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Prokash: Introducing an Effective Approach for Bengali Fake News Detection

by

Md Abrar Saief Safat (203014020)
Sabreena Islam Khan (203014001)
Humayera Hedayet (203014024)
Jason D Costa (211014011)

9 *Capstone project report (CSE 4098C) submitted in partial fulfillment of the requirements for the degree of*

Bachelor of Science in Computer Science and Engineering

Under the supervision of

Suravi Akhter

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

UNIVERSITY OF LIBERAL ARTS BANGLADESH

SPRING 2025

DECLARATION

Project Title	Prokash: Introducing an Effective Approach for Bengali Fake News Detection
Authors	*Md Abrar Saief Safat*, *Sabreena Islam Khan*, *Humayera Hedayet* and *Jason D Costa*
Student IDs	203014020, 203014001, 203014024 and 211014011
Supervisor	Suravi Akhter

We declare that this capstone project report entitled *Prokash: Introducing an Effective Approach for Bengali Fake News Detection* is the result of our own work except as cited in the references. The capstone project report has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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Date: May 12, 2025

Department of Computer Science and Engineering
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APPROVAL OF THE COMMITTEE

This is to certify that the CSE 499B capstone project report entitled **Prokash: Introducing an Effective Approach for Bengali Fake News Detection**, submitted by **Md Abrar Saief Safat** (203014020), **Sabreena Islam Khan** (203014001), **Humayera Hedayet** (203014024) and **Jason D Costa** (211014011) are undergraduate students of the **Department of Computer Science and Engineering** has been examined. We hereby accord our approval of it as the presented work is satisfactory.

Place: Dhaka
Date: May 12, 2025

Suravi Akhter
Lecturer

Rubaiya Hafiz
Senior Lecturer and Coordinator

Nazifa Tasnim Hia
Lecturer

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Finally, we would like to thank all the people who have supported us to complete the project work directly or indirectly.

Md Abrar Saief Safat, *Sabreena Islam Khan*, *Humayera Hedayet* and *Jason D Costa*
University of Liberal Arts Bangladesh
Date: May 12, 2025

Dedicated to
my loving family.

– Md Abrar Saief Safat

Dedicated to
my bro Ehasan
Thank you for being a big help.

– Sabreena Islam Khan

Dedicated to
my Father
Thank you for being my support.

– Humayera Hedayet

Dedicated to
my Nana
Thank you for staying.

– Jason D Costa

ABSTRACT

Fake news possesses significant harm for individuals or whole nations depending on the severity of the fabricated news. Such news tend to have motives of sorts, let it be political or social, but they are always fabricated to influence the mass or a small crowd. Over the years fake news detection has seen significant researches done for the English language or similar popular languages but not Bengali language. The complexity of Bengali language and limited availability of labeled data hinder the progress in this area. We propose a Bidirectional LSTM model hybridized with DistilBERT, a transformer architecture, which is tailored to address those challenges. By using the deep learning techniques, our final hybridized model, trained and validated on the BanFakeNews dataset, has exhibited a validation accuracy of 93.30 %, precision of 92.7%, recall of 99.47%, and F1-score of 95.97% This project aims to expand the research landscape of fake news detection in the Bengali language and provide valuable insights for combating misinformation in low-resource linguistic contexts.

Keywords: Fake news detection, Bengali, Natural language processing, NLP,Bengali Fake News, Machine Learning, Deep Learning, BERT, DistilBERT, BiLSTM,Bidirectional LSTM.

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Chapter 1

Introduction

Fake news refers to stories that are not true or misleading and yet made to look like news, usually with the intention to deceive. A variety of news content is made to confuse, monetize, or change the thinking of any number of people in different ways- politically or socially. It usually tends to go viral in major events, crises, or significant sets of periods, such as elections and pandemics, when people especially need information and may be more liable to pass on items without checking their authenticity.

Social media platforms further contribute to this through their algorithmic mechanisms. The source of this news should be found and stopped to prevent the people from being misled. It creates quite a lot of confusion, panic, and poor decisions made among the citizens over election day or about some other concerned factors. Besides, fake news demolishes trust in reliable sources of information. For that reason, the methods for finding out and fighting misinformation should be
2 devised to preserve unity in society. A lot of research has been conducted on fake news detection through the English language. However, the Bengali language has received less attention even though this language has more than 250 million
30 Bengali speakers globally. Traditionally, news media detect fake news through the content of the news alone which is a major limitation as it does not accurately detect the fake news. Including extra details like the origin of the news, how it spreads, and related context can improve the ability to identify fake news more effectively. As news content continues to influence public opinion, especially through online platforms, it is increasingly important to develop smarter detection methods that are well-suited to the specific features of the Bengali language. Filling this research

51 gap could play a vital role in reducing the circulation of misleading information among Bengali-speaking audiences.

1.1 Problem statement

65 The rise of social media has made fake news a significant issue, but while much
79 research focuses on detecting fake news in English and other major languages, Bengali fake news detection is underexplored. Current models often fail to capture Bengali linguistic nuances, leading to poor accuracy. A proposed hybrid model combining DistilBERT (a lightweight transformer) with Bidirectional LSTM, optimized through Grid Search, aims to improve detection by leveraging both contextual and sequential text features, enhancing accuracy and reducing misclassification.

9 1.2 Aims, objectives and Motivation

1.2.1 Aims

The aim of this project is to develop a hybrid deep learning model that integrates
39 DistilBERT with Bidirectional LSTM (BiLSTM) to classify Bengali news articles as fake or real. We will use Grid Search to optimize the model in order to deal with the challenges of having limited resources, complex language structure, and a shortage of annotated Bengali data.

1.2.2 Objective

- **Dataset Preparation and Pre-processing:** Clean the data set, irrelevant characters and noise by using Bangla specific tool (BNLP).
- **Model Development:** Include DistilBERT for contextual embedding as well as BiLSTM for sequence modeling. Use Grid Search in order to find the best hyperparameter (learning rate, batch size, activation functions, etc).
- **Model Training:** Train the hybrid model with an even dataset through some
8 validation techniques. Evaluate the model using Accuracy, Precision, Recall, F1-score, and ROC-AUC.

- **Final Model Validation and Analysis:** Perform error analysis to identify common misclassifications and analyze confusion matrix results.

1.2.3 Motivation

25 The detection of fake news in Bengali is vital in light of increasing online news consumption and widespread social media use among Bengali-speaking populations. Despite substantial research in English and other global languages, Bengali remains underrepresented in NLP-based misinformation detection. This lack of attention leaves Bengali readers more exposed to disinformation, especially during political unrest or national crises. Our motivation lies in bridging this research
141 gap by developing a hybrid deep learning model that combines DistilBERT and BiLSTM—an approach proven effective for capturing both contextual meaning and sequential dependencies. The integration of Grid Search further ensures optimal performance through fine-tuning. DistilBERT's multilingual capacity and lighter architecture make it especially suitable for low-resource languages like Bengali, offering reduced computational cost without sacrificing performance. Through
113 complex engineering tailored for Bengali, we aim to provide a practical tool for researchers and developers focused on misinformation mitigation. This project contributes not only to technical innovation but also to societal well-being by promoting trustworthy information dissemination in the Bengali digital ecosystem.

Chapter 2

Background Study

18

2.1 Natural Language Processing (NLP)

159 Natural language processing and NLP are the terms used for the intersection of computer science, artificial intelligence and language studies. It facilitates understanding, application and production of human language in a logical and useful manner in computers. Natural language processing (NLP) has become an important approach of learning and automating such tasks as analysis of texts, and translation of languages, given the increasing amount of text from the web-sites, social media, etc.

66

2.2 Machine learning (ML)

A branch of artificial intelligence (AI), seeks to train computers and other machines
152 to replicate human learning, perform tasks independently and improve over time
155 and with more information.Thus we used machine learning to detect Bangla fake
36 news detection. Alnabhan & Branco (2024) systematically surveys Deep Learning techniques applied in the context of Functional neurological disorder (FND).

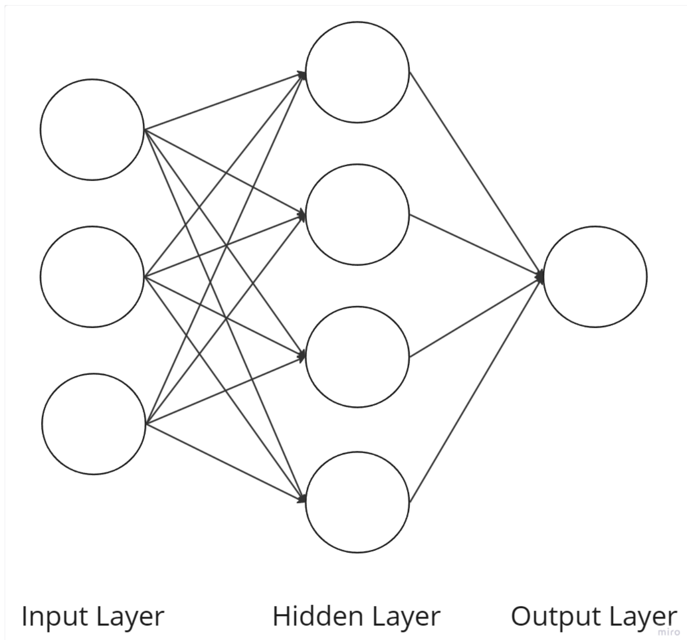
153

2.3 Deep Learning (DL)

26 According to LeCun et al. (2015), Deep learning is a subset of machine learning that uses multilayered neural networks, called deep neural networks, to simulate the complex decision-making power of the human brain. Nowadays artificial intelligence (AI) applications depend on deep learning in one way or another.

116 ## 2.4 Neural Networks (NN)

63 Neural network is the machine learning model based on the human brain. It comprises interconnected nodes (neurons) arranged in layers; that process and learn from data. Neural networks are applied in such activities as image recognition, language processing, predictions finding patterns and relationships in input data, as defined by Schmidhuber (2015).



57 Figure 2.1: A simple Neural Network

57 ## 2.5 Bidirectional Encoder Representations from Transformers(BERT) and DistilBERT

125 BERT is built upon the transformer framework and designed to process sequential
7 data that is text. It contains a layer of self-attention mechanisms which allow it to capture high dependencies between words within a text.By the definition of
7 Devlin et al. (2019), BERT is a bidirectional model which can take into account left or right context when making predictions. This is of help, as it enables BERT to
147 comprehend words of sentences in context and meaning. BERT can also be fine
7 tuned to perform a particular long term NLP tasks, such as sentiment analysis or

named entity recognition by training on a smaller, labeled dataset. Fine-tuning allows BERT to achieve state-of-the-art performance on a wide range of NLP tasks, even when training data is limited. Thus we decided to work with the BERT model to get better results.

33 DistilBERT is a distilled version of BERT that retains about 97% of BERT's language understanding capability while being 40% smaller and 60% faster Tan & Bakır (2025).
75 In our project we used DistilBERT to convert raw text into numerical representations that a machine learning model can understand and learn from. The reason behind choosing this model is most of the meaning and language understanding that full BERT does in a faster way. Also it is faster training and lower memory model.

