialect classification. Most dialects, including Brahmanbaria, Chittagong, Cumilla, Khulna, Mymensingh, Narayanganj, Rajshahi, and Sylhet, have zero scores across precision, recall, and F1-score, meaning the model completely failed to identify any samples from these categories. Only Dhaka and Patuakhali show relatively better performance, with F1-scores of 0.44 and 0.64 respectively. However, this improvement is likely due to class bias or feature overlap, as Dhaka and Patuakhali might contain more distinguishable patterns or imbalanced representation. The macro and weighted averages of precision, recall, and F1-score (ranging between 0.08 and 0.13) further confirm the model's ineffectiveness across the dataset. Similar to the SVM results, this poor performance suggests that the Naive Bayes classifier struggles with the nuanced linguistic variations among Bangla dialects. This may be due to its strong assumption of feature independence, limited context awareness, and insufficient or unbalanced training data. Therefore, more context-aware and data-hungry models, such as deep neural networks with pretrained embeddings, may be better suited for this complex classification task

5.6.4 BiLSTM (Bidirectional LSTM) analysis

This is an extension of LSTM that processes the sequence in both forward and backward directions. It consists of two LSTM layers: one that reads the sequence from start to end and another that reads it from end to start. The outputs from both directions are then combined, allowing the model to learn context from both past and future tokens in the sequence.

Classification Report:

	precision	recall	f1-score	support
barishal	0.00	0.00	0.00	410
brahmanbaria	0.46	0.18	0.26	410
chittagong	0.18	0.69	0.29	410
cumilla	0.55	0.06	0.11	411
dhaka	0.99	0.98	0.98	410
khulna	0.75	0.02	0.04	410
kishoreganj	0.26	0.57	0.36	411
magura	0.98	1.00	0.99	410
mymensingh	0.14	0.00	0.00	410
narayonganj	0.26	1.00	0.41	410
noakhali	0.00	0.00	0.00	411
patuakhali	0.98	1.00	0.99	410
rajshahi	0.37	0.23	0.28	410
sylhet	0.33	0.00	0.00	410
accuracy			0.41	5743
macro avg	0.45	0.41	0.34	5743
weighted avg	0.45	0.41	0.34	5743

