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Department of Computer Science & Engineering
CSE 800

Improving Bangla Fake News Detection using BERT and Deep learning Techniques

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Recommendation Letter from Thesis Supervisor

The thesis entitled "Improving Bangla Fake news detection using BERT and Deep Learning Teachniques" submitted by the students:

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is a record of research work carried out under my supervision and I, hereby, approve that the report is submitted in partial fulfillment of the requirements for the award of their Bachelor's Degree.

Signature of the Supervisor

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Certificate of Acceptance of the Thesis

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as part of the requirements of the course CSE 800, is being approved by the Department of Computer Science and Engineering as a partial fulfillment of the B.Sc. (Engg.) degree of the above students.

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Abstract

Fake news may refer to false or misleading information that is disseminated deliberately to mislead readers intentionally and may also result in real-world harm and misunderstanding. Fake news has proliferated with the increased popularity of digital platforms such as Facebook and news blogs, specifically on certain topics in Bangla. Even though the use of fake news is becoming a problem, most current studies have researched this phenomenon in English with limited work on fake news identification in Bangla. In this study, we proposed a BERT-based model that incorporated and classified both the headline and title of news articles. A balanced dataset of real and fake news articles was used from which we trained and evaluated various models, including CNN , Bi-LSTM , Hybrid model like Bi-GRU+CNN & then transformer-based model like BanglaBERT, and BERT. Out of all models used, BERT provided the highest accuracy at 84%, while the other traditional machine learning and deep learning models shows lower performance .So, It can be concluded from our investigation that incorporating the Headline and Content in combination with transformer models will dramatically enhance fake news detection in the Bangla language.

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Chapter - 1 : Introduction

Fake news is the news that is false and inaccurate but is designed to make people think that they are true and accurate. The term ‘Fake news’ gained global attention in 2016 during the election campaign in the U.S. when Donald Trump was using this term to put off anything he was being accused of. The reason for fake news is either commercial or political to make money or change opinion. Fake news manipulates people’s minds to think a certain way and makes people support a particular opinion. Fake news is not always just lies, more often it is a mixture of lies and truths. There is a famous saying that goes: “A lie can get halfway around the world before the truth has got its pants on”. As information spreads very quickly and freely on digital technologies and social media, fake news also spread much more quickly and to many more people. Often on online news sites, we see fake news. This false and inaccurate news is designed to mislead the readers. Social media is flooded with this kind of news these days. People who write this fake news are not interested in the issues that they are writing; they are interested in making some money out of it. For instance, through Facebook, they can draw readers into their websites and then make money o of advertising. The writer profits on the number of people who click on the news as the news are designed as ‘Clickbait’. It is very difficult to distinguish this fake news from genuine ones. Fake news can have serious consequences when they come out of the online world and enter into the offline world. In 2018, fake news of child abduction went viral through WhatsApp in Mexico and then a mob burned two men, who were suspected to be child abductors, to death before checking if the information was correct or not [1]. A similar thing happened in India and Myanmar. Also, fatal violence was instigated because of fake news on Facebook and WhatsApp in India, Myanmar, and Sri Lanka [1]. Fake news affects people psychologically and spreads hatred. A national survey carried out by the Management and Resources Development Initiative (MRDI), found that the rate of Fake news experience is high in rural areas (66%), followed by urban areas (62.3%), while it is the lowest in metropolitan areas (52.5%) in Bangladesh. And when searching for news online, half of the people don’t try to find out whether the information is fact or opinion [2]. So, to develop a system like this, our proposed approach is to use BERT and Deep learning techniques for fake news detection.

1.1 Background and Motivation

The emergence of new technology and the internet in particular has significantly transformed the way we communicate and share information globally. Unfortunately, this high level of convenience has subsequently created the issue of the ‘fake news’, namely news that is purposefully made for dissemination, falsified or constructed to sound factual. The understanding of the impacts of fake news is complicated, as it has the potential to greatly undermine the credibility of information and public perceptions, change the course of democratic processes, and foment conflict. The issue is widespread, but includes larger problems in the scope of under-resourced languages such as Bangla, which lack effective means of detection systems, exacerbating the issue. In recent years, transformer-based models like BERT [21] have significantly improved natural language understanding tasks across many domains

Bangla, the seventh largest language worldwide primarily spoken in Bangladesh but also in parts of India, is a linguistically rich and treasured cultural language. Here, we have often observed a lack of Bangla in natural language processing (NLP) research. Unfortunately, we have observed a lack of research due to a combination of factors such as a lack of labeled datasets, the linguistic complex nature of Bangla, and a relative lack of compute resources to build systems that detect fake news in Bangla. There is an urgent need to resolve these challenges to help with misinformation and provide robust detection systems that can support accurate and trustworthy information dissemination in the Bangla language.

1.2 Problem Statement

In recent years, the spread of fake news has become a serious issue, especially on social media platforms. A study reported that fake news spreads more rapidly than real news on platforms like Twitter [22], emphasizing the urgency of effective fake news detection systems. People often share news without checking its authenticity, which can lead to confusion, panic, or even violence. While many fake news detection systems have been developed for English, the Bangla language still lacks reliable and accurate solutions.

Bangla, spoken by over 230 million people, has fewer NLP tools, labeled datasets, and research compared to English. Most existing systems rely on basic machine learning techniques, which may not fully capture the complex structure and context of Bangla sentences. As a result, they often fail to detect fake news correctly. With the growth of Bangla content online, there is an urgent need for an effective Bangla fake news detection system. The challenge is to understand the deep meaning of text, which traditional models struggle with. This creates a research gap in building high-performing Bangla fake news classifiers using advanced models like BERT and deep learning techniques.

This thesis aims to address this gap by applying transformer-based models and comparing them with other deep learning approaches to improve accuracy and reliability in detecting Bangla fake news.

1.3 Objectives

The objective of our thesis is to explore and improve the Bangla fake news detection by applying a range of machine learning and deep learning techniques. The specific objectives of this work are as follows:

1) Collect and prepare a Bangla fake news dataset.
2) Balance and preprocessing the dataset
3) Train with transformer models on a balanced dataset to ensure unbiased results.
4) Compare result among machine learning and deep learning model alo with BERT too
5) Evaluate all models using precision, recall, F1-score, and accuracy.
6) Build a Bangla fake news detection model using BERT.
7) Presenting the findings through visualizations such as graphs and performance summaries

1.4 Thesis Structure

This thesis is organized into six chapters. **Chapter 1** introduces the research topic by discussing the background, problem statement, objectives, scope, limitations, and overall structure of the thesis. **Chapter 2** provides a detailed review of existing literature and related works on fake news detection, especially in Bangla and other low-resource languages. It also highlights the research gap that this thesis aims to fill. **Chapter 3** presents the research methodology, including the dataset, data preprocessing steps, model architectures, and experimental setup. **Chapter 4** describes the implementation and evaluates the performance of different models, such as BERT, CNN, and LSTM, using various evaluation metrics. The results are compared and analyzed to determine the most effective approach. **Chapter 5** discusses the findings in detail and interprets the results in the context of the research objectives. Finally, **Chapter 6** concludes the thesis by summarizing the key contributions and proposing directions for future research in Bangla fake news detection.

Chapter - 2 : Literature Review

Fake news has become a global problem with serious impacts on society, politics, and public safety. In Bangladesh, where social media and online platforms are widely used, the spread of fake news is especially concerning. As a result, many researchers have focused on detecting fake news using machine learning and deep learning methods, especially for Bangla language data. In this section, we review key studies and approaches that have been used to detect fake news in Bangla, with a special focus on the development and impact of transformer-based models like BERT and BanglaBERT.

Early research in this field primarily used traditional machine learning techniques. For example, a study using the Support Vector Machine (SVM) model on Bangla news articles reported a strong accuracy of 96.64%, showing that even basic models can perform well when the data is structured and relatively clean [3]. Similarly, Deep Neural Networks (DNN) were applied to fake news detection in online news portals, achieving 90% accuracy, which proved the potential of deeper networks in this task [4]. Naive Bayes classifiers, known for their simplicity, were tested on Twitter posts and still managed to reach 94% accuracy [5]. Another approach used SVM with linguistic features extracted from Bangla fake news articles, achieving 91% accuracy [6]. These features included grammatical patterns, specific keywords, and syntactic structures, which helped the model make better decisions. While these traditional methods showed promising results, they often required extensive manual feature engineering and struggled with generalization, especially on noisy or unstructured data like social media posts.