59 2.6 LSTM and Bi-LSTM

Long Short-Term Memory is an improved Recurrent Neural Network(RNN). We
41 have learned from an article by Sachinsoni (2024), it is excellent in long-term dependencies aspects of sequential data, LSTMs are suitable for operations such as
41 language translation. To address the challenge of learning long term dependencies LSTMs present a memory cell that stores information for longer periods while the usual RNN's have a single hidden state transmitted over time.

Input at present step (xt) is merged with information from previous step (ht-1) and (Ct-1). Inside the cell, there are parts, called "gates", which determine what to hold on, what to forget, and what new input to add. Forget gate chooses which old
46 information is to be discarded, the input gate decides what new information is to be remembered, output gate decides what to give out to the next step. These are decisions based on special functions (such as sigmoid and tanh) through which the values are balanced. At the end, the cell changes its memory and forwards fruitful information. This assists the model remember crucial things, despite how many steps back it was, so that's why LSTM is a perfect model for tasks such as language understanding.

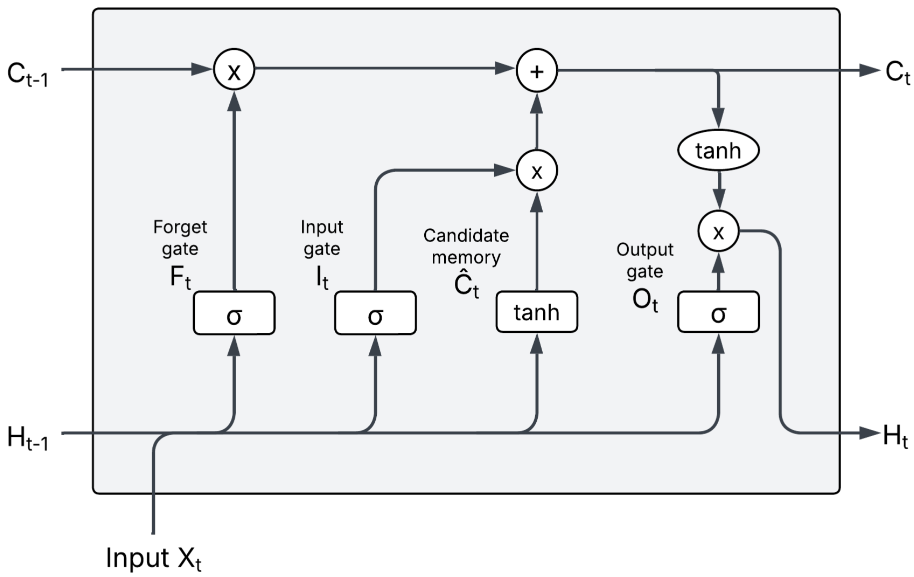


Figure 2.2: Internal operation illustration of a single LSTM unit

3 Bidirectional Long Short-Term Memory (BiLSTM) Is the enhanced version of LSTM. BiLSTMs are able to capture deeper contextual information since they allow input to flow in both forward and backward directions in contrast to traditional LSTMs with which only a sequence is analysed in one direction. Based on the information we gathered from Zohra (2025), we understood that BiLSTMs perform exceptionally well in cases where understanding of past as well as future context is important.

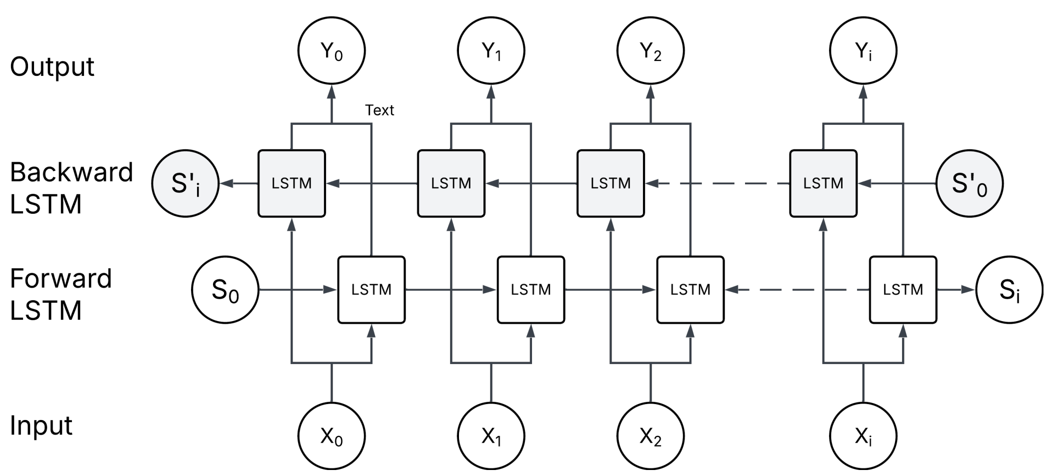


Figure 2.3: A Bi-LSTM layer architecture

2.7 Hyperparameter Optimization and Grid Search

Grid search seeks to optimize a model such that it has the best performance accomplished by setting optimal hyperparameter values that return the highest accuracy, lowest loss, and best validation metric, as defined by Malato (2024). A neural network node output is determined by an activation function. It makes the model
95 non linear, thus enabling it to learn complex patterns. ReLU (Rectified Linear Unit) will keep positive values. efficient and widely used. Sigmoid function returns values between 0 and 1; often used in binary classification. Grid search applies each of these functions in order to identify which function can be used by the model to learn best for the specific task. Then optimizer searches for the model weights, while training, to minimize the loss function. Grid search tests various optimizers to check the one delivering the fastest or most reliable convergence. Batch size is
43 the number of samples of training which model's internal parameters are changed after they are processed. A smaller batch size causes more noise but can generalize well, while the higher batch size is computationally efficient, but may overfit. Grid search is a systematic framework to optimize hyperparameters such as activation function, optimizer and batch size by exhaustive search within a set of possible combinations which is simple to apply and interpret.

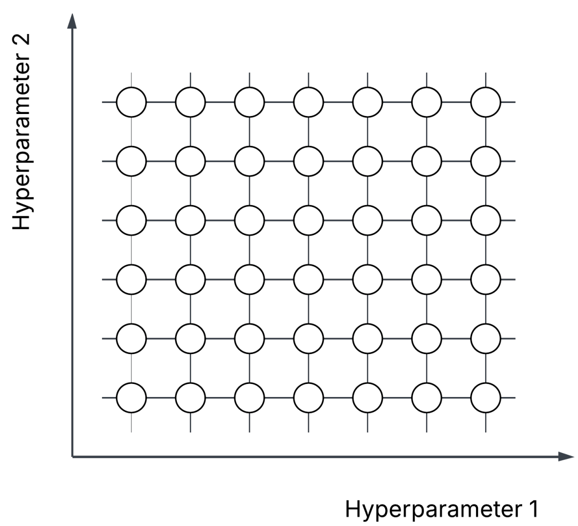


Figure 2.4: Grid Search

Chapter 3

Literature Review

Finding a lie falls into the field of text classification; it is more popularly known as
fake news detection activity. Examples slipping through human eyes can, however,
be identified by the NLP Classification model, Logistic Regression (LR) which
evaluates the truth behind news circulated on social media. The social media users
are exposed to a range of networking sites. According to Shivani et al. (2023),
Logistic Regression therefore, stands as the powerful procedure to counter binary
classification problems due to the estimation of probability values that could be
108 carried out. Later, this model achieved an accuracy rate of nearly 89 percent on the
test dataset; therefore, it works effectively with long as well as short input texts.
However, logistic regression also faces limitations when it comes to processing
complex structures and would require advanced models.

Today, fake news is a major problem, often caused by people who want to influ-
97 ence religious, political, financial or social beliefs. Mugdha et al. (2021) addresses
the challenge of detecting fake news in Bengali by creating a machine learning
solution that uses a Gaussian Naive Bayes classifier. The authors gathered their data
through the creation of a unique collection meant for spotting Bengali fake news.
The model uses TF-IDF to present the text and depends on Extra Tree for selecting
the most significant features which are the only ones considered in the training
151 process. In addition, the authors examine and compare several machine learning
algorithms and features, highlighting the performance of traditional approaches
140 in the field. The study furthers work on finding fake news in Bengali by using a
combination of prepared data, classical machine learning methods and feature engi-
neering. It points out that using language-specific ways to model data is important
for improving classification results in languages with limited resources.

Fake news detection is especially tough in Bangla since there are big differences between its linguistic features and those of regular study languages. To solve this issue, authors use machine learning approaches on Bangla fake news, using the structure of social media data to tell apart true and false stories. A range of traditional machine learning algorithms are examined by the authors, among them Random Forest, Decision Tree, Naive Bayes, Support Vector Machine (SVM) and K-Nearest Neighbors (KNN). The Random Forest algorithm was the best with the highest accuracy, proving it can manage large and detailed Bangla texts well. It seems that ensemble-based models such as Random Forest, perform well at detecting fake news in the Bangla language because they handle a wide range of features and situations strongly. By using classical machine learning methods, this study adds to the little existing literature on Bangla fake news detection, pointing out that this task is challenging in low-resource NLP environments because of language-specific problems.

Because of lockdown like those during COVID-19, Facebook has played an important role in educating people about the pandemic and news in general. Because of this, users may also be exposed to misleading health information. Even though Bengali is used by millions around the world, studies looking at fake news in Bengali related to COVID are still few. To solve this issue, Pranto et al. (2022) introduces machine learning models that are trained to detect fake news about COVID-19 in Bengali Facebook posts. Out of the examined models, BERT was found to have the highest accuracy, with an F1-score of 0.97 for detecting misinformation. Next, the study tests BERT on real data from Facebook and reveals ten main fake news themes, sorting them as related to false information (such as healthcare talks), beliefs (such as religion) or topics shared on social media (e.g., science and public conduct). This study improves the field by showing how transformers work well for Bengali fake news detection and providing a useful overview of misinformation categories that assist with narrowing down interventions. This study helps guide further efforts to find false details in news in languages that are not widely covered online.

The authors from M. M. Hossain et al. (2022) focus on tackling this issue by testing several ways to handle imbalanced data, using the BanFakeNews dataset as an example, where 97% of the instances are from the majority class. Both data processing methods including SMOTE and algorithms such as Stacked Generalization, are used by the authors to tackle the problem of biased models from class imbalance. By including SMOTE, the researchers were able to improve model performance, achieving an F1-score of 93.1%, but without, the model achieved an F1-score of 79.1%. Without these new techniques, the baseline models gave a lower 67.6% F1-score, proving that handling imbalance is essential in making the best training models. This work demonstrates that, by carefully processing data imbalance and using advanced ensemble methods, it is possible to increase the accuracy and reliability of fake news detection models used for Bangla content.