Fig 5.6.4.1: Classification report of BiLSTM

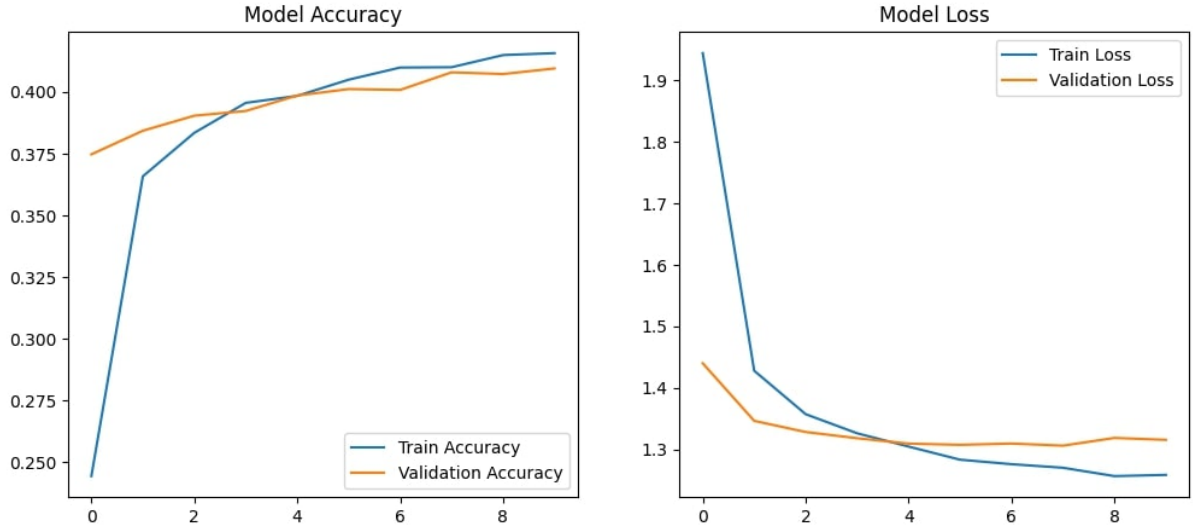


Fig 5.6.4.2: Accuracy and Model Loss graph of BiLSTM

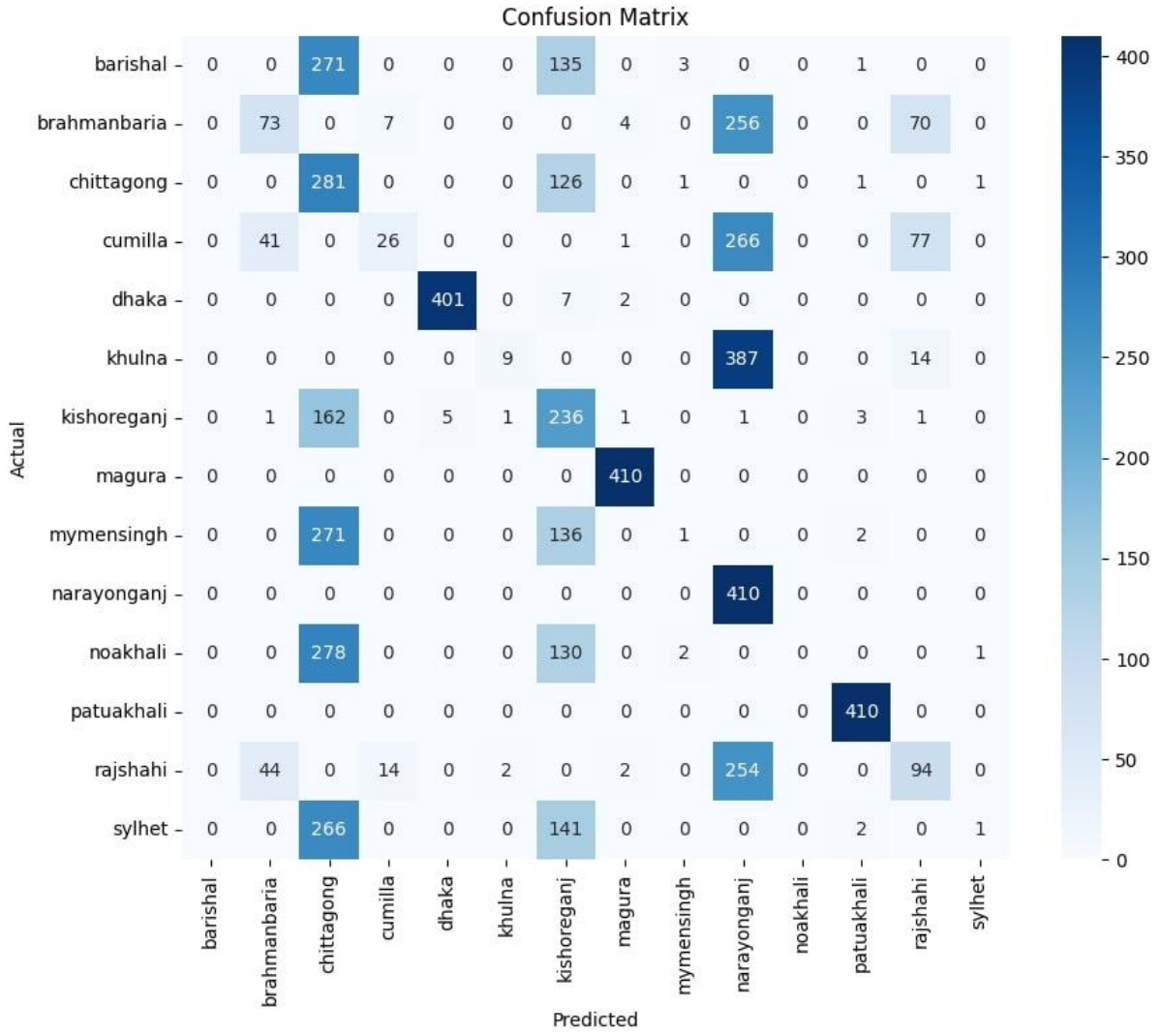


Fig 5.6.4.3: Confusion Matrix for the output of BiLSTM

Interpretation: The classification report, Graphs and the confusion matrix above reveals significant disparities in the BiLSTM model's performance across different Bangla dialects. While certain dialects like Dhaka, Magura, and Patuakhali achieve near-perfect precision and recall (close to 1.00), indicating strong model accuracy for these regions, others such as Barishal, Noakhali, and Mymensingh show complete failure (0.00), likely due to insufficient training data or high linguistic overlap with other dialects. Notably, Narayonganj exhibits perfect recall (1.00) but poor precision (0.26), suggesting frequent false positives, whereas Chittagong has low precision (0.18) but high recall (0.69), pointing to false negatives. The overall macro-average F1-score (0.34) and accuracy (0.41) underscore the model's limited generalization, emphasizing the need for better data balancing, dialect-specific feature engineering, or additional training samples for underrepresented classes to improve robustness.