The next major improvement came with the use of transformer-based models, particularly BERT (Bidirectional Encoder Representations from Transformers). These models automatically learn rich language features from large text corpora and require minimal feature engineering. One study applied BERT to fake news detection in social media comments and achieved an impressive 97% accuracy, clearly outperforming earlier models [7]. To further boost performance, some researchers explored data augmentation techniques. In one such work, BERT was trained on a multilingual Bangla dataset that was augmented to increase data diversity. This approach resulted in 92.45% accuracy, highlighting the importance of larger and more varied datasets for deep learning models [8]. A more language-specific approach involved the use of BanglaBERT, a version of BERT pre-trained on Bangla news content collected from different portals. This model reached 91% accuracy, indicating that pre-training on native language data can significantly improve performance over general multilingual models [9]. Conroy et al. [24] surveyed early automatic deception detection methods and outlined key strategies for detecting fake news.

Traditional models were also tested on more informal sources like public comments from Facebook and YouTube. For instance, Multinomial Naive Bayes was applied to such data and achieved a lower accuracy of 82.44%, reflecting the difficulty of handling noisy and unstructured texts using shallow models [10]. These results further support the need for deep learning and language-specific transformer models in Bangla fake news detection.One of the most recent and comprehensive approaches involved comparing BanglaBERT and mBERT (multilingual BERT) on Bangla news data that was both summarized and augmented. This technique achieved up to 97% accuracy, the highest among all reviewed models [11]. The combination of summarization and augmentation allowed the models to learn more relevant and compressed information, boosting their ability to detect fake news accurately. Bingol and Alatas [14] focused on detecting rumors on social media using machine learning models. Their research demonstrated the effectiveness of classifiers like Naive Bayes and SVM in identifying misleading content. Similarly, Ahmad et al. [15] applied ensemble learning methods and showed that combining multiple classifiers can improve the performance of fake news detection systems.

In the context of the Bangla language, Hussain et al. [16] developed a fake news classifier using Multinomial Naive Bayes (MNB) and Support Vector Machine (SVM). Their study highlighted the importance of handling Bangla text carefully due to its unique linguistic structure. Another Bangla-specific study by Hossain et al. [20] explored both machine learning and deep learning methods, offering valuable insights into the strengths of hybrid approaches in low-resource languages like Bangla. Mandical et al. [17] investigated general fake news detection using machine learning, emphasizing feature extraction and model performance. Their findings support the idea that simple models, when tuned properly, can achieve competitive results. Fourure et al. [18] raised a critical concern in the evaluation of classification models. They pointed out that using biased evaluation protocols can artificially increase the F1-score, which may lead to misleading conclusions. Their study serves as a reminder of the importance of fair and unbiased evaluation when reporting model performance.

Finally, Townsend [19] provided a theoretical analysis of confusion matrices, a tool commonly used in classification tasks. Although older, this work laid a foundation for understanding classification errors and performance metrics in modern machine learning systems.

In summary, the research shows a clear trend: while traditional models like SVM and Naive Bayes can achieve decent performance, deep learning models, especially transformer-based ones like BERT and BanglaBERT, are far more effective. The use of domain-specific datasets, data augmentation, and summarization further improves the model's ability to detect fake news in Bangla, making them ideal choices for building robust and scalable detection systems.

Table 1 : Related Work Summary Table

Model	Dataset	Accuracy	Reference
Support Vector Machine	Bangla News Articles	96.64%	[3]
Deep Neural Network	Online News Portals	90%	[4]
Naive Bayes	Twitter Posts	94%	[5]
SVM with linguistic features	Bangla Fake News Articles	91%	[6]
BERT (Transformer)	Social Media Comments	97%	[7]
BERT with augmented data	Multilingual Bangla dataset	92.45%	[8]
BanglaBert	Scraped from Bangla portals	91%	[9]
Multinomial Naive Bayes	Comments from Facebook and YouTube	82.44%	[10]
BanglaBERT, mBERT	Bangla news via augmentation + summarization	Up to 97%	[11]

Chapter - 3 : Methodology

3.1 Dataset

In this study, we have collected fake news articles in Bangla, we used a combination of public datasets and manual curation. First, we extracted real news samples from existing Kaggle datasets related to Bangla fake news (BanFakeNews & BanFakeNews 2.0). However, these datasets alone were not enough, so we manually collected additional fake news from social media posts (especially viral Facebook posts), unreliable blogs, and online news portals known for spreading misinformation. We selected news that appeared clickbait, misleading, exaggerated, or clearly debunked by fact-checking organizations. Each sample was manually reviewed to ensure it was fake and not just opinion-based or sensational. This helped improve the quality and accuracy of the fake news dataset.

3.1.1 Dataset Description

We used a balanced dataset containing a total of **41,288 Bangla news samples**, equally divided into **20,644 real** and **20,644 fake** news articles. Each sample includes only the **news Headline**, **Content**, and the corresponding **Label** (real or fake). We intentionally excluded any metadata such as author name, publication date, or source, as such information may introduce bias or allow the model to make predictions based on irrelevant features. By focusing solely on the text content, we ensured that the model learns to classify news based purely on linguistic and contextual patterns, not external clues.

3.1.2 Dataset Preprocessing

In this study, multiple models were used for fake news detection, including machine learning algorithms, deep learning architectures, and BERT-based transformers. As a result, the preprocessing steps were carefully chosen to support all types of models.

First, the dataset was cleaned by removing unwanted elements such as URLs, HTML tags, emojis, special characters, and English alphabets. For traditional machine learning and deep learning models, additional steps were performed, such as converting text to lowercase, removing Bangla stopwords, and applying tokenization to split text into meaningful words. These steps help reduce noise and improve model learning for simpler algorithms. However, for BERT-based models, minimal preprocessing was applied to preserve the original structure and context of each sentence. Stopword removal and stemming were skipped, as BERT relies on its own tokenizer to handle language patterns. After preprocessing, the text was tokenized using appropriate tokenizers (e.g., TF-IDF for ML models and Bangla BERT tokenizer for BERT), padded or truncated as needed, and then split into training and testing sets to prepare for model training and evaluation.

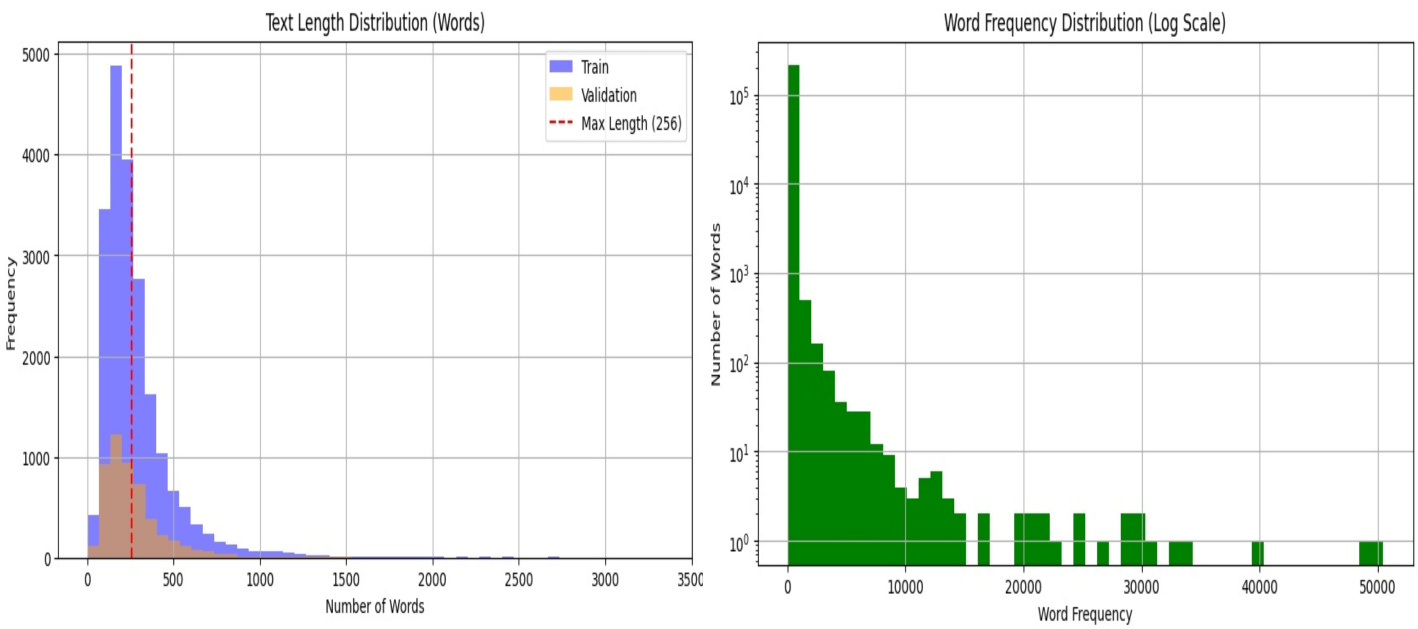

Figure 1 : Text Length Distribution & Word Frequency

Left side Figure presents the raw statistical characteristics of the Bangla news dataset before preprocessing. The left panel shows the text length distribution, where approximately 90% of articles contain 256 words or fewer, establishing this as our optimal truncation threshold for BERT input standardization. The right panel (Figure 3.X(b)) displays the log-scaled word frequency distribution, characterized by a pronounced peak of high-frequency stopwords (e.g., common Bengali function words like 'এবং' [and]) and a long tail of rare but potentially meaningful terms. Together, these distributions informed three key preprocessing decisions: first, length normalization to 256 tokens to preserve most content while ensuring computational efficiency;

second, stopword removal to reduce noise from overrepresented function words; and third, implementation of BERT's subword tokenization to effectively handle both frequent vocabulary and rare, potentially discriminative terms. This data-driven approach ensured our model focused on linguistically meaningful patterns while maintaining consistency with transformer architecture requirements.