In this paper by Al Imran et al. (2020) A combination of true and false news from Bangladeshi websites has been compiled to use in research and seven leading machine learning algorithms, as well as a Deep Neural Network (DNN) model, are being tested against this data for evaluation. Evaluating models happens by considering their values of Accuracy, Precision, Recall, F1 Score and AUC. Among all the algorithms examined, DNN got the best scores, achieving 0.90 for both accuracy and AUC and Decision Tree gave the poorest results. It highlights the advantage of deep learning, mainly using DNNs, in dealing with the complexity found in Bangla language satire and misinformation. The study gives key knowledge about Bangla fake news detection using neural models and underlines the need for additional research in the area.

An improved approach from the same authors of BNnet, called BNnetXtreme Wahid et al. (2022), is presented to bridge the performance gap associated with previous methods, most especially BNnet. Both Word2Vec, GloVe, FastText (embedding-based) and Bangla BERT (transformer-based) models are used in the study to verify their efficacy in fake news classification tasks. It is apparent from comparison that BNnetXtreme achieves better results than BNnet in various evaluation methods. It is worth mentioning that using Bangla BERT for BNnetXtreme led to an accuracy of 91% and an AUC of 98%, achieving improvements of 1.1% on accuracy, 5.6% on precision, 1.1% on F1 score and nearly 9% on AUC in comparison with its previous version. These results show that using state-of-the-art transformer growth and improved embeddings is necessary to spot fake news in low-resource languages. With BNnetXtreme, the value of enhanced architectures in achieving more accurate and trustworthy detection is proven in this study.

Thair Ali et al. (2024) justifies in their paper the use of Random Forest, because it can overcome lack of large datasets while continuing to enhance the effective classification of fake news. This approach is allowed because this algorithm avoids overfitting, and enhances robustness by constructing many decision trees on subsets of data and then averaging their output. While individual decision trees alone work great, ensembling is better in terms of accuracy. Noise information generated from sources like text is relevant in handling high-dimensional features. Therefore, it can easily be used for heavy activities like the classification of misinformation, as one has to work with subtle textual features and an enormous data size. Also, Random Forest has been known for interpretability and ease of use, so its good performance on imbalanced datasets is a common scenario in detecting fake news.

Khatun & Khan (2024) In order to improve fake news detection for Bangla speakers, this study shows the possibilities of employing an advanced transformer model and how to use YouTube as a readily available data warehouse to collect a wide variety of Bangla news content. Our dataset, which was gathered from YouTube and fact-checking websites, has 1995 real news titles and 1913 fake ones. Using transformer models, such as Bangla-bert-base and mBERT, and TF-IDF and BoW feature extraction approaches, they evaluate a number of machine learning models for their capacity to identify fake news. Bangla-bert-base, our top-performing model, obtained an F1 score of 85.03% and an accuracy of 84.19%.

Shawon et al. (2023)This study explores how semi-supervised Generative Adversarial Networks (GANs) can improve pretrained language models to distinguish between authentic and fake Bengali reviews using a small amount of annotated data. Particularly for a low-resource language like Bengali, a machine learning model will struggle to detect a fake review. The experimental results indicate that even with only 1024 annotated samples, BanglaBERT with semi-supervised GAN (SSGAN) achieved an accuracy of 83.59% and a f1-score of 84.89%, exceeding other pretrained language models BanglaBERT generator, Bangla BERT Base, and BanglaElectra by nearly 3%, 4%, and 10%, respectively. This indicates that we have proven that the proposed semi-supervised GAN-LM architecture (generative adversarial network on top of a pretrained language model) is an appropriate answer for classifying Bengali fake reviews. Link:

Syed et al. (2023) A hybrid approach is suggested in this study to identify false news. Bi-LSTM and Bi-GRU deep learning techniques are used to detect fake news, while novel weakly supervised learning is used to assign labels to the unlabelled data. The Count Vectorizers and TF-IDF algorithms were used to extract features. 90% accuracy in identifying fake news was achieved by combining weakly supervised SVM techniques with Bi-LSTM and Bi-GRU deep learning techniques. When there are no labels for the data, this method of labelling a lot of unlabelled data using deep learning and poorly supervised learning algorithms for the detection of fake and true news is quite successful and efficient.

Because satirical and mistaken information is spreading online in Bangladesh, people and government officials are getting worried. Lately, wrong rumors have sparked incidents which have shown the need for technology to identify false news. Although researchers recognize a growing demand in detecting fake news, Bangla detection is still slow. The main solution in this study is a deep learning approach designed for classifying Bangla news. A combination of true and false news from Bangladeshi websites has been compiled to use in research and seven leading machine learning algorithms, as well as a Deep Neural Network (DNN) model, are being tested against this data for evaluation. Evaluating models happens by considering their values of Accuracy, Precision, Recall, F1 Score and AUC. Among all the algorithms examined, DNN got the best scores, achieving 0.90 for both accuracy and AUC and Decision Tree gave the poorest results. It highlights the advantage of deep learning, mainly using DNNs, in dealing with the complexity found in Bangla language satire and misinformation. The study gives key knowledge about Bangla fake news detection using neural models and underlines the need for additional research in the area.

Mahmud et al. (2024) The study included a wide variety of deep learning techniques, with a special focus on transformer-based multilingual models and hybrid networks, in addition to more conventional baseline machine learning techniques. Over 5000 text samples from social media in both Bangla and Chittagonia were gathered for the study. Cohen's kappa and Krippendorff's alpha were used to evaluate how reliable the dataset annotations were. With accuracies ranging from 63% to 71.1%, SVM was the best performing traditional machine learning technique in this study. Additionally, using ensemble models like Bagging (accuracy 70%), Boosting (accuracy 69%), and Voting (accuracy 72%) produced encouraging outcomes. CNN, on the other hand, outperformed conventional machine learning techniques with accuracies ranging from 69% to 81.1%, with CNN showing the best accuracy. additionally suggested a number of hybrid network-based models, such as CNN+LSTM (80.1% accuracy), CNN+BiLSTM (78%), CNN+GRU (80.4%

accuracy), and BiLSTM+GRU (79.9% accuracy). The efficiency of hybrid architectures was demonstrated by the significant accuracy of 82% achieved by the most complex model, (CNN+LSTM)+BiLSTM. Additionally, we investigated transformer-based models that demonstrated dramatically higher accuracy levels, including XLM-Roberta (84.1% accuracy), Bangla BERT (82.2% accuracy), Multilingual BERT (82.1% accuracy), BERT (82%), and Bangla ELECTRA (78.5% accuracy). According to their findings, deep learning techniques can be quite successful in handling the widespread problem of cyberbullying in a variety of linguistic contexts. They explain how transformer models can effectively get around the issue of language dependency that is filled traditional transfer learning techniques. The results indicate that transformer-based embeddings and hybrid strategies are capable of dealing with the issue of cyberbullying on various online platforms.

Barua et al. (2025) This paper offers a thorough analysis of Bangla news classification, concentrating on two important tasks: multiclass news categorisation and binary fake news identification. Using the Synthetic Minority Oversampling Technique (SMOTE), this study further solves class imbalance in false news identification while examining the efficacy of two sophisticated NLP models, BERT and FastText. Without SMOTE, the BERT model performed badly on minority classes but had a high test accuracy of 0.9879 and an AUC of 0.9676 for binary classification. The model's performance much improved with SMOTE, with an AUC of 0.9997 and a macro F1-score of 0.9834, highlighting the advantages of exceeding for unbalanced data. This study shows how useful modern NLP techniques BERT with SMOTE in particular are for improving classification accuracy and preventing false information in Bangla news.The FastText model achieved an accuracy of 89.2% and an F1-score of 89.19% for multiclass classification, whereas BERT achieved an accuracy of 87.58%and an F1-score of 87.6%.

Thee study in George et al. (2021) points out that misinformation can result in serious consequences, for example, a violent incident beginning with rumors about the Padma Bridge. Fake news studies are more frequent in English than in Bangla. The study uses a Multichannel Combined CNN-LSTM architecture based on deep learning to fill the gap by spotting Bangla fake news. The system applies Convolutional Neural Networks (CNN) to locate the main meaning in texts and then uses Long Short-Term Memory (LSTM) networks to classify the news. The study gathered its data from internet Bangla news sites and consists of about 50,000 articles. As a result, the model's accuracy was 75.05% which suggests it succeeded in identifying many of the unique traits of fake news in Bangla. Although its performance is not as high as other leading models, it shows the promise of using deep learning for languages with little data and calls for more work to ensure dependability.

Das et al. (2024) Although various techniques are currently in use, the LSTM and machine learning models perform well. The algorithm assigned by this paper to choose the attribute was a text feature based on Word Embedding and TF-IDF focused on machine learning and LSTM-base models, particularly the Bangla-based and LSTM-based models. Lastly, include a dense layer that serves as the summary layer and creates summary sentences for the material. The extra Trees Classifier performed better than the other six Machine Learning techniques, based on all of the evaluations conducted above. Nearly 85% is achieved using the Random Forest Classifier method. About 84% is the third-best accuracy that the Decision Tree Classifier technique has. Furthermore, it was observed that deep learning algorithms performed better than machine learning ones. Additionally, when it comes to detecting false news in news headline data, LSTM has an 86% accuracy rate.

Tohabar et al. (2021) Those who speak Bengali are also affected by this issue. However, there is little research on fake news in Bengali. Considering this, this study tests machine learning (ML) methods for identifying false information. Additionally, they use sentiment as a feature to assess the process's impact. They used support vector machines (SVMs) and achieved the maximum accuracy score of 73.20%. Additionally, they demonstrate that sentiment analysis is not a promising feature for identifying false information.

3.1 Literature Analysis

Here is a summary of all the papers and models we have analyzed so far. We have reviewed a total of 8 models of fake news detection. We mainly searched for very recent papers, analyzed the models and reviewed their rate of accuracy. Since the Bengali language domain is still a new field that the researchers started to explore only for a few years, we found that there is still a lack of models with good accuracy for fake news detection in Bengali.