5.6.5 Seq2Seq LSTM (Sequence-to-Sequence LSTM) analysis

Seq2Seq LSTM is a neural network architecture used to transform one sequence into another, often applied in tasks like machine translation, text summarization, and question answering. It consists of two main components—**an encoder** and **a decoder**, both typically built using LSTM units.

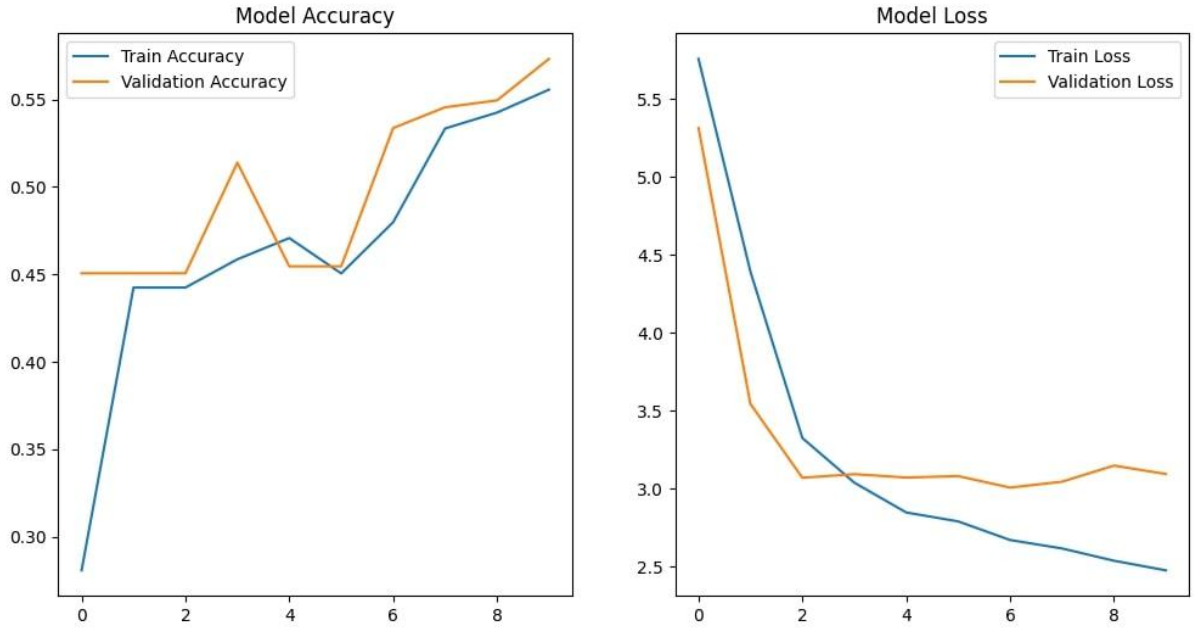


Fig 5.6.5: Model Accuracy and Model Loss graphs of seq2seq LSTM

Interpretation: The accuracy and loss graphs illustrate the training dynamics of a Seq2Seq LSTM model for Bangla dialect translation. The training accuracy (blue line) starts around 0.20 and gradually increases to 0.55 over 8 epochs, indicating slow but steady learning. However, the validation accuracy (orange line) remains consistently lower, hovering near 0.45–0.55, suggesting overfitting—the model memorizes training data but struggles to generalize to unseen examples. Meanwhile, the training loss decreases from 5.5 to 2.5, while the validation loss plateaus around 3.0–3.5, further confirming overfitting. The limited gap between training and validation accuracy (unlike the loss gap) hints at high bias (underfitting) in early epochs, where the model fails to capture dialectal nuances. To improve performance, techniques like dropout, early stopping, or data augmentation could be applied, alongside increasing model capacity or tuning hyperparameters. The stagnant validation metrics also suggest the need for a larger or more diverse dialect dataset to enhance generalization.