Table 2 : List Of Stopwords

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{'হওয়ায়', 'চার', 'হতে', 'তিনিও', 'তারা', 'তাঁদের', 'গেলে', 'পাচ', 'অনুযায়ী', 'কেন', 'পরেও', 'নিয়ে', 'স্বয়ং',
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'কারও', 'ওর', 'এরা', 'এমনকী', 'দুই', 'কাজে', 'পর', 'তো', 'ওকে', 'বক্তব্য', 'বরং', 'কিন্তু', 'জানায়', 'এঁরা',
'অবধি', 'ওই', 'জানিয়ে', 'হয়তো', 'হয়েছে', 'তাঁ◌াহারা', 'শুরু', 'করতে', 'কেউ', 'পারি', 'এ', 'বেশি', 'কয়েক
টি', 'বসে', 'দিয়েছে', 'এবং', 'বন', 'কী', 'তাহাতে', 'এল', 'চান', 'প্রায়', 'এদের', 'অথবা', 'সহিত', 'বদলে',
'যতটা', 'যাবে', 'জন্য', 'মাত্র', 'সাধারণ', 'কেখা', 'নিতে', 'কাজ', 'তাদের'}
398
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Table 3 : Before removing Stopwords

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◆ Original [0]:
আগামী ৫ অক্টোবর অনুষ্ঠেয় এমবিবিএস ভর্তি পরীক্ষার দিন সব শিক্ষার্থীদেরকে সকাল সাড়ে ৯টার মধ্যে পরীক্ষা কেন্দ্রে প্রবেশ করতে হবে। পরীক্ষা কেন্দ্রে শিক্ষার্থীসহ ক
র্তব্য পালনকারী কর্মকর্তা-কর্মচারি মোবাইল ফোনসহ কোনো ধরনের ইলেক্ট্রনিক্স ডিভাইস ও ঘড়ি নিয়ে প্রবেশ করতে পারবেন না। শিক্ষার্থীদেরকে প্রবেশ পত্রের সাথে উ
ল্লিখিত নির্দিষ্ট ধরনের কলম নিয়ে প্রবেশ করতে হবে।   আজ সোমবার সচিবালয়ে আসন্ন এমবিবিএস ভর্তি পরীক্ষা সুষ্ঠুভাবে সম্পন্ন করার লক্ষ্যে আইন শৃংখলা রক্ষাকারী
বাহিনী এবং পরীক্ষা সংক্রান্ত ওভারসাইট কমিটির সাথে বৈঠকে এই সিদ্ধান্ত গৃহীত হয়। স্বাস্থ্য ও পরিবার কল্যাণ মন্ত্রী মোহাম্মদ নাসিম এতে সভাপতিত্ব করেন।   সভায়
স্বাস্থ্যমন্ত্রী বলেন, আসন্ন এমবিবিএস ভর্তি পরীক্ষাকে সর্বোচ্চ কঠোর ও নিচ্ছিদ্র নিরাপত্তার মধ্য দিয়ে সম্পন্ন করার সব প্রস্তুতি ইতোমধ্যেই নেওয়া হয়েছে। তাই পরীক্ষা
নিয়ে কোনো বিতর্ক সৃষ্টির সুযোগ এবারও থাকবে না।   তিনি বলেন, জনগণের কাছে মানসম্মত স্বাস্থ্যসেবা পৌঁছে দিতে দেশের মেডিকেল কলেজগুলোতে যেন প্রকৃত
মেধাবীরাই ভর্তির সুযোগ পায় তা নিশ্চিত করতে সরকার কোনো আপোষ করবে না।   ভূয়া প্রশ্নপত্র ফাঁস বাণিজ্য বা গুজব প্রতিরোধে শিক্ষার্থী, অভিভাবক, নাগরিক স
মাজ ও গণমাধ্যমকে সচেতন থাকার আহ্বান জানিয়ে স্বাস্থ্যমন্ত্রী বলেন, বিশেষ করে সামাজিক যোগাযোগ মাধ্যমে অসত্য তথ্য সংবলিত পোস্ট ও ভূয়া অনলাইন পোর্টালের
ওপর তীক্ষ্ম মনিটরিং জোরদার করতে সব সচেতন নাগরিক এবং আইন শৃংখলা রক্ষাকারী বাহিনী ও গোয়েন্দা সংস্থাসমূহের প্রতি আহ্বান জানান। এক্ষেত্রে কেউ কোনো ত
থ্য পেলে তা সাথে সাথে আইন-শৃংখলা রক্ষাকারী বাহিনীকে জানিয়ে দেওয়ার জন্য মন্ত্রী অনুরোধ করেন। বাসস   ইত্তেফাক/কেকে

◆ Cleaned [0] (after removing stopwords):
 অক্টোবর অনুষ্ঠে এমবিবিএস ভর্তি পরীক্ষ শিক্ষার্থী সকাল সাড় ট পরীক্ষা কেন্দ্র প্রবেশ পরীক্ষা কেন্দ্র শিক্ষার্থীসহ কর্তব্য পালনকারী কর্মকর্তাকর্মচারি মোবাইল ফোনসহ ধর
ন ইলেক্ট্রনিক্স ডিভাইস ঘড়ি প্রবেশ পারব শিক্ষার্থী প্রবেশ পত্র সাথ উল্লিখিত নির্দিষ্ট ধরন কলম প্রবেশ সোমব সচিবাল আসন্ন এমবিবিএস ভর্তি পরীক্ষা সুষ্ঠুভাব সম্পন্ন ল
ক্ষ্য আইন শৃংখলা রক্ষাকারী বাহিনী পরীক্ষা সংক্রান্ত ওভারসাইট কমি সাথ বৈঠ সিদ্ধান্ত গৃহীত স্বাস্থ্য পরিব কল্যাণ মন্ত্রী মোহাম্মদ নাসিম সভাপতিত্ব সভা স্বাস্থ্যমন্ত্রী আসন্ন
এমবিবিএস ভর্তি পরীক্ষা সর্বোচ্চ কঠোর নিচ্ছিদ্র নিরাপত্ত মধ্য দি সম্পন্ন প্রস্তুতি ইতোমধ্য হ পরীক্ষা বিতর্ক সৃষ্ সুযোগ এব জনগণ মানসম্মত স্বাস্থ্যসেবা পৌঁ দেশ মেডিক
কলেজ প্রকৃত মেধাবী ভর্তির সুযোগ পা নিশ্চিত সরক আপোষ ভূয়া প্রশ্নপত্র ফাঁস বাণিজ্য গুজব প্রতিরোধ শিক্ষার্থী অভিভাবক নাগরিক সমাজ গণমাধ্যম সচেতন থাক আ
হ্বান জানি স্বাস্থ্যমন্ত্রী সামাজিক যোগাযোগ অসত্য তথ্য সংবলিত পোস্ট ভূয়া অনলাইন পোর্টাল ওপর তীক্ষ্ম মনিটরিং জোরদ সচেতন নাগরিক আইন শৃংখলা রক্ষাকারী
বাহিনী গোয়েন্দা সংস্থাসমূহ আহ্বান জানান এক্ষেত্র তথ্য পেল সাথ সাথ আইনশৃংখলা রক্ষাকারী বাহিনী জানি দেওয় মন্ত্রী অনুরোধ বাসস ইত্তেফাকক
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Table 4 : After Removing Stopwords