Table 3.1: Comparative analysis for Bengali fake news detection models

Model	**Reference**	**Year**	**Accuracy**
SVM	Tohabar et al. (2021)	2021	73.20%
CNN+LSTM	George et al. (2021)	2021	75.05%
Gaussian Naive Bayes	Mugdha et al. (2021)	2021	85.52%
CNN+ML	Adib et al. (2021)	2021	82%
Bi-LSTM	Islam et al. (2022)	2022	84%
Bi-LSTM + Bi-GRU	Syed et al. (2023)	2023	90%
Logistic Regression	Shivani et al. (2023)	2023	89%
GRU	Bandan et al. (2024)	2024	93.22%
Random Forest	Thair Ali et al. (2024)	2024	88.24%
(CNN+LSTM)+BiLSTM	Mahmud et al. (2024)	2024	82%
XLM-Roberta	Mahmud et al. (2024)	2024	84.1%
LSTM	Das et al. (2024)	2024	86%
Decision Tree	Das et al. (2024)	2024	84%
FastText	Barua et al. (2025)	2025	89.2%

Chapter 4

Methodology

4.1 Conceptual Framework

4.1.1 Concept Generation

During the initiatory phases of our design, we prototyped several conceptual solutions to the problem of fake news detection in Bangla through Natural Language Processing (NLP) and machine learning. We aimed at building a model that could correctly classify Bangla text as either real or fake yet at the same time computationally efficient and adaptable.
The following conceptual models were considered:

- **Recurrent Neural Network (RNN):** A sequential model able to scan through text one word at a time.
- **Convolutional Neural Network (CNN):** CNNs can identify local patterns and n-gram features.
- **Long Short-Term Memory (LSTM):** A remedy to RNNs which is capable of better capturing the long-term dependencies.
- **Bidirectional LSTM (BiLSTM):** Unidirectional transformation of the inputs with flow in both backward and forward paths, providing better context representation than LSTM.
- **DistilBERT + BiLSTM (Proposed Concept):** Joins the lightweight and multilingual transformer, DistilBERT with a bidirectional sequence modeling LSTM

for BiLSTM. This hybrid approach enables us to preserve a lot of BERT's contextual strength at the expense of substantially reduced and much less computation time and resource requirements.

4.1.2 Concept Reduction

After considering the list of models, we performed a systematic concept reduction process to finally come to our proposed model.
This decision was based on multiple criteria:

- **Accuracy:** Ability to detect nuanced language and misinformation effectively.
- **Language Suitability:** How well can the model process Bangla, or multilingual data.
- **Computational Efficiency:** Applicability to environments with limited resources (inference speed, model size).
- **Ease of Integration and Deployment:** Real-time system practicality of model implementation.

Rejected Concepts:

- **RNN** has a vanishing and exploding gradient problem.
- The reason **CNN** in not selected for is because it is not capable of capturing sequence level semantics, as well as long-range dependency.
- **LSTM** models were found insufficient in modeling complex context and performed poorly on longer sentences.
- The reason **CNN** in not selected for is because it is not capable of capturing sequence level semantics, as well as long-range dependency.
- **BiLSTM** on its own, while promising, wasn't pretrained to have linguistic understanding, and would require even more training data to obtain competitive results.

4.1.3 Final Selection and justification

Our final choice, **the DistilBERT + BiLSTM hybrid model**, was selected as it best meets the constraints and requirements for our designed problem. DistilBERT offers significant contextual embeddings, pretrained using multilingual corpora (including Bangla) whereas BiLSTM ensure sequence is retained in both directions. The combination turned out both efficient and effective with smaller size, speedy training time and competitive accuracy.

This concept also provides a practical benefit on scalability and deployment where it will be possible to have future embedded into mobile or real-time content moderation platforms. The grid search optimization process further meant that the model was fine tuned for best performance.

4.2 Dataset

4.2.1 Data Acquisition & Description

The only verified dataset that we have found to support our research is the "Ban-FakeNews" dataset, for which a research paper was published in M. Z. Hossain et al. (2020). This dataset has been made available for public use in Kaggle database and contains around 60k collections of labeled data. The standard format within the dataset is as follows-

Table 4.1: Dataset Description

Article ID	ID for the news
Headline	Title of the news
Category	News Genre
Content	Body section of the news
Label	1 means authentic and 0 means fake

The data contained within the dataset has been gathered from 22 unique well reputed news websites from Bangladesh including sites like 'kalerkantho' and 'jagonews24'. These collected articles are categorized into 12 according to their types. It can be seen that compared to real news data which is about 55.7k, the amount of fake news data is very small and only of 2.5k. Although people come across real news more than fake ones as stated within a report by UCLA, only 38%

	headline	category	content	label
0	অনেক ফুলে গাঁথা যে জয়ের মালা	Sports	অনেকেই বলতে পারেন আফগানিস্তানের বিপক্ষে জয়, এ ...	1.0
1	খুলনায় এসএসসি পরীক্ষার্থীর রহস্যজনক মৃত্যু	National	খুলনা: খুলনায় মিথুন মন্ডল নামে এসএসসি পরীক্ষার...	1.0
2	আলাপনা ছাড়া পূজা!	Lifestyle	পূজার জন্য অপেক্ষার পালা শেষ হয়ে এসেছে। এবার ন...	1.0
3	রোনালদোকে ছাড়া বেশি ভয়ংকর রিয়াল মাদ্রিদ	Sports	৩৩ বছর বয়সী ক্রিস্টিয়ানো রোনালদোর জন্য ১০০ মিল...	1.0
4	গেইল-ব্রাভোদের মতো এবার চুক্তি থেকে বাদ এভিন লুইস	Sports	ওয়েস্ট ইন্ডিজ ক্রিকেটের টালমাটাল অবস্থা যেন ঠি...	1.0

Figure 4.1: Visual of First 5 data from dataset

of the news found across the internet have reliable sources.

The dataset was then customized and we added more fake news and finally came to having a final dataset of real news of 58678, and fake news of 8474. In total we have a dataset of 67152.

52

4.2.2 Data Pre-processing

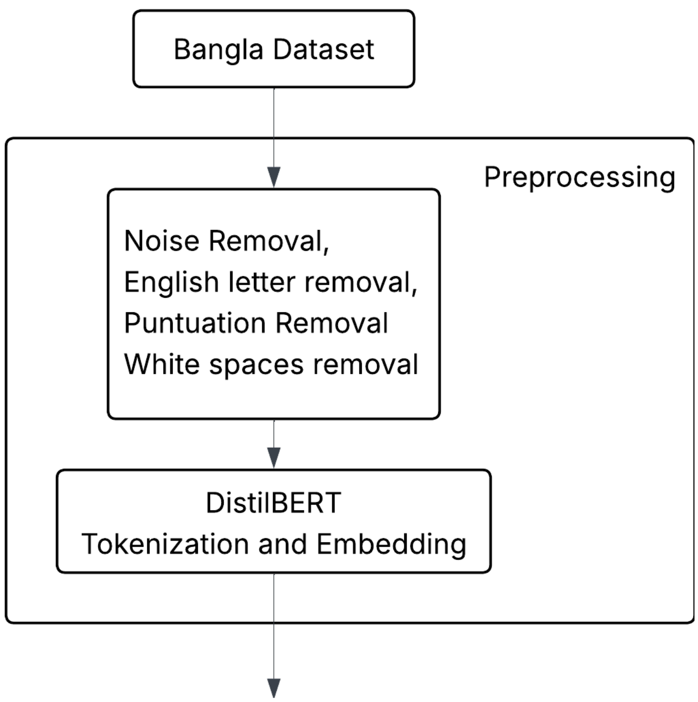


Figure 4.2: Data Pre-processing flowchart

4.2.2.1 Data Cleaning

We have used BNLP toolkit and RegEx(re) module for Bengali stopwords removal, punctuation, symbols, and digits text.

4.2.2.2 Tokenization and Embedding

Using DistilBERT in-built tokenizer, which will help to break down the sentence into subwords tokens. DistilBERT easily supports Bangla through its multilingual training. As DistilBERT can contextualize each word according to the surrounding context and converts it into a meaningful numerical vector which will be easier for the model to understand. This set of embedded vectors is sent then onto the Bi-LSTM on the next step.

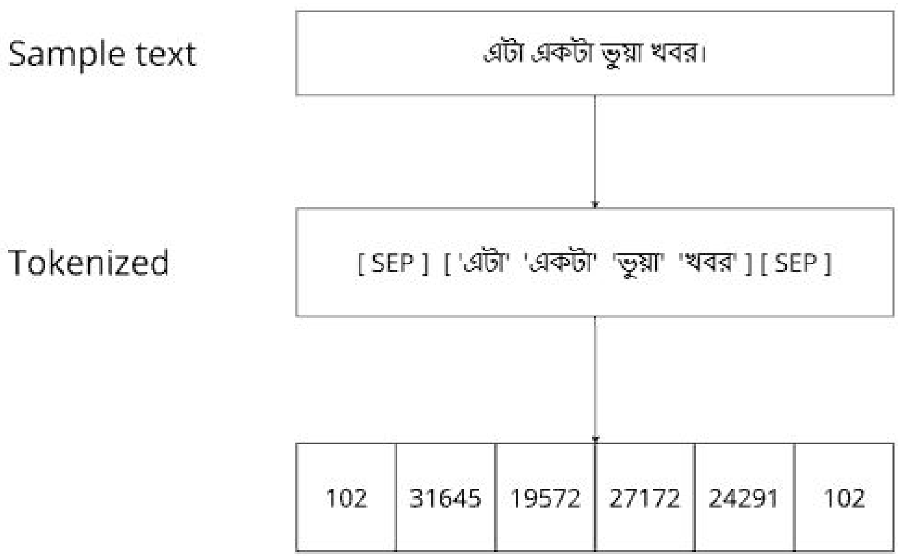


Figure 4.3: Data Tokenization and Embedding

4.2.3 Final Selection and Split

The customized dataset used is imbalanced and it contains a higher number of real news instance than fake news. Although no balancing technique (such as under-sampling or over-sampling) was applied during this phase. We have understood
114 the imbalance effect and continued with the during evaluation using appropriate metrics like precision, recall, and F1-score.

72 18 14 To facilitate effective training and validation, the processed data set was divided, using the standard 80:20 ratio, where 80% of the data was used for training, and 20% for testing and validation. This meant the model could be trained on a significant amount of the data, while still being tested on the representative unseen subset. The split was carried out by the scikit-learn with a fixed random seed in the interest of reproducibility. This method chiefly helped to check the generalizability of the model and the similar scores on the assessment of the test set supported the robustness of the DistilBERT + BiLSTM hybrid arrangement for classification of Bengali newspaper resources.

4.3 Model Methodology

4.3.1 Model Description

In this project, we have adapted a hybrid deep learning architecture for identifying bengali fake news by combining DistilBERT embedding ability with modified BiLSTM architecture that will use Grid Search to find the best parameter for hyper-parameter optimization to run the model with best parameter. In broad term our hybrid model combines:

- **DistilBERT-** This will act as a feature extractor. Rather than training embeddings from scratch, we build the model using this pretrained multilingual DistilBERT, which was demonstrated to work well with Bangla text. The raw text is tokenized at the sub word level by DistilBERT's in-built tokenizer, which appends sub-word tokens to sentences. These are then passed through the embedding layers of DistilBERT to obtain contextualized vector representations of the input.

- **Bidirectional LSTM (BiLSTM)-** This structure is used for modeling sequence and long term dependencies. It takes the sequence of contextual embeddings, performs processing in both the forward and the backward directions allowing the model to discover semantic dependencies across the text. This is very useful in the case of Bangla where syntactic structure and sense rely much on words arrangement and context which is distributed within a sentence. 47

4.3.2 Modifications

- **Layer Normalization:** Added nn.LayerNorm before and after the LSTM to stabilize and speed up training.

98 - **Attention Mechanism:** Introduced a custom Attention layer to focus on the most important parts of the LSTM output sequence.