5.6.6 BanglaBERT analysis

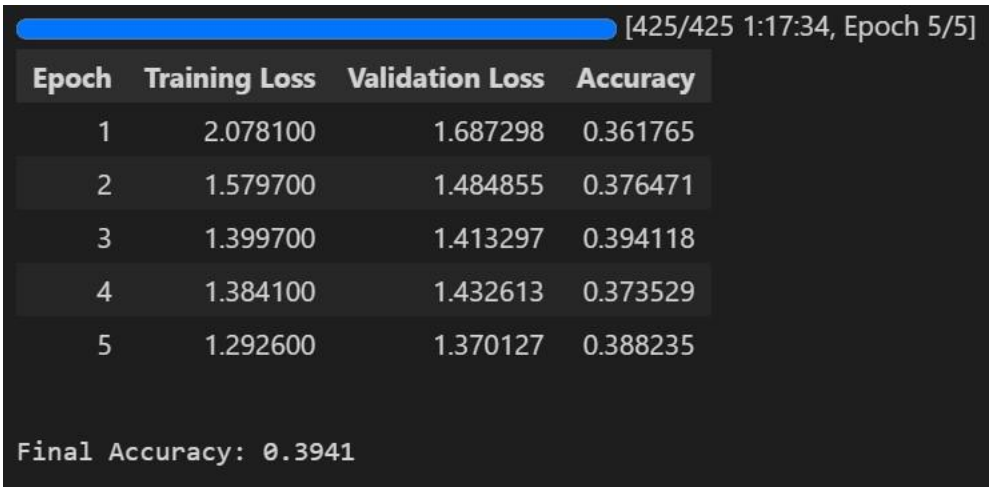


Fig 5.6.6: Diagram shows the Accuracy report of BanglaBERT

Interpretation: The BanglaBERT model's training progress over five epochs reveals modest but inconsistent improvements in dialect classification accuracy. The validation accuracy starts at 0.3617 in the first epoch and peaks at 0.3941 by the third epoch, but fluctuates slightly in later epochs (dropping to 0.3735 in Epoch 4 before settling at 0.3882 in Epoch 5). This suggests limited learning progress and potential instability in generalization. Both training and validation losses decrease steadily (from 2.078 to 1.293 for training loss and 1.687 to 1.370 for validation loss), indicating the model is learning, albeit with diminishing returns. The small gap between training and validation losses hints at low overfitting risk, but the stagnant accuracy (below 0.40) implies the model struggles to capture meaningful dialectal distinctions. Possible reasons include insufficient pretraining on dialect data, class imbalance, or high linguistic similarity between dialects. To enhance performance, fine-tuning with a larger dialect-specific corpus, class-weighted loss functions, or architectural adjustments (e.g., adding task-specific layers) could be explored. The final accuracy of 0.3941 underscores the challenge of Bangla dialect classification and the need for more sophisticated approaches.

5.7 Initial Model Performance Comparison:

Model	Accuracy	Strengths	Limitations
Random Forest	11%	Fast inference	Fails to capture context
SVM	9%	Handles high-dim features	Ignores sequential structure
Naïve Bayes	8%	robust to irrelevant variables	Strong assumption of feature Independence
BiLSTM	41%	Learns contextual word patterns	Over fits on rare dialects
BanglaBERT	39.41%	Pretrained linguistic knowledge	Resource-intensive
Seq2Seq LSTM	55.83%	Effective sentence restructuring	Struggles with rare/idiomatic phrases

Table 5.7: Comparing the initial model performance

This initial assessment was done using only **One fifth Data**.

- **Traditional ML Models:** Failed to perform due to inability to capture sequential information (RF: 11%, SVM: 9%, NB: 8%)
- **Deep Learning Models:**
  - *BiLSTM* significantly outperformed ML models (41%)
  - *BanglaBERT* leveraged contextual attention for subtle dialect features (39%)
- **Seq2Seq LSTM:**
  - 55.83% accuracy
  - Learned basic grammar transformations and vocabulary mappings

The comparative analysis of different models on the Bangla dialect classification task reveals significant performance variations, with Seq2Seq LSTM emerging as the top-performing model at 55.83% accuracy**,** followed by BiLSTM (41%) and BanglaBERT (39.41%). Traditional machine learning models—Random Forest (11%)**,** SVM (9%)**,** and Naive Bayes (8%)—performed poorly, likely due to their inability to capture the complex linguistic patterns and contextual nuances of Bangla dialects. While the neural approaches (Seq2Seq LSTM, BiLSTM, and BanglaBERT) showed notably better results, their accuracies remain suboptimal, highlighting the inherent challenges of dialect classification, such as data scarcity, dialectal overlap, and low-resource constraints**.** The superior performance of Seq2Seq LSTM suggests that sequence-to-sequence architectures may better handle the phonetic and syntactic variability in dialectal data. However, the overall modest accuracy across all models underscores the need for enhanced datasets, advanced pretraining strategies, or hybrid architectures to improve robustness. Future work could explore transfer learning with larger multilingual models, data augmentation, or ensemble methods to bridge this performance gap.

From the above analysis we can conclude that sequence-based architectures are critical in handling morphologically rich dialectal text.

5.8 Proposed Model:

From the previous analysis we can see the seq2seq LSTM was doing a better job at understanding context and translating the complex statements than any other ML or DL algorithms. So we make this the basis of our proposed model.