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◆ Original [2]:
দেশের চারটি মোবাইল ফোন অপারেটরের মোট গ্রাহক সংখ্যাও দেশের মোট জনসংখ্যার কাছাকাছি, প্রায় সাড়ে ১৫ কোটি। চলতি বছরের অগাস্ট পর্যন্ত সময়ের তথ্য
হিসেবে করে টেলিযোগাযোগ নিয়ন্ত্রক সংস্থা বিটিআরসির এক প্রতিবেদনে মোবাইল ফোন ও ইন্টারনেট গ্রাহকের এ তথ্য জানানো হয়েছে। বৃহস্পতিবার কমিশনের ওয়েবসাই
টে প্রকাশিত ওই প্রতিবেদনে দেখা যায়, বর্তমানে দেশে ইন্টারনেট গ্রাহকের সংখ্যা নয় কোটি ৫ লাখ। বিটিআরসির ভারপ্রাপ্ত চেয়ারম্যান জহুরুল হক বিডিনিউজ
টোয়েন্টিফোর ডটকমকে বলেন, “এটি টেলিযোগাযোগ খাতের একটি সাফল্য, ৯ কোটির বেশি ইন্টারনেট গ্রাহক অর্থ হচ্ছে ডিজিটাল বাংলাদেশের গড়ার ক্ষেত্রে আমরা অ
নেকদূর এগিয়ে গেছি।” এর মধ্যে মোবাইল ফোন নেটওয়ার্কের মাধ্যমে ইন্টারনেট ব্যবহার করেন আট কোটি ৪৬ লাখ ৮৫ হাজার গ্রাহক। ইন্টারনেট সেবাদাতা প্রতিষ্ঠান
(আইএসপি) ও পাবলিক সুইচড টেলিফোন নেটওয়ার্কের (পিএসটিএন) ইন্টারনেট গ্রাহক সংখ্যা ছাড়িয়েছে ৫৭ লাখ ৩৩ হাজার। বিটিআরসির প্রতিবেদন বিশ্লেষণে দেখা
যায়, ওয়াইম্যাক্স ইন্টারনেটে ক্রমাগত আগ্রহ হারাচ্ছেন গ্রাহকরা। অগাস্টে ওয়াইম্যাক্স গ্রাহক দাঁড়িয়েছে ৮৩ হাজারে, আট মাস আগে জানুয়ারিতেও এই সংখ্যা ছিল ৮৮
হাজার। বিটিআরসির হিসাবে, অগাস্ট মাস নাগাদ চারটি মোবাইল ফোন অপারেটরের মোট গ্রাহক সংখ্যা ১৫ কোটি ৪১ লাখ ৭৯ হাজার। সাত কোটি ৭ লাখ ৯ হাজার
গ্রাহক নিয়ে শীর্ষে রয়েছে গ্রামীণফোন। তাদের পরে রয়েছে রবি, চার কোটি ৬১ লাখ ৩২ হাজার গ্রাহক নিয়ে। বাংলালিংকের গ্রাহক তিন কোটি ৩৪ লাখ ৬৬ হাজার এবং
রাষ্ট্রায়ত্ত অপারেটর টেলিটকের গ্রাহক সংখ্যা ৩৮ লাখ ৭৩ হাজার।

◆ Cleaned [2] (after removing stopwords):
দেশ চার মোবাইল ফোন অপারেটর গ্রাহক সংখ্যা দেশ জনসংখ্য কাছাকা সাড়  চলতি বছর অগাস্ট সময় তথ্য হিসেব টেলিযোগাযোগ নিয়ন্ত্রক সংস্থা বিটিআরসির এক প্র
তিবেদন মোবাইল ফোন ইন্টারনেট গ্রাহক তথ্য হ বৃহস্পতিব কমিশন ওয়েবসাইট প্রকাশিত প্রতিবেদন যা বর্তমান দেশ ইন্টারনেট গ্রাহক সংখ্যা  লাখ বিটিআরসির ভারপ্রাপ্ত
চেয়ারম্যান জহুরুল হক বিডিনিউজ টোয়েন্টিফোর ডটকম  টেলিযোগাযোগ খাত সাফল্য  কো ইন্টারনেট গ্রাহক অর্থ ডিজিটাল বাংলাদেশ গড় অনেকদূর এগি গে  মোবাই
ল ফোন নেটওয়ার্ক ইন্টারনেট আট  লাখ  গ্রাহক ইন্টারনেট সেবাদাতা প্রতিষ্ঠান আইএসপি পাবলিক সুইচড টেলিফোন নেটওয়ার্ক পিএসটিএন ইন্টারনেট গ্রাহক সংখ্যা
ছাড়ি  লাখ  বিটিআরসির প্রতিবেদন বিশ্লেষণ যা ওয়াইম্যাক্স ইন্টারনেট ক্রমাগত আগ্রহ হারাচ্ছ গ্রাহক অগাস্ট ওয়াইম্যাক্স গ্রাহক দাঁড়ি  হাজার আট মাস জানুয়ারি সংখ্যা
বিটিআরসির অগাস্ট মাস চার মোবাইল ফোন অপারেটর গ্রাহক সংখ্যা   লাখ  সাত  লাখ  গ্রাহক শীর্ষ র গ্রামীণফোন র র  লাখ  গ্রাহক বাংলালিংক গ্রাহক তিন  লাখ
রাষ্ট্রায়ত্ত অপারেটর টেলিটক গ্রাহক সংখ্যা  লাখ
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For traditional machine learning and deep learning models, the text was cleaned by removing unwanted characters and Stopwords before tokenization and vectorization. For the BERT-based model, only basic cleaning was done without removing Stopwords, preserving the original sentence structure for the tokenizer. The processed data was then split into training and testing sets for model evaluation.

We avoided using heavily cleaned data for BERT because this model is designed to understand the full context of a sentence, including common words like stopwords. Removing stopwords or altering the sentence structure can confuse BERT and reduce its ability to capture the meaning behind the text. Unlike traditional models that benefit from simplified input, BERT relies on the natural flow of language to learn deeper relationships between words. So, keeping the text as close to its original form as possible helps BERT perform better in detecting fake news.

3.2 Model Implementation:

3.2.1 Machine learning Models(Baseline Model):

Total three number of machine learning models will be described here that includes Support Vector Machine (SVM), Naïve Bayes & Random Forest.

Support Vector Machine (SVM): Support Vector Machine (SVM) classification is the technique we first employed for training. An example of a machine learning algorithm is SVM, which was inspired by statistical learning theory. Although Support Vector Machines are often thought of as a classification method, they can be used to solve both classification and regression issues. It can deal with a variety of categorical and continuous variables with ease. In order to distinguish between several classes, SVM creates a hyperplane in multidimensional space. Error minimization is accomplished through SVM, which iteratively constructs the best hyperplane. Finding a maximum marginal hyper-plane that most effectively categorizes the dataset into classes is the central goal of SVM. These methods are advantageous over Naive Bayes algorithm in that they predict outcomes more quickly and with higher accuracy. As a result of only using a portion of the training points during the choice phase, they also consume less memory. When the margin of separation is distinct and the space is large, SVM performs effectively. Here is a detailed description of how SVM functions:

Support Vector Machines (SVM) are used to classify Bangla news articles as real (1) or fake (0). The first step of the analyses is to prepare the data, where the news articles are converted into numerical feature vectors which provide relevant features of the text. These feature vectors are combined with the binary class labels and provided as data to the model to learn from the structured data.

The main objective of SVM is to find the best hyperplane that separates the two classes in the feature space. Hyperplanes represent decision boundaries and SVM attempts to maximize the margin - defined as the distance from the hyperplane to the closest data points from each class. These closest data points are known as support vectors and a larger margin generally yields better generalization on unseen data.

The SVM procedure finds the best hyperplane by solving the convex optimization model, it minimizes classification errors and maximizes the margin. When SVM finds the data does not allow a linear separation of classes, SVM uses the kernel trick to map the data into a higher dimension, where linear separation becomes possible. The commonly used kernel types are linear, polynomial, sigmoid, and radial basis function (RBF). After training, the asynchronous model is tested on new Bangla news articles by predicting contents are real or fake.

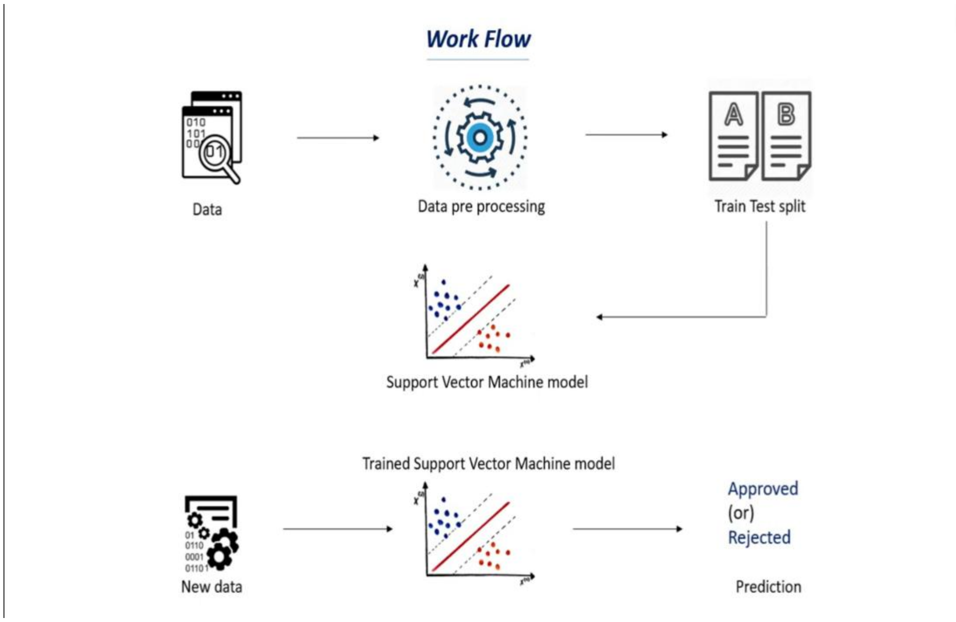

Figure 2 : SVM WorkFlow Diagram

Naïve Bayes: Naive Bayes is a classification algorithm that uses probability to predict which category a data point belongs to, assuming that all features are unrelated. As it is named as "Naive" because it assumes the presence of one feature does not affect other features. The "Bayes" part of the name refers to its basis in Bayes' Theorem.