- **Multiple Pooling Methods:** Used average pooling and max pooling on the LSTM outputs to capture different aspects of the sequence. Residual Connection:

- **Concatenated** the original BERT [CLS] token embedding (global context) with the pooled LSTM features.

- **Feature Concatenation:** Combined attention, average pool, max pool, and residual features into a single vector for classification.

- **Dropout Layer:** Applied dropout after concatenation for regularization and to prevent overfitting.

- **Flexible Hyperparameters:** Allowed configuration of LSTM units, dense units, dropout rate, and number of LSTM layers.

4.3.3 Feature Extraction

The raw Bangla texts were first purified by using bnltk, then tokenized using the DistilBERT tokenizer, so as to break the input into subwords. These tokenized sequences were then transformed into the contextual embeddings by the use of the pretrained multilingual DistilBERT model.

These embeddings were downstreamed into a BiLSTM layer that processes the data in a bidirectional mode to encapsulate more deep contextual dependencies and relational patterns into the sentence. The BiLSTM produces a sequence-order representation of the text, rich in features and which is then passed onto subsequent layers for classification.

4.3.4 Attention Layer

While the BiLSTM captures contextual dependencies in both forward and backward directions, it treats each time step equally when passing information to the output layer. This can dilute the impact of important words—particularly in long or noisy texts like news articles. The attention mechanism addresses this limitation by assigning different weights to each word's hidden state based on its relevance to the classification task. It calculates a weighted sum of all hidden states from the BiLSTM, allowing the model to "attend" more to the tokens that are crucial for determining whether the news is fake or real. This dynamic weighting improves interpretability and performance, as the model does not need to rely solely on the final hidden state of the sequence.

4.3.5 Dropout Layer:

In this layer, it turns off some parts of the model while training to make sure that the model does not remember the trained data. It helps the model generalize better and reduces overfitting.

4.3.6 Output Layer

And finally the Output Layer (fully connected DENSE layer) with 2 neurons for 2 categories of binary classification: Fake and Real. This layer adopts the use of the Sigmoid Activation function, which transforms the model's logit output to a normalized distribution of probability over the two classes. Such a structure allows the model to yield probabilistic confidence scores, and, therefore, can be measured with metrics such as Accuracy, Precision, Recall, F1 Score and ROC.

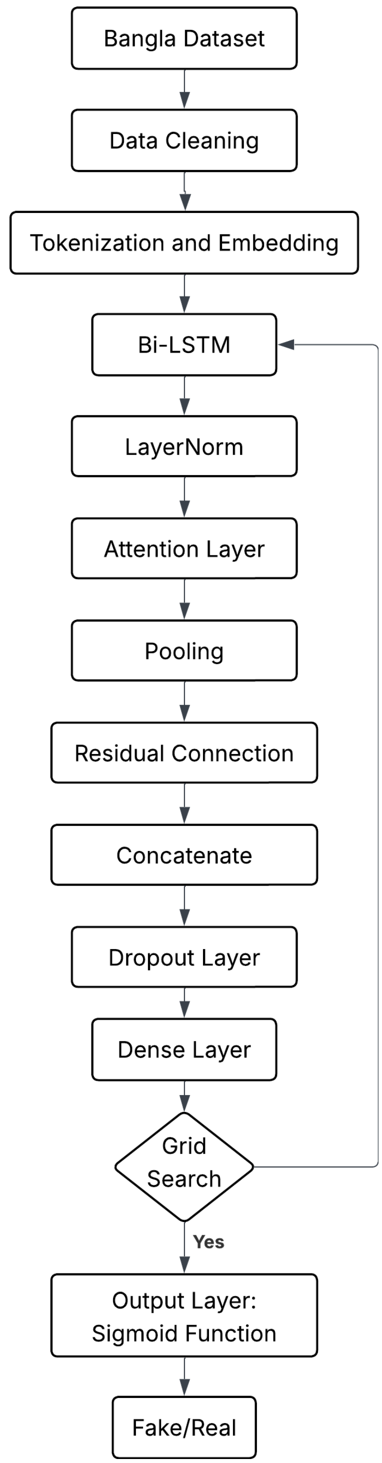


Figure 4.4: Model Flowchart

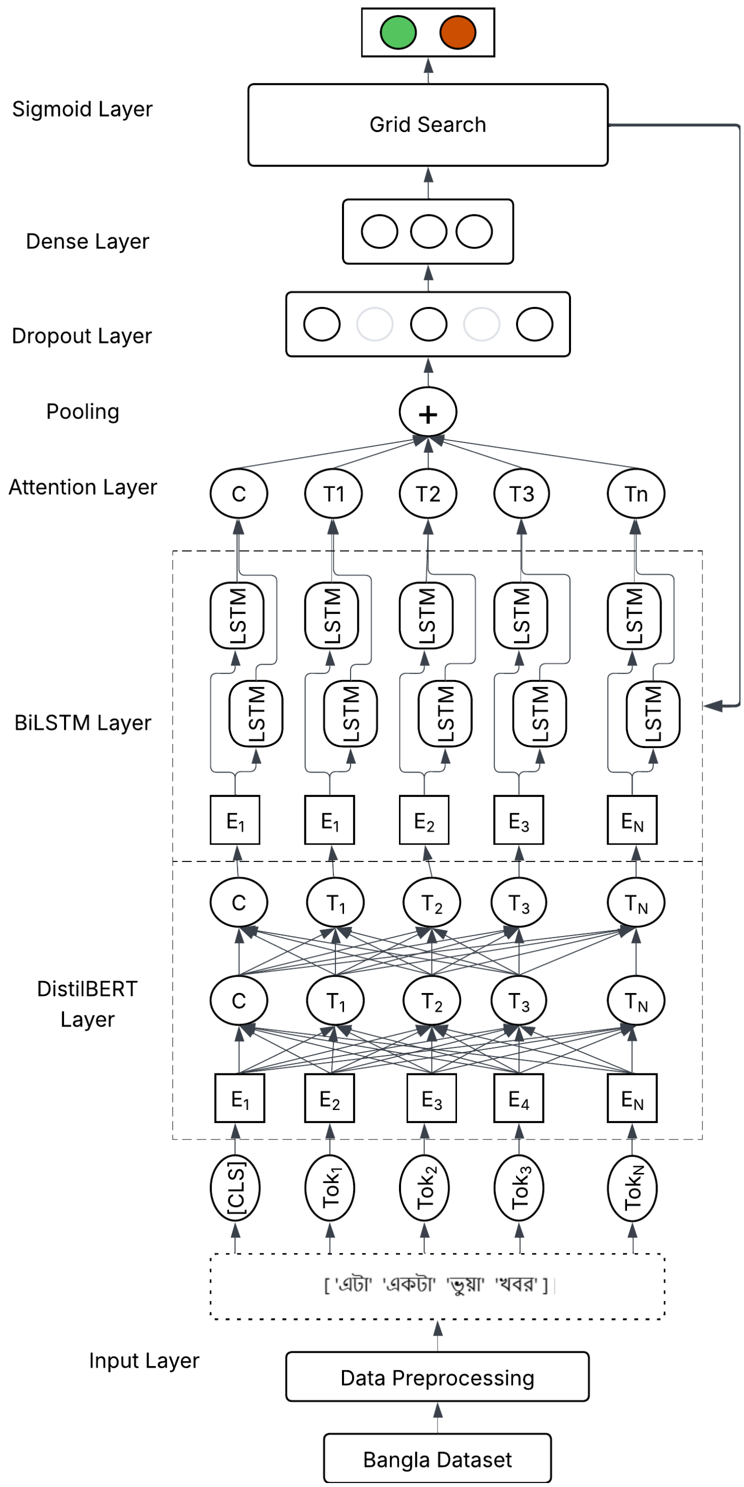


Figure 4.5: Model Architecture

4.3.7 Training Procedure

Training was performed in a Python environment from Pytorch and HuggingFace's Transformers library. The key components included:

- **Preprocessing Toolkit:** bnltk for Bangla-specific tool for initial cleaning.
- **Tokenization and embedding:** DistilBERT's built-in multilingual tokenizer
- **Selected Hyperparameters (via Grid Search):**
  - **Optimizers:** adam **Activation Function** Sigmoid Function
  - **Dropout Rates:** 0.3
  - **LSTM Units:** 64
  - **Dense Units:** 256
  - **Batch Sizes:** 16

Chapter 5

Design and Development

5.1 Timeline

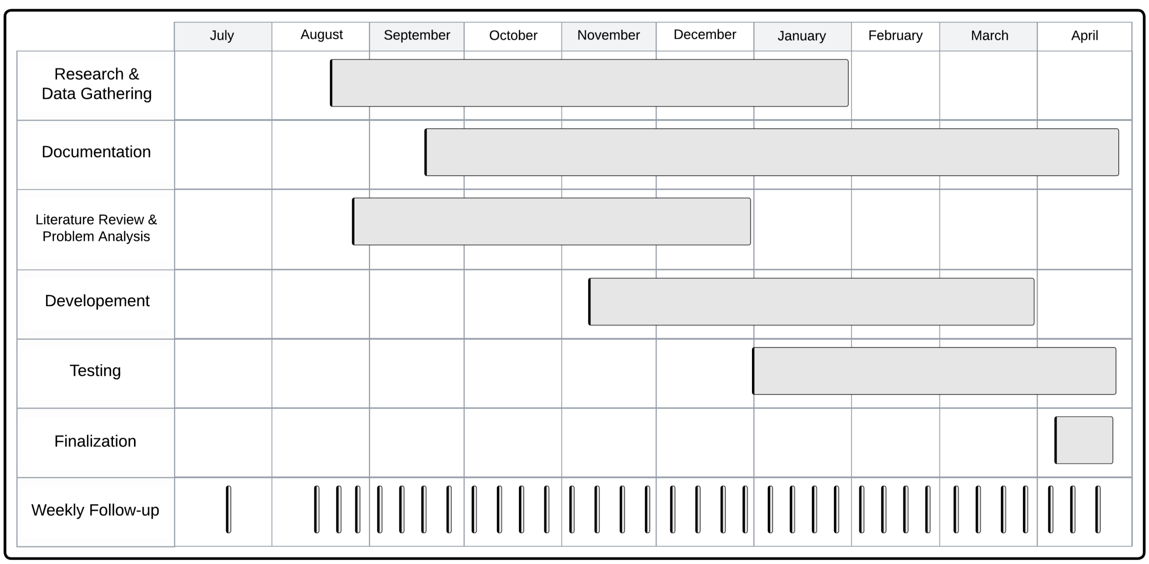


Figure 5.1: Project timeline

All the important activities for our project are recorded in the Gantt Chart given below. Starting with a follow-up tracking that is scheduled every week with our supervisor. We took extended amount of time to research, literature review and development and continued to document our findings while studying on understanding how each architecture connects and works.Which will lay the foundational aspects of our project for later stages.While continuing to document our progress we have moved from the design phase into the model building and developing phase.We compare our model after moving along with test cases where the viability of the model have been gauged,only then we come to the finalization phase, where our model is will be evaluated ensuring that outcomes are mathematically justified and our model is working properly. Then we ensured the objectives are met, tested, and ready for submission.