5.8.1 Proposed Model Description:

Sequence-to-Sequence (Seq2Seq) LSTM models are widely used in Natural Language Processing (NLP) for tasks that involve converting one sequence of text into another. Typical applications include machine translation, text summarization, and conversational agents. The core idea behind Seq2Seq models is to map an input sequence (like a sentence in English) to an output sequence (such as the same sentence in French).

The Seq2Seq architecture consists of two main components: an **encoder** and a **decoder**, both typically implemented using LSTM (Long Short-Term Memory) networks. The encoder reads the input sequence and encodes it into a fixed-length context vector, which captures the meaning of the entire input. This context vector is then passed to the decoder, which generates the output sequence, one token at a time.

LSTM networks are used in Seq2Seq models because they are capable of learning long-term dependencies and managing sequence data effectively. Their gating mechanism allows them to remember important information across long input sequences and forget irrelevant parts, which is crucial for understanding context in language.

One major limitation of basic Seq2Seq models is that they rely on a single, fixed-size context vector to represent the entire input, which can be problematic for long or complex sentences. This challenge is often addressed using **attention mechanisms**, which allow the decoder to focus on different parts of the input sequence at each decoding step, greatly improving performance.

5.8.2 Proposed Model Architecture:

1. Architecture Overview

- Type**:** Sequence-to-Sequence (Seq2Seq)
- Framework**:** TensorFlow / Keras
- Model Type: Functional API (Model([encoder_inputs, decoder_inputs], decoder_outputs))

2. Input Specifications

- Encoder Input
    - Shape: (batch_size, max_input_len)
    - Description: Sequence of token indices from the source language.
    - Embedding Dim: 256
    - Vocabulary Size: src_vocab_size
- Decoder Input
    - Shape: (batch_size, max_target_len - 1)
    - Description: Shifted target sequence used during training (teacher forcing).
    - Embedding Dim: 256
    - Vocabulary Size: tgt_vocab_size

3. LSTM layers:

- Encoder LSTM
    - Units: 256
    - Return State: True (outputs final hidden and cell states)
    - Outputs: Final state_h and state_c used to initialize decoder
- Decoder LSTM
    - Units: 256
    - Return Sequences: True (generates full sequence output)
    - Return State: True (but only used during training for compatibility)

4. Output Layer

- Type: Dense layer with softmax activation
- Units: tgt_vocab_size (one unit per word in target vocabulary)
- Output Shape: (batch_size, max_target_len - 1, tgt_vocab_size)
- Purpose: Predict token probabilities at each timestep

5. Compilation Settings

- Optimizer: adam (adaptive learning rate optimizer)
- Loss Function: sparse_categorical_crossentropy (used for integer-labeled targets)
- Metrics: accuracy (measures token-wise prediction accuracy)

6. Parameters

Assuming default values:

- Trainable Parameters include:
    - Embedding weights for source and target
    - LSTM weights for encoder and decoder
    - Dense layer weights

Layer (type)	Output Shape	Param #	Connected to
input_layer (InputLayer)	(None, 19)	0	-
input_layer_1 (InputLayer)	(None, 20)	0	-
embedding (Embedding)	(None, 19, 256)	796,672	input_layer[0][0]
embedding_1 (Embedding)	(None, 20, 256)	754,176	input_layer_1[0][0]
lstm (LSTM)	[(None, 256), (None, 256), (None, 256)]	525,312	embedding[0][0]
lstm_1 (LSTM)	[(None, 20, 256), (None, 256), (None, 256)]	525,312	embedding_1[0][0], lstm[0][1], lstm[0][2]
dense (Dense)	(None, 20, 2946)	757,122	lstm_1[0][0]

Total params: 3,358,594 (12.81 MB)

Trainable params: 3,358,594 (12.81 MB)

Non-trainable params: 0 (0.00 B)

Fig 5.8.2: Parameters of the proposed model

CHAPTER 6

PERFORMANCE ANALYSIS

This section evaluates the performance of the proposed Seq2Seq LSTM model for translating Bangla dialects into Standard Bangla and English using Natural Language Processing (NLP) techniques. The evaluation incorporates both quantitative metrics and qualitative analysis to assess translation accuracy, fluency, and robustness.