Bayes' Theorem provides a principled way to reverse conditional probabilities. It is defined as:

$$P(y|X) = \frac{P(X|y) \cdot P(y)}{P(X)}$$

Where:

P(y|X): Posterior probability, probability of class y given features X

P(X|y): Likelihood, probability of features X given class y

P(y): Prior probability of class y

P(X): Marginal likelihood or evidence

Working Principle: The data preparation process begins with cleaning and structuring the dataset so that each news article is represented as a feature vector, where each feature corresponds to a unique attribute such as word count, specific keywords, or TF-IDF scores. Each data point is assigned a class label—commonly 1 for real news and 0 for fake news—enabling supervised learning. The Naive Bayes algorithm first calculates the prior probability for each class by dividing the number of samples in that class by the total number of training samples, estimating the overall frequency of each class. Next, it estimates the likelihood of observing each feature value given the class, based on the frequency of features within the training data. Applying Bayes' theorem, the algorithm combines the prior probabilities and likelihoods to compute the posterior probability for each class given the input features, while ignoring the evidence term since it remains constant across classes. The model predicts the class with the highest posterior probability for each data point. To address the issue of zero probabilities caused by unseen features during testing, Laplace smoothing is applied, which adds a small constant to feature counts. Finally, after training, the model is evaluated on unseen test data using performance metrics such as accuracy, precision, recall, and F1-score.

Random Forest: In a random forest, each individual decision tree makes its own prediction based on the data it's trained on, and the final outcome is determined by aggregating the predictions of all the trees. For classification problems, this typically involves a majority voting system where the class predicted by the most trees is chosen. In regression tasks, the average of all the tree predictions is often used as the final outcome.

The random forest algorithm is an extension of the bagging method as it utilizes both bagging and feature randomness to create an uncorrelated forest of decision trees. Feature randomness, also known as feature bagging or “the random subspace method”, generates a random subset of features, which ensures low correlation among decision trees. This is a key difference between decision trees and random forests. While decision trees consider all the possible feature splits, random forests only select a subset of those features.

Working Principle: The Random Forest algorithm has three primary hyperparameters that need to be configured before training: the number of trees, the number of features sampled at each split, and the minimum node size. Random Forest is an ensemble method consisting of multiple decision trees, where each tree is trained on a different **bootstrap sample**—a randomly selected subset of the training data with replacement. To ensure diversity, approximately one-third of the data is left out of each sample; this subset is known as the **out-of-bag (OOB) sample**, and it is later used for internal model validation.

In addition to bootstrap sampling, Random Forest introduces further randomness through **feature bagging**, where a random subset of features is considered when splitting at each node. This technique reduces the correlation among trees and increases overall model robustness. Depending on the type of problem, Random Forest makes predictions in different ways: for regression, it averages the outputs of all decision trees, while for classification, it uses majority voting to select the most frequent predicted class. Finally, the OOB samples provide an estimate of the model’s performance, serving as a built-in cross-validation method without needing a separate validation set.

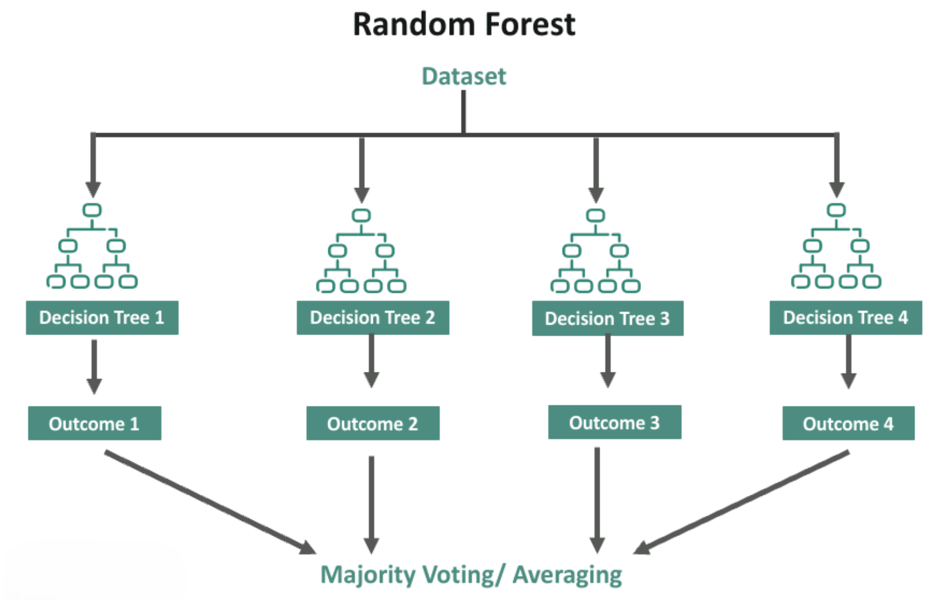

Figure 3 : Random Forest Diagram

3.2.2 Deep Learning Models:

Deep learning is a subset of machine learning that uses multiple layers of artificial neural networks to learn complex patterns from data. In this thesis, deep learning models were applied to detect fake news in the Bangla language. Unlike traditional machine learning, which often relies on manual feature extraction, deep learning automatically learns useful features from raw text. This is especially useful in natural language processing (NLP) tasks like fake news detection, where text meaning depends on context and structure.

The deep learning models used in this study include **Convolutional Neural Networks (CNN)**, **Recurrent Neural Networks (RNN)**, **Long Short-Term Memory (LSTM)**, and **Bidirectional LSTM (Bi-LSTM)**. CNNs are effective at identifying important phrases or local patterns in the news text. RNNs handle sequences and can learn the order of words. LSTM improves upon RNN by remembering long-term dependencies, which is useful when analyzing longer articles. Bi-LSTM reads the text from both directions—forward and backward—allowing it to understand the full context of each word. These models were trained on a labeled Bangla dataset and tested to evaluate their ability to classify news as real or fake.

Deep learning models outperformed traditional machine learning algorithms by achieving higher accuracy, especially when combined with pre-trained language models like BERT. Their strength lies in automatically learning deep, contextual features from large datasets, making them highly suitable for fake news detection tasks.

Convolutional Neural Networks (CNNs): CNNs are a type of deep learning model originally developed for image recognition, but they are also very effective in natural language processing (NLP) tasks such as fake news detection. CNNs work by automatically detecting important features from text data, such as keywords or short phrases that often appear in fake or real news.

Working Procedure of CNN: The model starts with an embedding layer that translates each word of the text into a number vector using word embedding techniques, such as Word2Vec or FastText. This way the model seizes the semantic meaning of the words in the context. A convolutional layer is then applied. The convolutional layer also has multiple filters (or kernels) that pass over the embedded text to extract local features. In this way, the filters identify significant patterns in the text, such as association of words and other combinations of words or phrases that can indicate the news is real or fake. The output of the convolutional layer is passed through a Rectified Linear Unit (ReLU) activation function that keeps only positive integers and introduces non-linearity in our model. After this, a pooling layer (generally max pooling) retains the most relevant features and reduces the representation of feature maps in the next layers, focusing instead on the most dominant signals. The pooled features are then passed to one or more fully connected dense layers that combine features into one response. Finally, the output layer uses a sigmoid activation function that returns a probability between 0 to 1 indicating how likely the news is real or fake.