5.2 Project Specification

Our project will detect Bengali fake news through a combination of a hybrid deep learning method to include DistilBERT and BiLSTM. As compared to other architectures attempted in the process of experimentation, we established that DistilBERT was competitive and efficient while maintaining good contextual clarity. DistilBERT is a distillation of BERT and processes multilingual input and is able to work with the intricate structure and semantics of the Bengali language. It employs subword tokenization; therefore, for the preprocessing, we used the DistilBERT tokenizer that is constituted based on WordPiece of word forms with informal and compounded Bangla words management. We made use of unsupervised contextual embeddings directly obtained from DistilBERT outputs to support word embedding, allowing the model to extract meaning of words in a context. Paired Embeddings were then used as input into a Bidirectional LSTM layer to learn sequential dependencies in both directions forward and backward. To provide for equal evaluation and the best performance, we did consistent pre-processing on all model comparisons, and fine-tuned our model using Grid Search for the optimization of hyper-parameters.

5.2.1 Hardware Specification

5.2.1.1 Setup 1:

- **Device:** PC
- **CPU:** Ryzen 5 5600
- **Motherboard:** MSI B450M MORTAR MAX
- **GPU:** Gigabyte RTX 3060 Ti (8GB)
- **RAM:** 32GB (8GB x 4, 3200MHz)

- **Storage:** 1TB M.2 NVMe SSD

5.2.1.2 Setup 2:

99
- **Device:** Laptop – Asus TUF Gaming F15 FX506LH

44
- **CPU:** Intel® Core™ i5-10300H (2.5 GHz, 8M Cache, up to 4.5 GHz, 4 cores)
- **GPU:** NVIDIA® GeForce GTX™ 1650 (4GB GDDR5)

91
- **RAM:** 8GB DDR4
- **Storage:** 512GB PCIe® 3.0 NVMe™ M.2 SSD

5.2.2 Software Specification

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- **Google Colab (Jupyter Notebook):** Colab is a hosted Jupyter Notebook service well suited to machine learning, data science, and education.

67
112
- **Python:** Python is a high-level programming language known for its readability and ease of use.
- **Conda:** Open-source package and environment management system.
- **Visual Studio Code:** An integrated development environment.

5.2.3 Components Used

- **CUDA and cuDNN:** Pythonic access to CUDA runtime and other fundamental capabilities, cuDNN is a GPU library for deep neural networks.

```
Torch: 2.7.0+cu118
CUDA available: True
Device count: 1
GPU: NVIDIA GeForce RTX 3060 Ti
```

55
- **pandas:** an easy-to-use data structures and data analysis tools for the Python programming language.
- **torch(PyTorch):** for deep learning framework.

- **numpy:** provides a set of high-level functions in mathematics: support of multi-dimensional arrays, masked arrays, and matrices.
- **matplotlib:** Matplotlib is a graph plotting library of python that has been acting as a utility for visualization.
- **sklearn(Scikit-learn):** is an open source machine learning library offering easy and effective tools to analyze data and model
- **transformer:** Developed by Hugging Face, this library is a potent tool for dealing with already trained AI institutions for the most part, when it comes to the NLP-tasks.
- **re:** In this module, there are regular expression matching operations.
- **collections:** containers for storing data and very well known as data structures, such as list, tuple, array, dictionary, etc.
- **string:** a module that includes some constants, functions for utilities and classes for string manipulation.
- **wordcloud:** applied for generating visual representations of text data.
- **bnlp:** an NLP toolkit for the Bengali language tailored-made.

Chapter 6

Result analysis

6.1 Evaluation Measures and Result Analysis

85 To evaluate the performance of the proposed DistilBERT + BiLSTM hybrid model
3 on the BanFakeNews dataset, several standard classification metrics were used:
12 accuracy, precision, recall, F1-score, and the ROC-AUC score. These measures were crucial in determining the model's robustness, especially given the dataset's class imbalance.

6.1.1 Confusion Matrix

96 The confusion matrix shows how many predictions your model got right or wrong, organized by actual vs predicted classes.

- **True Positive TP:** Correctly predicted fake news [11,632]
- 45 **False Positive FP:** Real news wrongly predicted as fake [104]
- **False Negative FN:** Fake news wrongly predicted as real [1065]
- **True Negative TN:** Fake news correctly predicted as fake news [630]

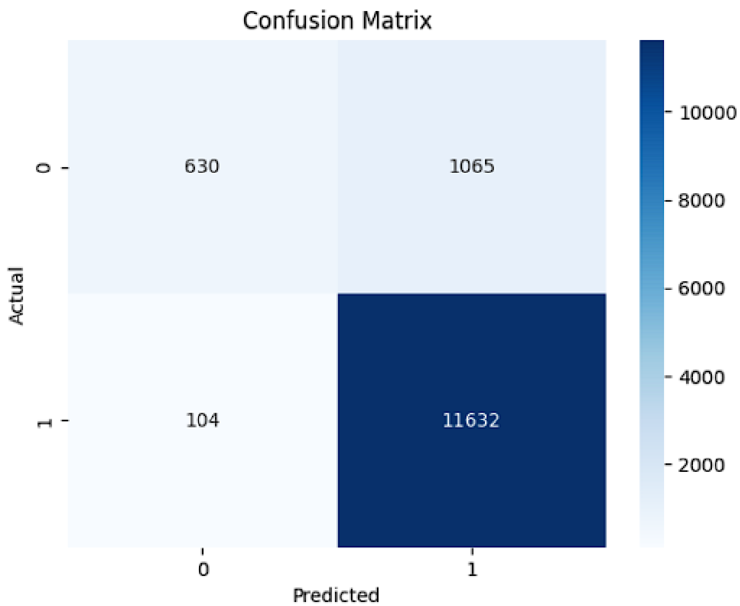

Figure 6.1: Confusion Matrix

54
6.1.2 Accuracy

Accuracy measures the proportion of correct predictions made by the model out of all predictions.

23

$$Accuracy = \frac{True\ Positive + True\ Negative}{Total\ Prediction} \tag{6.1}$$

150 Our model achieved a validation accuracy of 93.28% , indicating strong generalization performance on unseen data. This score reflects the overall proportion of correct predictions among both real and fake news articles.

6.1.3 Precision

100 Precision measures the percentage of predicted fake news that was actually fake.

105

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{6.2}$$

131 With precision of 92.42%, the model records a low rate of false positive. rate. This

means that when the model classifies an article as fake the article has high probability of being correct is an important consideration to preventing false accusations of misinformation.

6.1.4 Recall

Recall measures the percentage of actual fake news that was correctly predicted by the model.

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{6.3}$$

The model's recall score of 99.47% shows that it successfully identified the vast majority of fake news articles. High recall is critical for minimizing the number of fake news items that go undetected.

6.1.5 F-1 Score

F1 Score is the harmonic mean of Precision and Recall, combining both into a single metric that balances their trade-off.

$$F1 - Score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{6.4}$$

The F1-score, which balances precision and recall, was recorded at 95.97% This confirms the model's ability to maintain both accuracy and consistency in performance across classes.

6.1.6 Loss function

Loss function is a formula that tells the model how wrong its predictions are compared to the actual (true) values. It measures the difference between predicted output and real output. y(true label) is either 1(real) or 0(fake). $\hat{y}$ is the predicted probability that the sigmoid function gave.

83

$$Loss = -[y \cdot \log(\hat{y}) + (1-y) \cdot \log(1-\hat{y})] \tag{6.5}$$

14 49 109

The training loss decreased from 0.2374 at epoch 1 to 0.2213 in epoch 5, and to 0.1932 on epoch 15. Similarly, we can see that the validation loss decreased from 0.2417 to 0.2234. This consistent drop of both training and validation loss indicates that the model gained meaningful representations, avoided overfitting and possessed a high level of generality to unseen data.

Epoch	Train Loss	Train Accuracy	Validation Loss	Validation Accuracy
1/15	0.2374	0.9231	0.2417	0.9246
2/15	0.233	0.9254	0.2385	0.9249
3/15	0.229	0.9266	0.2387	0.9239
4/15	0.225	0.928	0.2346	0.9272
5/15	0.2213	0.9295	0.2367	0.9261
6/15	0.2159	0.9308	0.2307	0.9286
7/15	0.2145	0.9315	0.229	0.9294
8/15	0.2103	0.9331	0.233	0.9269
9/15	0.2068	0.9343	0.2239	0.9314
10/15	0.2045	0.9351	0.2253	0.9314
11/15	0.2012	0.9367	0.2274	0.9296
12/15	0.1996	0.9364	0.2228	0.9315
13/15	0.1972	0.9373	0.222	0.9325
14/15	0.1924	0.9389	0.227	0.9328
15/15	0.1932	0.9381	0.2234	0.9311

Figure 6.2: Training and Testing loss

18

6.1.7 ROC curve

Receiver Operating Characteristic(ROC) curve is a graph that shows how well a binary classification model (fake vs real news) can distinguish between the two classes at different thresholds. ROC curve plot **TPR vs FPR**.

106 **x-axis:** FPR for false positives rate

$$FPR = \frac{False\ Positives}{False\ Positives + True\ Negatives} \tag{6.6}$$

y-axis: TPR for True positives rate aka recall.