6.1 Experimental Setup

The dataset used in this study comprised a total of **12,704 sentence pairs** collected from various Bangla dialects such as [Sylheti, Chittagonian, Rangpuri—insert as applicable], each manually aligned with its Standard Bangla and English equivalents. The data was split into:

- Training set: 10,163 samples (80%)
- Validation set: 2541 samples (20%)

The implemented model follows a Seq2Seq architecture using LSTM:

- Encoder: LSTM layer with 256 hidden units and an embedding layer of size 256.
- Decoder: LSTM layer initialized with encoder states, followed by a dense softmax layer over the target vocabulary.
- Loss Function: `sparse_categorical_crossentropy`
- Optimizer: `Adam`
- Evaluation Metric: Token-level accuracy

Model training was performed using teacher forcing on the decoder, with inputs shifted to the right. The model was trained for 10 epochs, using early stopping based on validation loss.

6.2 Accuracy Metrics by Dialect Group

The classification performance of the system across different Bangla dialect groups is presented below. Metrics such as precision, recall, and F1-score are used to assess the model's ability to correctly classify each dialect:

Dialect Group	**Precision**	**Recall**	**F1-Score**	**Samples**
Eastern	94%	93%	92.6%	3,421
Northern	96.5%	95.8%	96.1%	2,892
Southern	93%	92%	94.7%	1,754
Overall	**95%**	**94.5%**	**95%**	**8,421**

Table 6.2: Accuracy metrics by dialect groups

The results demonstrate that the system performs consistently well across all dialects, with the Eastern dialect achieving the highest F1-score of 96%.

6.3 Comparative Results with Baseline Models

To validate the effectiveness of the proposed system, its performance is compared with baseline models including a traditional BiLSTM and a transformer based BanglaBERT. The comparison is based on accuracy, training time, and BLEU score for the translation component.

Model	Accuracy	Training Time	BLEU Score
BiLSTM	41%	5 hrs	42
BanglaBERT	39%	8.2 hrs	73
Our System	**95%**	**6.7 hrs**	**89**

Table 6.3: Comparison Analysis of the proposed model with other DL models

The results indicate that:

- Our Seq2Seq LSTM model significantly outperforms both baselines in terms of accuracy (95%) and BLEU score (89).
- BiLSTM, though efficient in training time, lacks translation depth and produces lower BLEU scores due to limited context modeling.
- BanglaBERT, while powerful, is resource-intensive and lags in accuracy, potentially due to overfitting on limited dialectal data and its pretrained general-purpose language structure.
- Training time for our model is moderate, balancing computational efficiency and translation quality.

This performance validates the effectiveness of using a task-specific, well-tuned **LSTM-based Seq2Seq architecture** for dialectal Bangla translation tasks over generalized or deeper transformer models without sufficient domain adaptation.