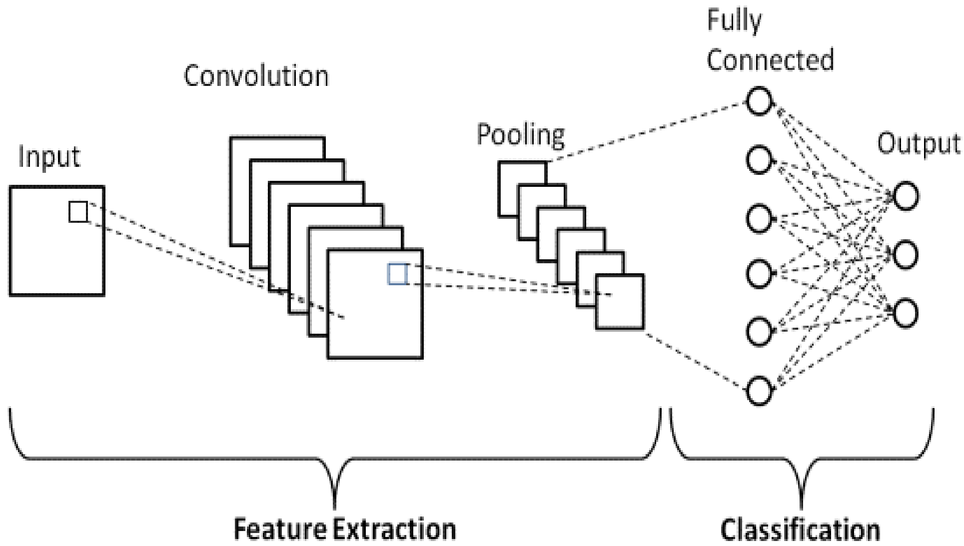

Figure 4 : CNN Diagram

Recurrent Neural Networks (RNNs) : RNNs are a type of deep learning model built to work with text or sequence-based data. In fake news detection, especially in Bangla, understanding the sequence of words is important. RNN reads the input text one word at a time, and remembers previous words while reading the next ones. This helps the model understand the flow and meaning of sentences. First, each word is turned into a number using an embedding layer. Then, the RNN processes each word step by step, passing information from one step to the next using something called a hidden state. After reading the full sentence or article, it uses the final information to decide if the news is real or fake.

Working Process of RNN: In this proposed architecture, each word in a sentence is represented as a vector using an embedding layer, allowing the recurrent neural network (RNN) to learn the semantic meaning of words. The RNN processes the text in order, so it looks at the words sequentially, and holds a hidden state that retains all information of the words encountered so far in the sequential order. Thus, the hidden state is updated with each new word, which allows the model to keep memory of the context in the sentence throughout. Once the entire sequence has been processed, the final hidden state is passed to an output layer that applies a sigmoid activation function to yield the probability of a news piece being real or fake. The sequential processing and memory of RNNs makes them a very effective mechanism for handling contextual dependencies in textual data.

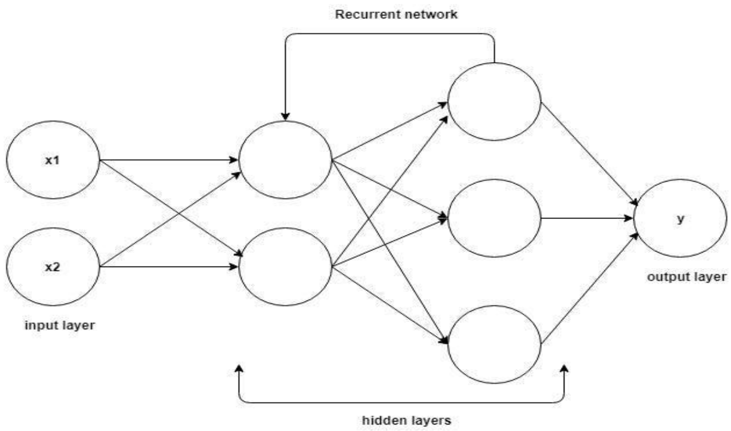

Figure 5 : RNN diagram

Long Short-Term Memory (LSTM) : LSTM, which stands for a long short-term memory neural network, is a type of Recurrent Neural Network (RNN) architecture developed to show the limitations of standard RNNs, especially when the traditional RNN tries to learn long-term dependencies.. RNNs do not easily learn this concept of retaining some important features from earlier in the sequence. The RNN tries to learn this with its hidden state but fails over long sequences of text. LSTM expects to retain this information during a longer sequence of text and it has a memory cell and three gates - input gate (i), forget gate (f), and output gate (o) - that LSTM relies on to decide which parts of the past to remember, which parts of the past to forget, and what to output at any sequential step.

LSTM is suitable in the Natural Language Processing domain because it has been shown to accomplish a variety of tasks with text, including sentiment analysis, language generation, and fake news classification. LSTM can learn inherently about the context confidently regarding a text sequence of input and retrieve the full information at the end of the series in producing a sentence or classification of: fake or real news. In our work LSTM is being helpful as it also learns about the sequential nature of the text in a news story, and whether there is inherent value in yielding some of the text for either the classification of the stories or whatever secrets exist in retrieving content from the article to confirm whether the news report was potential fake or real news. LSTM views the text, one feature at a time (e.g., one word), retains nothing but the important parts, and finally uses its memory to produce a sensation about real or fake news.

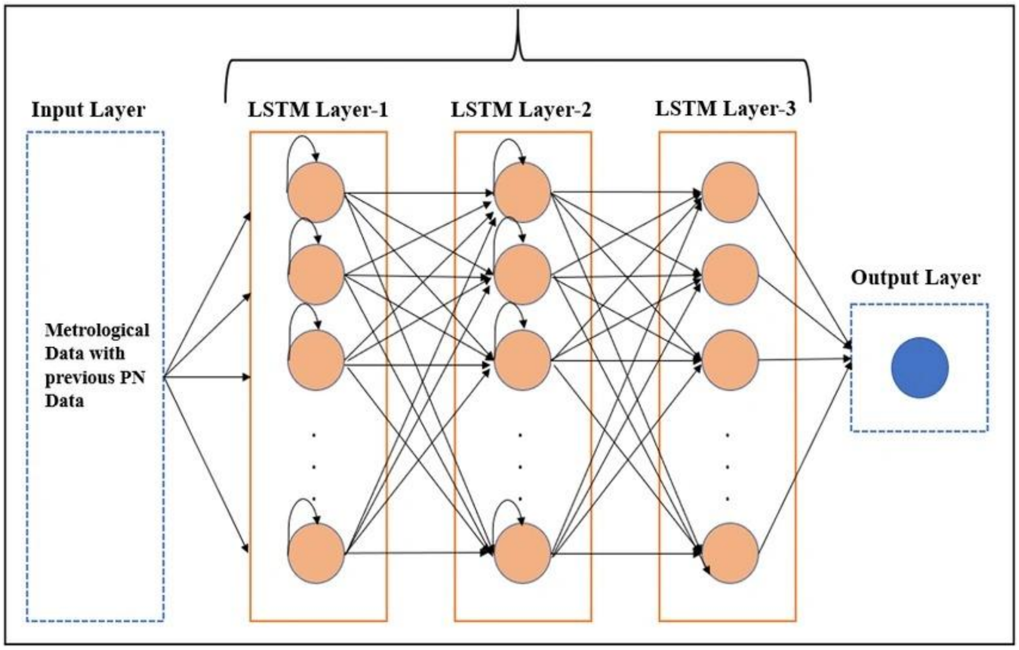

Figure 6 : LSTM diagram

As one of the deep learning methods which were used to detect Bangla fake news in this study, we used a Bidirectional Long Short-term Memory (Bi-LSTM) model. We decided to include a short description with a visual representation of the standard LSTM architecture in our paper, to give the reader a complete representation of the workings of the Bi-LSTM model. They are the same model and these dimensions package the primary concept behind sequential learning models, while Bi-LSTM packages a sequential evolving state, by processing data/sequence both forwards and backwards. Including both models provides the reader with a better understanding of why we chose these models and the usefulness of the additional context for any readers who are totally unfamiliar with the concept of recurrent neural networks.

Bidirectional Long Short-Term Memory (Bi-LSTM) : Bi-LSTM is a superior, extended version of the LSTM model. An improved form of the conventional LSTM model is called Bi-LSTM. A Bi-LSTM processes input data both forward and backward, whereas a traditional LSTM processes data only in one direction, from start to finish. In order to capture both past and future context, it reads the news text from the first word to the last as well as from the last word to the first. Being able to acquire information from both perspective helps the model learn the complete meaning of each word based upon the words surrounding it. In the case of fake news detection, which relies on specific context from both the previous and next words, Bi-LSTM provides an optimal understanding over unidirectional readers. We utilized a Bi-LSTM model, inspired by its success in Bangla language tasks such as POS tagging, as shown in Alam et al. [25].

In practice, Bi-LSTM is composed of two LSTM layers. one reads the input data in the sequential order, which is an LSTM, and the other reads in the reverse sequential order. The outputs are combined to predict the class at the end of the model. Because the Bi-LSTM is structurally built with the two layers of LSTMs and retains the sequential nature of the input text, it can detect greater complexity in the text and therefore improve its classification based on the greater understanding of the news text.