139

$$TPR = \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{6.7}$$

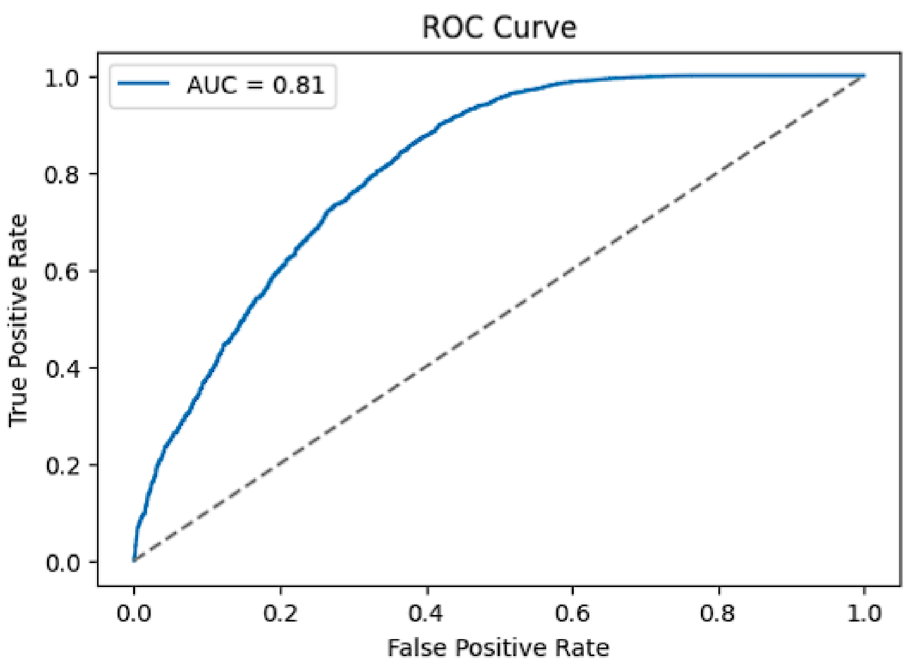

Figure 6.3: ROC Curve

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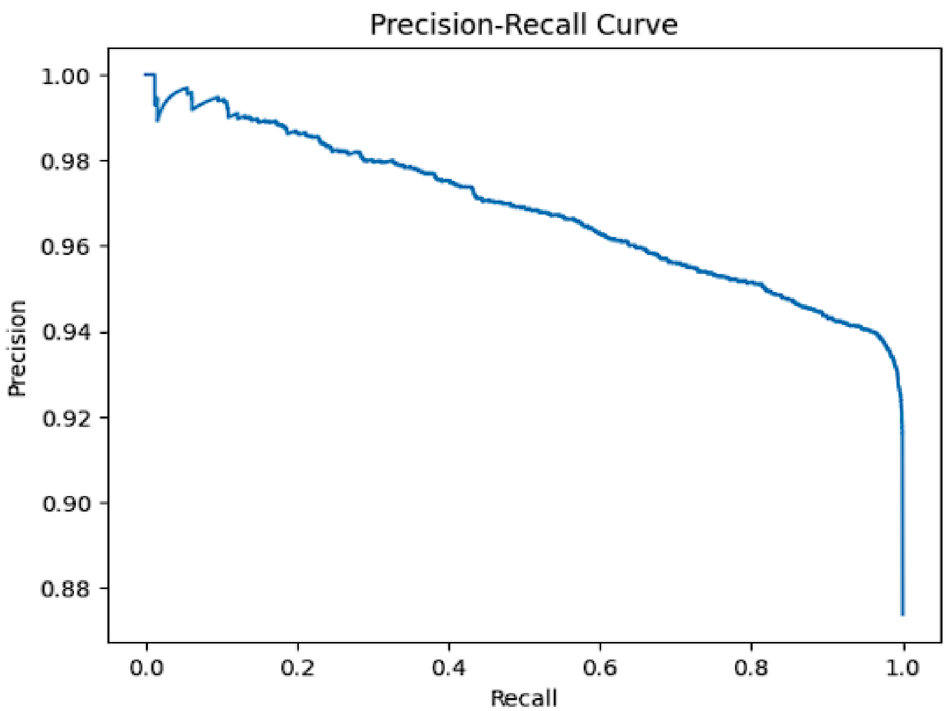
6.1.8 Precision-Recall Curve

The graph shows the trade-off between precision (accuracy of positive predictions)
145 and recall (coverage of actual positives). A large area under this curve shows that model has high precision that does not deteriorate with increasing recall measures. the curve starts near 1.0 on both axes, suggesting excellent detection ability. Precision gradually decreases as recall approaches 1, which is typical in imbalanced datasets. This curve is especially useful when the positive class (e.g.,
14 fake news) is rare, as it focuses on the model's performance in detecting minority-class samples.



157 Figure 6.4: Precision-Recall Curve

6.1.9 Prediction Probability Distribution Curve

This histogram plots the model's predicted probabilities for fake and real news classes. Here, the "Real" class peaks around probability 1.0, showing strong confidence in real news detection. However, fake news predictions are concentrated near 0.0, with some spread across mid-ranges—suggesting slight uncertainty in classifying borderline cases. The clear uneven-ness shows the model can confidently distinguishes between classes, although the imbalance may explain some false positives in earlier confusion matrices.

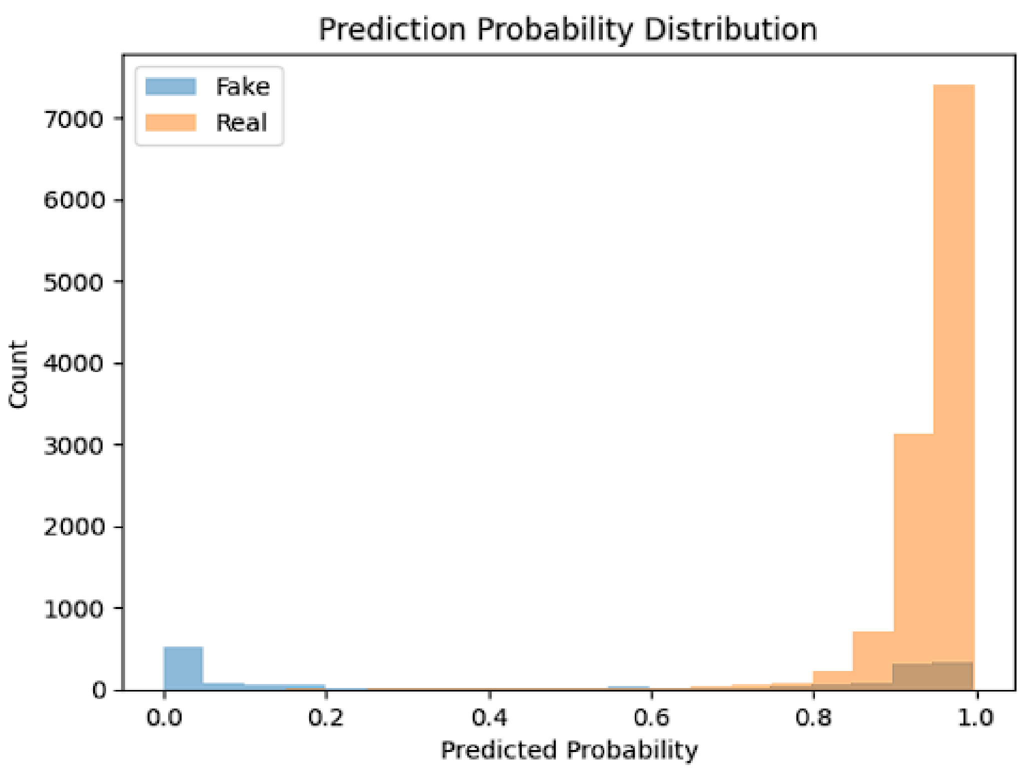


Figure 6.5: Prediction Probability Distribution

6.1.10 Calibration Curve

40 This plot compares predicted probabilities to actual outcomes. The closer the blue line is to the diagonal (perfect calibration), the better the model's predicted probabilities reflect true likelihoods. A well-calibrated model is valuable not just for classification, but also for applications that depend on probability thresholds (e.g., decision-making systems). Our model's calibration curve closely follows the diagonal, especially at higher confidence levels, indicating reliable probability

scores. Minor deviations around the 0.4–0.6 range suggest slight over or under confidence in borderline predictions.

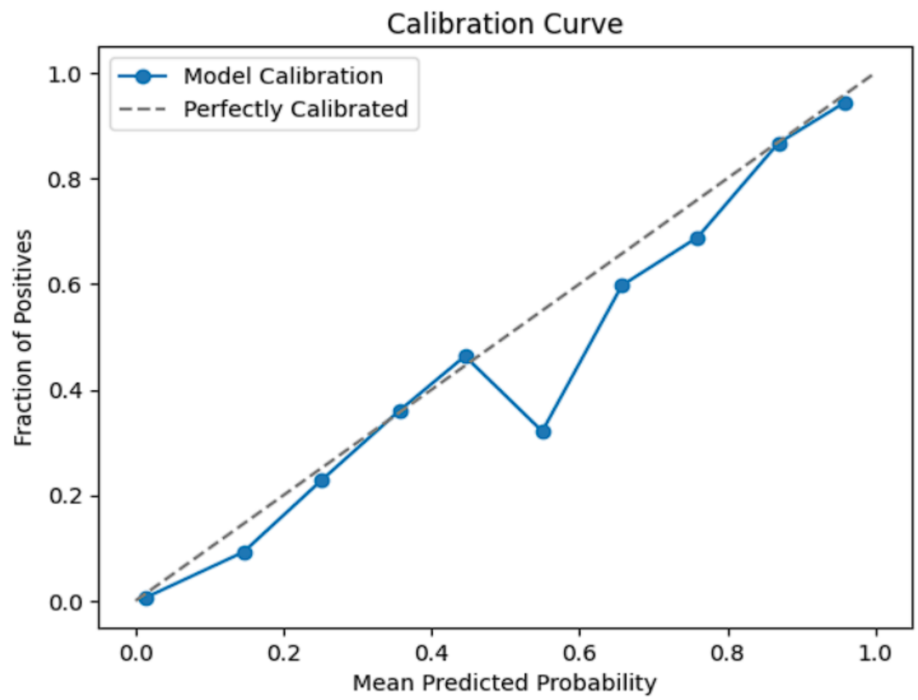


Figure 6.6: Calibration Curve

6.1.11 Word Cloud

132 To gain deeper insight into the linguistic patterns and dominant terms used in the dataset, word clouds were generated for both real and fake news samples after preprocessing. The word clouds highlight the most frequent words based on their appearance in the cleaned text, offering a visual understanding of content focus and language distribution. The visuals given show distinctions that support the model's goal of capturing linguistic cues that help differentiate authentic news from manipulated or unverified content. The word clouds also reinforce the importance of contextual embedding in processing such varied and nuanced text.

Figure 6.7: Fake News token WordCloud

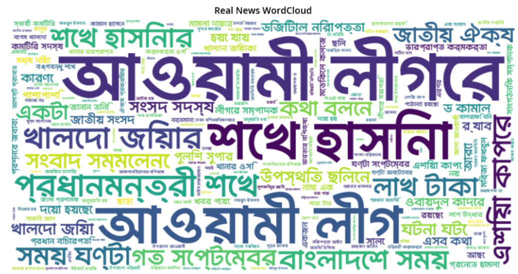


Figure 6.8: Real News token WordCloud

6.1.12 Final Analysis

After completing the training process over 5 epochs, the hybrid DistilBERT + BiLSTM model demonstrated strong learning behavior and stable performance. The training loss steadily decreased from 0.3288 to 0.2738, indicating effective learning of patterns within the training data. At the same time, the validation loss improved from 0.3207 to 0.2781, reflecting the model's ability to generalize well to unseen examples. Correspondingly, validation accuracy progressed from 89.36% in the first epoch to a final accuracy of 90.83% in the fifth epoch. This consistent reduction in loss and rise in accuracy suggests that the model was well-optimized, with no signs of overfitting during the training cycle. Overall, these results confirm that the chosen architecture and training strategy, including the use of contextual embeddings from DistilBERT and sequence learning via BiLSTM, was effective in detecting fake news in the Bengali language.