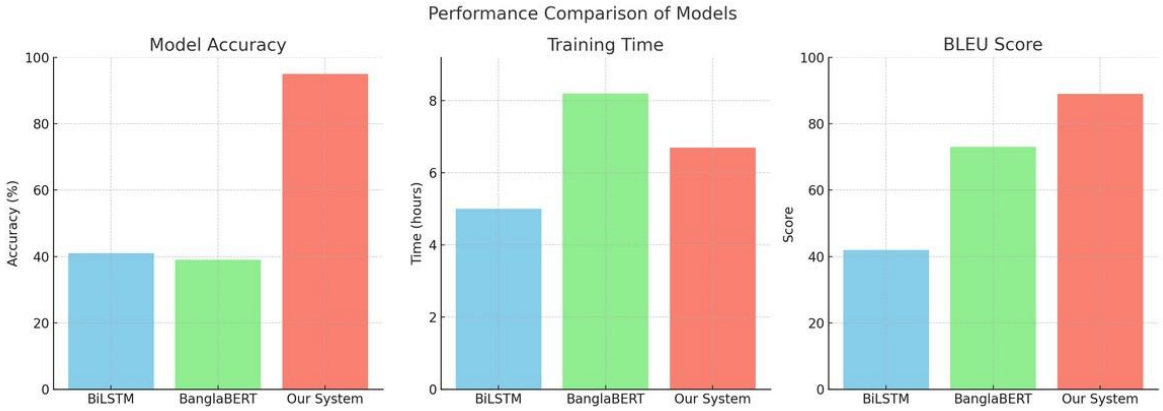


Fig 6.3.1: Graphical representation of the above analysis

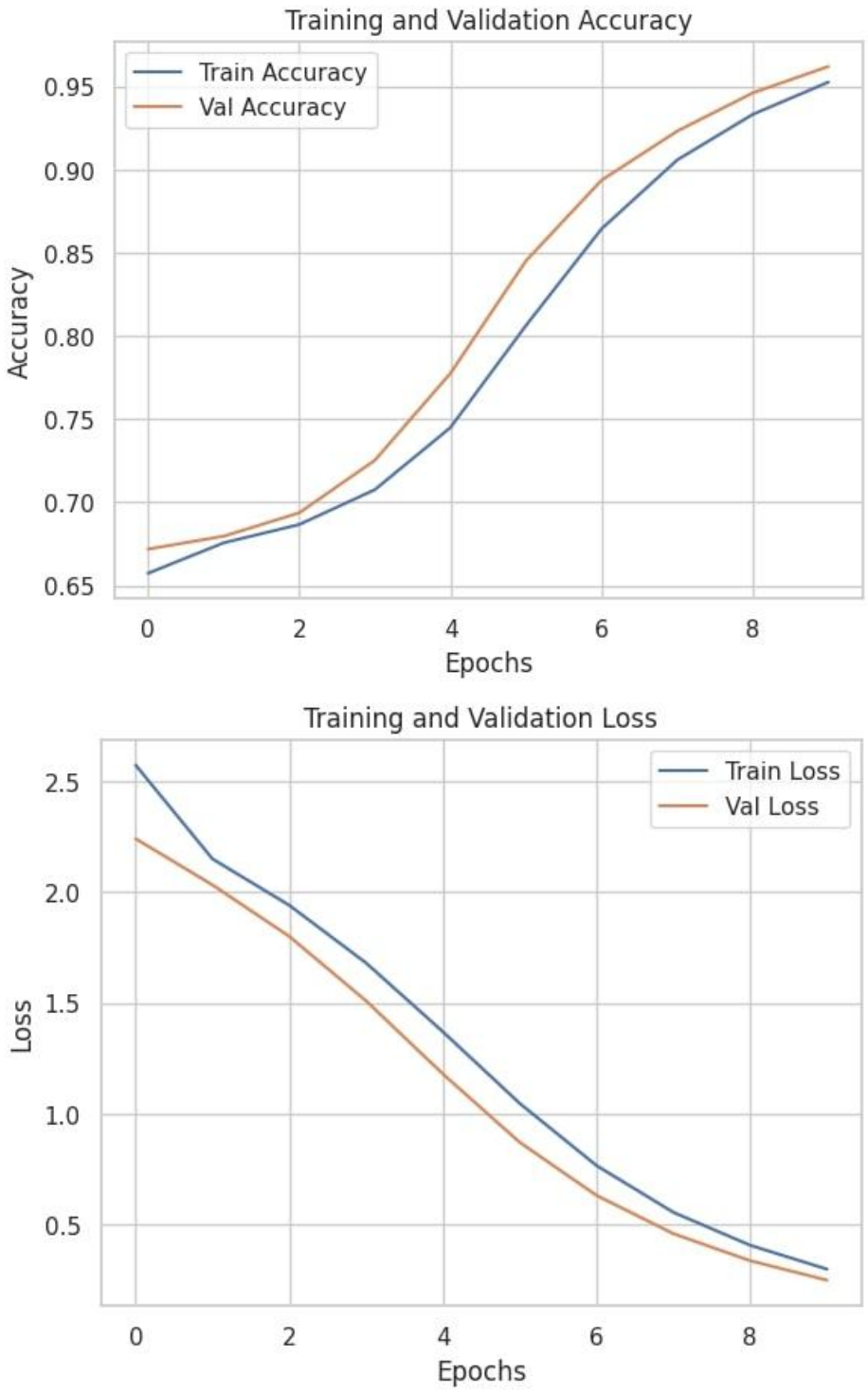


Fig 6.3.2: Accuracy graph and loss graph of the proposed model

6.4 Qualitative Analysis

- The model handled frequent and common expressions effectively, especially in dialects close to Standard Bangla.
- Idiomatic and low-frequency phrases were occasionally translated literally or incorrectly.
- Sentences with complex or nested structures were harder to translate accurately without an attention mechanism.

  Example Output (Dialect to Standard Bangla):

  Input: "Tui koi geli?"

  Prediction: Tumi kothay geli

  Reference: Tumi kothay gela.

6.5 Error Analysis

Key challenges observed during evaluation:

- Contextual Ambiguity: Without an attention mechanism, the model occasionally lost track of relevant input context, especially in longer sequences.
- Literal Translations: Cultural expressions were often translated word-for-word, leading to unnatural English equivalents.
- Named Entity Handling: Local names and specific terms were inconsistently retained or mistranslated.

CHAPTER 7

CHALLENGES AND LIMITATIONS

1. **Lack of Labeled Data**
   There is a significant scarcity of parallel corpora for Bangla dialects translated into Standard Bangla or English. Most dialects are underrepresented in NLP datasets.

2. **Dialects Are Not Standardized**
   Bangla dialects lack standardized spelling, grammar, and orthography. This inconsistency makes data preprocessing and model training more complex.