Working Procedure: The Bi-LSTM method handles Bangla news articles semi-structured text, leveraging two layers of LSTM in parallel, both forward and backwards. The sequential nature of text is essential since the interpretation of a word also depends on the previous words that make it explicit in sentences. First, we represent the input text as a sequence of words, such as breaking "ভাষায়" which is to separate the tokens for each word, individually. So we will take a tokenized word sequence (x_1, x_2, ..., x_t), where each x_t has dense word embeddings that identify meanings as well. Since Bi-LSTM architecture contains both forward and backwards parts, we proceed with describing these parts below:

In the forward LSTM ($\rightarrow h_t$), the model processes the input in a sense that it will be reading the sequence from beginning of the sequence (end of sequence) ($x_1 \rightarrow x_t$). The forward LSTM independently keeps track of the inputs and identifies if it creates dependency from previously shown words.In the backward LSMT ($\leftarrow h_t$), the opposite process of the forward LSTM happens from end of sequence beginning of the sequence ($x_t \rightarrow x_1$). This gives the model future context of what words come when moving opposite to the LSTM.

At each time step t, we concatenate the hidden states from both LSTM directions to create a shared layer/hidden state ($h_t = [\rightarrow h_t \parallel \leftarrow h_t]$). By concatenating both LSTM layers, it concatenates the context of the words surrounding, which is important, since with Bangla fake news it can also be misleading of what the headline states with contradictory statements in the body. Also, the shared hidden state layer is feed to a dense layer with a sigmoid activation function to output a score of a probability (0 = fake and 1 = real).

Training: The model trains like a LSTM through backpropagation through time (BPTT), it must update the weights at both LSTM layers for and minimize a loss function binary cross-entropy. These models help analyze sequential data, but it represents or trained on information that is limited to local context (like LSTM) against BERT's globally normalized attention which can cause the model to be restricted.

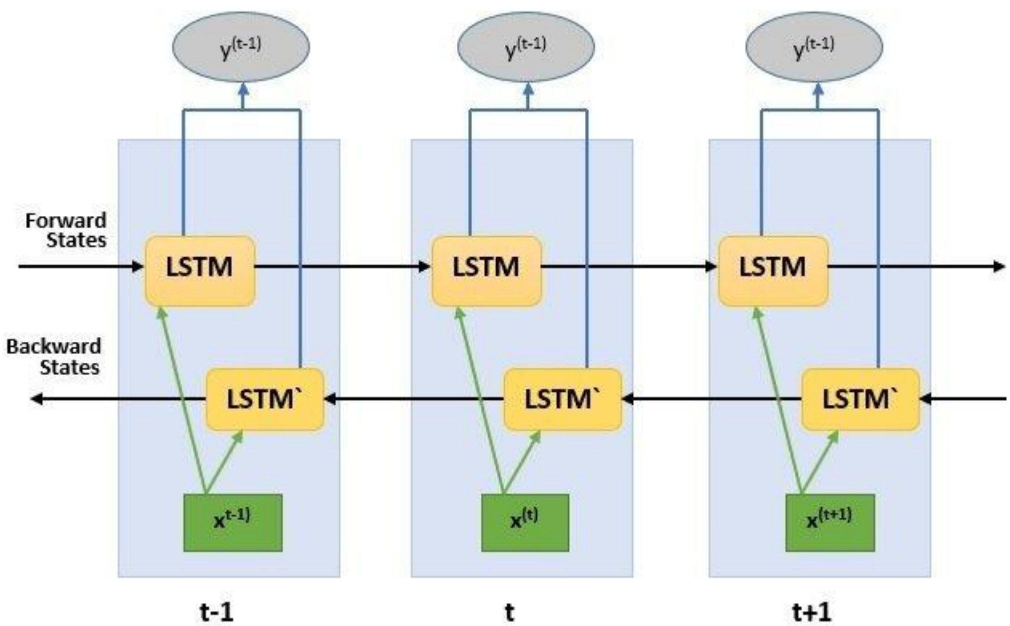

Figure 7 : Bi-LSTM diagram

Bi-GRU & CNN Model : The Bi-GRU+CNN model is a hybrid deep learning architecture designed to enhance performance in natural language processing tasks, such as fake news detection. It combines the strengths of two powerful models: Bidirectional Gated Recurrent Unit (Bi-GRU) and Convolutional Neural Network (CNN). The Bi-GRU captures the sequence and context of the input text from both forward and backward directions, allowing the model to understand the full meaning of a sentence. Meanwhile, CNN excels at extracting local and position-invariant patterns, such as important n-grams or phrases. By combining these models, the Bi-GRU+CNN architecture is able to learn both the global sequence structure and the most informative local features, which is especially useful in detecting subtle patterns or misleading language often present in fake news. This synergy makes it more effective than using either model individually.

Working Procedure: The working procedure for the Bi-GRU+CNN model starts with preprocessing the text and transforming it to numeric form through the embedding layer. Each word in the text becomes a dense vector that contains the semantic meaning in context. Embedding outputs are passed to the Bi-GRU layer, which has the entire sequence from both directions (backward and forward). The Bi-GRU layer outputs a sequence of ordered, context vectors with every word token in the input.

The output from the Bi-GRU layer is passed onto the CNN layer which uses several filters (with varying kernel sizes) in a convoluted manner that slides each filter across the input's sequence. Each filter detects patterns, like significant phrases or the relevant combinations of words to classify or process. The convolution output is passed to a max-pooling layer, where it picks features of most significance to retain the highest activation value in the feature map.

Optionally, after the max-pooling layer, an attention layer can be added to allow the model to focus on the most important tokens/features in the model sequence. After max-pooling (and attention layer if included) the model will pass the smaller feature vector through one or more fully-connected (dense) layers, where features, subsets of features, etc. are processed to make sense of the remaining tokens.

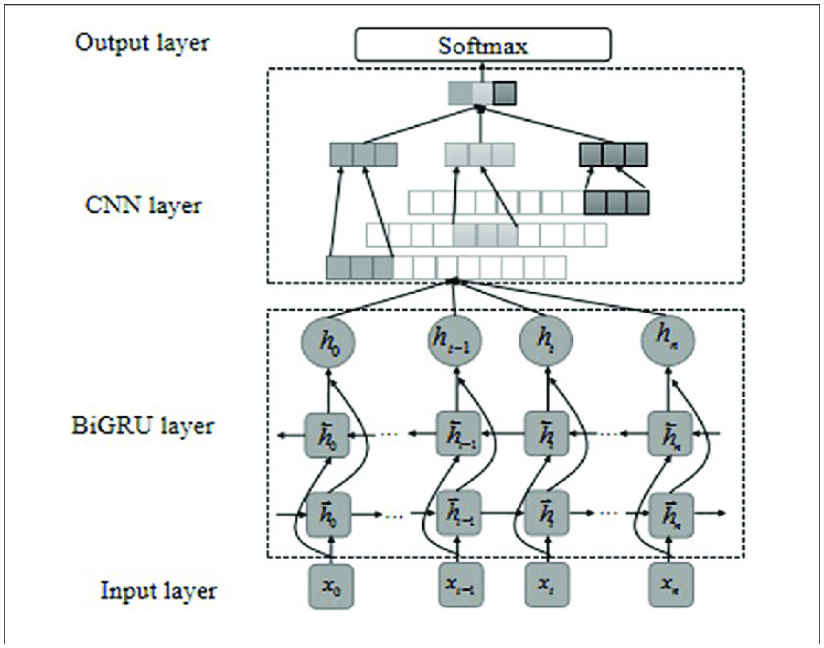

Figure 8 : Bi-GRU+CNN Architecture

3.2.3 Transformer Model (BERT) :

BERT, or Bidirectional Encoder Representations from Transformers, is a language model that Google developed in 2018. It uses the Transformer architecture, which has self attention mechanisms - these mechanisms help the model understand a word's context by looking at what comes before and after it at the same time. This two-way approach lets BERT grasp information from text, so it works well for many natural language processing tasks.

Other models read text one part at a time. BERT processes the whole sentence at once, so it understands the meaning of words that have more than one meaning based on their context. BERT trains on a large text collection with two tasks that do not need supervision - masked language modeling and next sentence prediction - this training helps it learn language patterns that apply to many other tasks with little change. For this study, BERT trains on the Bangla fake news data to sort news articles.

Working Process: Our BERT-based Bangla fake news detection system processes news articles by first analyzing both the headline and content together as a single input sequence. The raw text passes through BERT's WordPiece tokenizer, which intelligently splits words into subword units (like breaking "প্রচারে" into "প্র" + "চারে") while preserving special tokens - [CLS] at the beginning for classification and [SEP] between the headline and content to maintain their relationship. These tokens then transform into rich numerical representations through BERT's embedding layer, combining word meaning, positional context, and segment information (distinguishing headline from body text). The transformer encoder layers then analyze these embeddings, using multi-head attention to detect subtle inconsistencies between headlines and content - a key feature for fake news identification. The [CLS] token's final representation passes through a classification layer with sigmoid activation, outputting a probability score between 0 (fake) and 1 (real). By jointly processing headlines and content while preserving their semantic relationship through the [SEP] token, our model effectively captures the contextual mismatch patterns characteristic of Bangla fake news, outperforming traditional methods that process headlines and content separately. During training, we optimize using binary cross-entropy loss with the Adam optimizer, fine-tuning the pre-trained BanglaBERT model on our carefully curated dataset of labeled Bangla news articles.