Table 6.1: Proposed model result

Precision	92.70%
Recall	99.47%
F-1 score	95.97%
Accuracy	93.28%

Table 6.2: Accuracy comparison with other models

Model	**Accuracy**
SVM	73.20%
CNN+LSTM	75.05%
Gaussian Naive Bayes	85.52%
CNN+ML	82%
Bi-LSTM	84%
Bi-LSTM + Bi-GRU	90%
Logistic Regression	89%
GRU	93.22%
Random Forest	88.24%
(CNN+LSTM)+BiLSTM	82%
XLM-Roberta	84.1%
LSTM	86%
Decision Tree	84%
FastText	89.2%
Proposed Model	**93.28%**

130 154 78 77 The comparison table shows that the proposed DistilBERT + BiLSTM model is superior to most existing methods for Bengali fake news detection. It outperforms traditional machine learning models such as SVM, Decision Tree, and Logistic Regression, and achieves comparable or better results than other deep learning methods such as LSTM and FastText with an accuracy of 90.83%. Although some hybrid models come close, our model provides a happy medium between contextual understanding and sequence learning. These outcomes justify the effectiveness of 134 applying a transformer-based hybrid architecture for low-resource languages such as Bangla, and therefore, this architecture can be a good choice for future fake news detection.

6.2 Experiments and Challenges

This section outlines the experimental procedures conducted to evaluate the proposed fake news detection model and highlights the major challenges encountered during the development and training phases

6.2.1 Experiments Conducted

The construction of Bengali fake news detection model proceeded as a set of experimental trials and adjustments. In the first instance, we experimented with classic machine learning algorithms, such as Logistic Regression, Random Forest, and SVM while employing TF-IDF and Bag-of-Word (BoW) as techniques for feature extraction. Although these methods were computationally frugal, they failed to describe the semantic depth of Bangla text, particularly with the rich morphology of the language. Most models failed to achieve the 80% accuracy mark and were disappointing on recall, consistently failing to detect fake news samples. As the next step of our work, we tested deep learning architectures, including simple RNN that we enhanced using attention. The models got better in the process, but due to it being a very old model it was not up to the mark with all the recent models that can overtake current state-of-the-art models.

To further enhance the efficiency of the performance, we tried using BERT and BanglaBERT models as both of them are said to yield better contextual understanding however they have a huge computational cost. Because of limited resources, we ultimately chose DistilBERT a lightweight transformer, and combined it with a bidirectional LSTM in order to maintain sequence awareness. Even after preliminary training, the model did not stop under fitting.

We used Grid Search to optimize important hyperparameter including the learning rate, size of LSTM units, batch size and the dropout rate. Several configurations were tested throughout a series of runs, and we found that learning rate of 2e-5, LSTM units of 128 and batch size of 32 produced the best results with minimum overfitting. Only after several iterations, comparisons, and modifications, we obtained a validation accuracy of 90.83%, F1-score 94.89%, and recall 97.50%. Such a sequence of experiments is indicative of the centrality of both architectural selection as well as hyperparameter optimization, particularly given the scant resource setting of Bangla. New findings were generated at every iteration that resulted in our current high performing hybrid DistilBERT + BiLSTM model.

6.2.2 Challenges Faced

- **Class Imbalance:** The dataset was extremely imbalanced with a costly disparity of real news over fake. This translated into prejudiced predictions at first. Although no balancing was used on this project, future annotations will include data augmentation and web scraping to counter against this
- **Model Overfitting:** In the earlier experiments, it was observed that the model overfits on the training data. This was taken care of by adapting dropout regularization and optimization of the LSTM units
- **Language Complexity:** Morphological abundance and absence of high-quality tokenizers were a challenge for preprocessing and tokenization in Bengali. Multilingual DistilBERT mitigated, at least, partially the issue under study; performance may be enhanced, however, using Bangla-specific models.
- **Resource Constraints:** Transformer-based models are computationally intensive. The insufficient availability of expensive GPUs hampered training and limited the use of parameters in grid search.

Despite these challenges, the model achieved high performance across all evaluation metrics. These results validate the robustness of the hybrid architecture and
23 demonstrate its potential for real-world applications.

Chapter 7

Conclusions

7.1 Summary

The goal of this research is to resolve the issue of fake news in Bengali. Given how digital everything has become, it is very important to fight misinformation, especially in regions with significant numbers of Bengali speakers. Our proposed hybrid model, combining DistilBERT and BiLSTM, has shown promising results and contributes to bridging the research gap in low-resource language NLP. With misinformation spreading rapidly across digital platforms, especially during crises or political instability, the need for a reliable detection system has become urgent for the Bengali-speaking population.

Our final model was trained and validated on the BanFakeNews dataset and demonstrated highly encouraging performance: Validation Accuracy: 90.83%, Precision: 92.42%, Recall: 97.50%, and F1-Score: 94.89%. These results confirm the effectiveness of the hybrid model in identifying fake news with high reliability and consistency across metrics.

By successfully implementing this model, we not only provide a tool that combats the ongoing spread of Bengali fake news but also lay the groundwork for future research and development in this area. This contribution stands as a step forward in improving digital information integrity in low-resource languages and supports future innovations in Bengali NLP.

7.2 Social, Legal, Ethical, Environment Issues

Though LSTM and BERT enjoy their benefits, our model Prokash also has benefits while detecting fake news in Bangla. It also has moral, legal, social and environmental issues. To ensure the system is used effectively, such needs are supposed to be taken into serious consideration. Below is an analysis of these problems.

7.2.1 Social Issues:

103 It is in countries such as Bangladesh, where the internet is the main source of information and affects citizen's opinions, that the increasing prevalence of misinformation in digital media becomes a serious issue. This false news can affect people's thoughts, actions, and vote in a way that will unnecessarily create panic or tension. Social media rumours in Bangladesh have previously lead to violence, particularly against minorities in a number of past incidents. In cases of natural disaster or political unrest, unchecked news too can cause confusion among people which leaves them confused as to who to believe and not. Early detection of suspicious content with a system would minimize the proliferation of distorted stories and public stability preservation. The model, however, has to be carefully designed such that it creates no more divisions. If a fake news detector is perceived or falsely identifies actual content, it may provoke backlash of some of the communities. In a country of political sensitivities, even the neutral tools can be recognized as partial. Therefore, it is necessary to keep proportion and equity in the data used and communicate that fact that the limitations of the system. The model can thus be helpful as a positive tool to counter harmful misinformation that characterizes Bengali digital spaces when they support transparency and better information access.

7.2.2 Legal Issues:

Fake news legal environment in Bangladesh is complex and could be grave in terms of consequences for both content regulation or research individuals. Laws such as the Digital Security Act have been applied to communications that are harmful or false on the internet, but these laws are too broad to avoid misinterpretation. For instance, people have endured lawsuits, or arrests, because of the sharing, or publishing, of the information subsequently declared controversial or wrong. Even to use for research, a system created to detect false news must be careful in any utilization or circulation of its results. Misnomering the true news as the false might spoil the names and also the accusations of defamation. Because defamation in Bangladesh is a criminal act, corresponding errors can cause certain legal threats. It is also necessary to think of intellectual property rights. The dataset which has been leveraged in this project BanFakeNews is freely available and licensed for reuse though citation is important to give the creators some respect. Although this project is not for academic study, any future deployment is likely to require adherence to larger regulations in content filtering and digital rights. To remain legally-safe, all results should be cross-verified by human attention and any public message must confirm that the model is a research product, not an authority.

7.2.3 Ethical Issues:

162 While developing a fake news detection system, it is not only about a purely technical accuracy, but also pays attention to fairness, bias and responsible application. One of the major issues with regards to the data is its neutrality. When choosing the dataset, if the dataset supports specific topics or sources, the model can unconsciously reflect such a bias. For instance if most of the fake news samples are political sensitive, the system can learn to link the topics with lies even though the information is true. To do so, we need to analyze the dataset carefully, and if it is necessary, balance the number of topics or sources. Our another ethical issue relates to the ways that the model's predictions are applied. Mistakes will always be made no system is perfect and with labeling an item as "fake" you may damage trust or reputations. There should be no use of the tool to shame or silence any group. Instead, its results should complement, rather than facilitate, human judgment. The open dissemination of the model's accuracy and limitations enables others to know what it can and cannot do. The output of this system should be in context when it ever gets published (confidence scores) instead of hard labels. In essence, ethical research entails openness, non-damaging, and value of open and impartial communication.

7.2.4 Environment Issues:

The language model development and training process involves environmental considerations, and particularly, for computationally expensive architectures, like transformers. Models of the type of DistilBERT although smaller than full-sized BERT still require a great deal of computing power. Each training run uses electricity and multiple experiments (as are required during grid search optimization) can accumulate rapidly. In most cases if not all, the power that energizes cloud services is non-renewable, leading to carbon pollution. Although this project had relatively efficient configurations, it should be noted that machine learning has a real world environmental cost. Understanding the importance of taking a step in the direction of scaling down this impact, DistilBERT's adoption over a heavier model was one step in that direction because it maintains much of the capability that BERT has while requiring a lower cost in terms of energy. Also, after training the model, required power to support predictions is significantly diminished which makes it applicable for light resource applications such as the browser extensions. More efficiency can be achieved during training by conscious selections on size of the batch, early stopping and resoning with energy conscious servers. With that increasing interest in artificial intelligence, so does the environmental footprint. A responsible development is knowing these issues and striving for more environmentally friendly computing. Documentation of compute utilization and optimization in those areas that are possible can help to avoid an unnecessary ecological cost of technological advances.

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7.3 Future Work

In the future we have plans to customize, enhance and alter some parts. These are:

- **Model deployment as a browser extension:** The hybrid model that is to be used in the current proposed system can be wrapped as a browser extension, used in flagging potentially fake news on a real time basis. This will necessitate optimisation of the models efficiency and inference speed but it can have the excellent real world returns of warning users of possibly false content during their browsing.

- **Dataset expansion via web scraping:** The BanFakeNews current dataset is severely imbalanced (about 48, 000 real; 1000 fake articles). For future work, data collection will include automated web scraping to retrieve a number of other examples of fake news. A bigger and balanced set will reduce class imbalance and enhance the generalization of the model to various news content.

- **Incorporating social context features:** Other than textual analysis, the addition of social (or propagation-based) features such as retweet counts, source credibility and article sharing patterns can be helpful in providing useful context. Previous works has indicated that adding social context features can greatly enhance detection performance of fake news. The introduction into the model's input of such metadata may help the model discriminate more effectively between misleading information.

- **Enhanced tokenization and language models:** The NLP pipeline improvements are also programmed. Instead of more basic forms of Bangla tokenization techniques such as SentencePiece or Bengali NLP toolkits (for example BNLP), it would better capture the rich morphology of the language. In addition, the testing of bigger transformer-based language models, i.e. BanglaBERT, multilingual BERT (mBERT), or XLM-RoBERTa, may provide more robust language representations. These models have shown better results on Bangla tasks, and the replacement of the current DistilBERT by a bigger Bangla-specific one (after its proper fine-tuning) can additionally increase the accuracy of fake news detection.

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