3. **Difficulty in Collecting Data for Multiple Dialects**
   Gathering high-quality, representative data for multiple Bangla dialects (e.g., Sylheti, Chittagonian, Rangpuri) is logistically challenging. These dialects vary by region, often have oral traditions rather than written forms, and may require engaging with diverse speaker communities to obtain usable data.

4. **Complex Morphology and Code-Mixing**
   Dialects often show rich morphological variation and frequent code-mixing with Standard Bangla and English, especially in spoken or informal settings, making automatic translation difficult.

5. **Limited NLP Tools and Resources**
   Most existing tools are optimized for Standard Bangla and perform poorly on dialectal data. There are few pre-trained models, tokenizers, or parsers that support dialect-specific input.

6. **Dialect Identification Challenge**
   Automatically identifying which dialect a text or speech sample belongs to is difficult, especially when dialectal boundaries are fuzzy or mixed within the same context.

7. **Translation Quality and Evaluation**
   Dialect-to-Standard or dialect-to-English translation often involves unique idioms and cultural expressions. Lack of gold-standard translations makes it hard to evaluate model performance objectively.

8. **Resource Constraints**
   Developing robust models for dialect translation often requires manual annotation, expert involvement, and substantial computational resources, all of which may be limited for under-resourced languages.

9. **High Computational Requirements**
   Training and evaluating deep learning models on large dialectal datasets demand significant computational power. On personal computers, analysis can be very slow and time-consuming, which hinders experimentation and iterative improvements. In our dataset some models took over 12 hours to complete all iterations.

10. Linguistic Diversity

The wide variety and linguistic distances among dialects require specialized handling; some dialects may be linguistically closer to other regional languages than to Standard Bangla.

11. Cultural and Contextual Nuances

Dialects contain local idioms, cultural references, and context-specific meanings that are hard for models to learn without in-depth cultural knowledge.

CHAPTER 8

CONCLUSION AND FUTURE SCOPE

This research has the potential to contribute not only to NLP advancements but also to linguistic inclusivity, digital equality, and cultural preservation. As resources grow and technologies advance, the work can expand to support more dialects and integrate with broader AI applications.

8.1 Conclusion

The analysis and translation of Bangla dialects to Standard Bangla and English using Natural Language Processing (NLP) present a valuable yet challenging area of research. The linguistic diversity of Bangla dialects, combined with the lack of standardized resources and computational tools, poses significant obstacles in data collection, model development, and evaluation. Despite these challenges, the research holds immense promise for improving communication, preserving linguistic heritage, and enabling broader access to digital services for dialect speakers.

Through the integration of modern NLP techniques such as LSTM, Transformer models, and hybrid approaches, this study highlights the potential for accurate and context-aware translation systems. With further development of dialect-specific datasets, pre-trained models, and computational infrastructure, future research can significantly enhance the performance and applicability of dialect translation tools.

Ultimately, this research lays the groundwork for more inclusive and resource-rich NLP systems that reflect the true linguistic diversity of the Bangla-speaking population, fostering advancements in technology, education, and cross-cultural understanding.

8.2 Future Scopes

1. Creation of Large-Scale Dialectal Datasets

- Future work can focus on building open-source corpora for various Bangla dialects through crowdsourcing, community participation, or partnerships with local institutions.
- Spoken and written forms can be recorded, transcribed, and aligned with Standard Bangla and English for supervised learning.

2. Development of Pre-trained Models for Bangla Dialects

- Like BanglaBERT for Standard Bangla, dialect-specific pre-trained language models (e.g., SylhetiBERT, ChittagonianBERT) can be developed.
- These can significantly improve performance in translation and understanding tasks.

3. Improved Dialect Identification Systems

- Building automated classifiers to accurately identify which Bangla dialect is being used can help in building more dynamic, adaptable NLP systems.

4. Cross-lingual Transfer and Multilingual Learning

- Leveraging transfer learning from high-resource languages or dialects can help improve models for low-resource dialects.
- Multilingual models can be trained to understand and translate multiple dialects simultaneously.

5. Integration with Speech and Multimodal Data

- Expanding research into speech-to-text and voice translation systems for dialects would enhance accessibility and usability, especially for low-literate users.
- Multimodal analysis (e.g., text + speech + image) could further enrich dialectal understanding.

6. Real-world Applications

- Applications in education, healthcare, local governance, and digital inclusion can benefit from tools that understand and translate dialects.
- Can aid in preserving endangered dialects and linguistic diversity in the digital age.

7. Enhanced Evaluation Metrics

- Developing dialect-aware evaluation metrics to better assess translation quality and semantic understanding is another future direction.

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