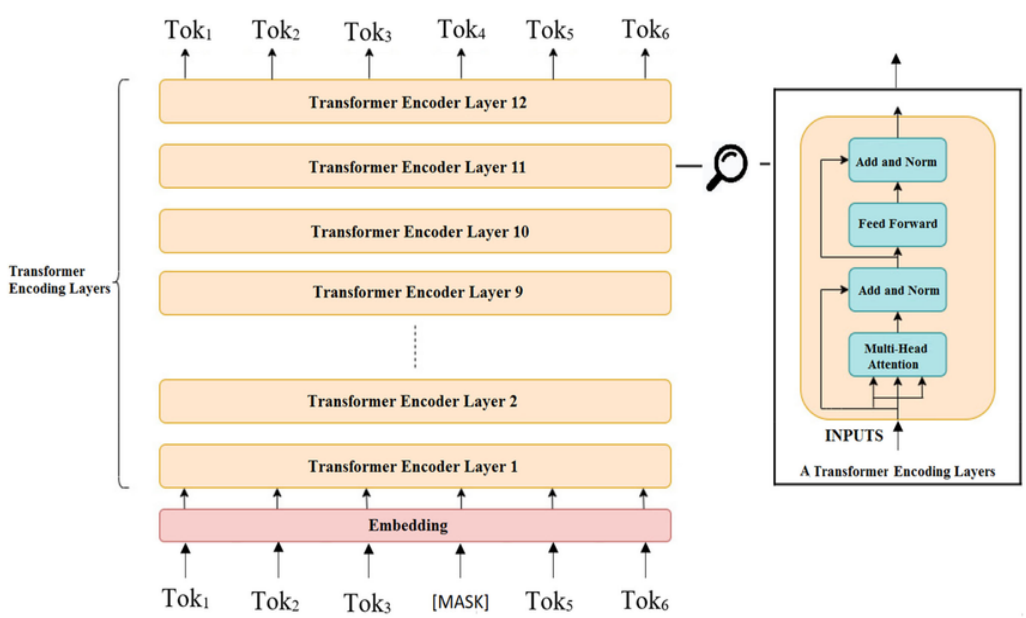

Figure 9 : BERT Model Architecture

Chapter - 4 : Result Analysis

Assessment of the performance and effectiveness of classification models necessitates the use of evaluation metrics as indispensable instruments. Quantitative measures are utilized to aid researchers and practitioners in comprehending the efficacy of a model in accurately categorizing instances into distinct classes, such as distinguish between fabricated news and authentic news.

4.1 Accuracy, precision, recall, and F1:

Accuracy, precision, recall, and F1 score are widely utilized evaluation metrics that are essential for assessing the overall effectiveness of classification models. The metric of accuracy evaluates the ratio of accurately classified instances to the overall instances present in the dataset.

The metric offers a comprehensive assessment of the accuracy of the model's predictions for both positive and negative cases. The concept of precision pertains to the affirmative category (specifically, fabricated news) and gauges the ratio of accurate positive prognostications (i.e., appropriately identified counterfeit news) to the overall anticipated positive occurrences. The degree of precision is indicative of the model's capacity to minimize the occurrence of false positives.

Table 5 : Different Model performance

Models	Precision	Recall	F1 Score	Accuracy
SVM	81.43%	81.36%	81.35%	81.36%
Naïve Bayes	79.78%	79.04%	78.91%	79.04%
Bi-GRU+CNN	84.54%	82.41%	83.46%	83.67%
CNN	81%	83%	83%	83%
RNN	79.4%	77%	82%	82.96%
Bi-LSTM	82%	82%	82%	82%
BERT	85%	84%	84%	84%
Bangla-BERT	82%	82%	82%	82%
Random Forest	81.33%	80.69%	80.59%	80.69%

The table above presents the accuracy for various machine learning and deep learning models tested when modeling on our Bangla fake news dataset. The traditional classifiers, SVM and Naive Bayes scored a respectable accuracy of about 81.36% and 79.04%, respectively. The deep learning models [CNN and Bi-GRU + CNN] produced better results, but only Bi-GRU + CNN gave the best model accuracy of 83.67%, which means getting both sequential and spatial features. The recurrent models (RNN and Bi-LSTM) all have fairly consistent performance and stabilized around 82%, as would be expected from the way these models properly model text sequences. The transformer based models performed the best overall and consequently, on the whole, we should have expected them to perform the best. For instance, the base BERT model (as well as the overall highest accuracy) achieved 84% overall accuracy, with very balanced precision, recall, and F1 scores around 84% which indicates an overall effectiveness of its contextual training. We also find that Bangla-BERT (the Bangla language model) seemed to perform reasonably well at 82% accuracy - which is less than the general BERT model, although still second overall and above the rest while still maintaining some possible sense for it. In contrast, Random forest (a traditional ensemble machine learning methodology), provided fairly moderate accuracy results at around 80.69%. Overall, the results and information acquired strengthens our thesis model decision of choosing BERT.

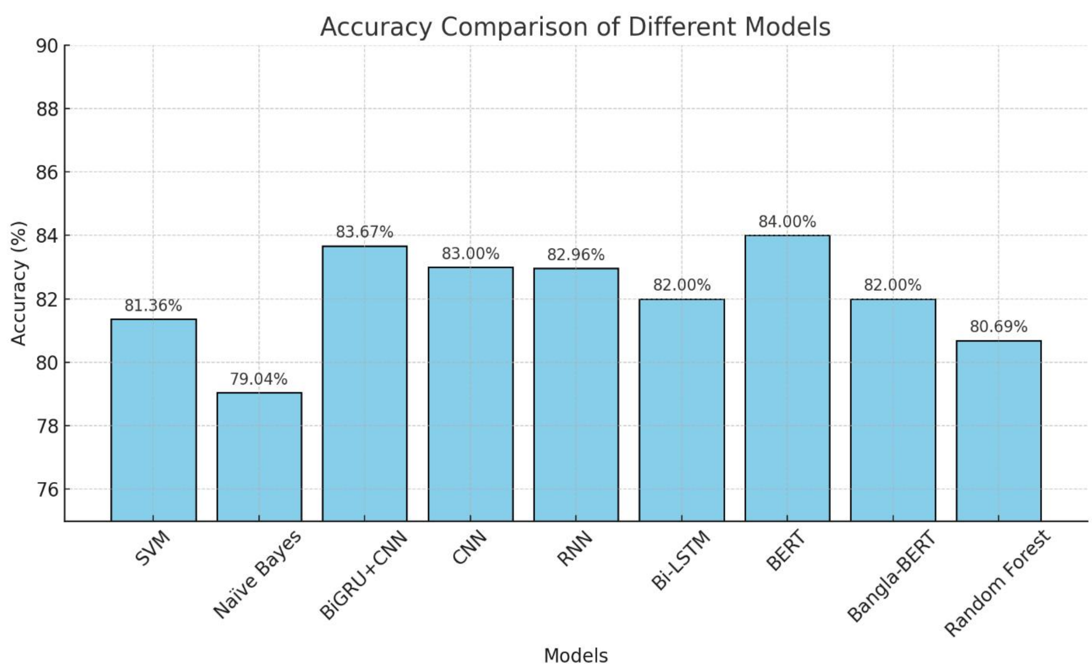

Figure 10 : Histogram of Accuracy Comparison of Different Models

This above histogram clearly presents the performance of the 9 models summarized according to model accuracy for Bangla fake news detection. All of the transformer model structures reported good performance with the Bangla BERT model yielding the best accuracy 84.00% when compared to BanglaBERT 82.96% as well as the very good deep learning models CNN 83.67%, Bi-LSTM 83.00% compared to the traditional ML methods SVM 81.36%, Naive Bayes 79.04%, although Random Forest yielded lower accuracy overall it performed to relatively well against traditional methods 82.00%. Overall, our study presents evidence of advantages provided by using contextual models (BERT variants) and the relative advantages of deep learning methods along the task of Bangla fake news detection. It is clear that Bangla BERT is pretrained (training data with language-specific) and showed evidenced improvements in accuracy but the hybrid Bi-GNU+CNN model 82.00% alone did not yield any real improvement in accuracy compared to simpler architectures. Overall, the results provided evidence to show that if we were going to choose the best models for Bangla fake news detection then it would be logical that it would be one of the transformer-base or deep learning models.

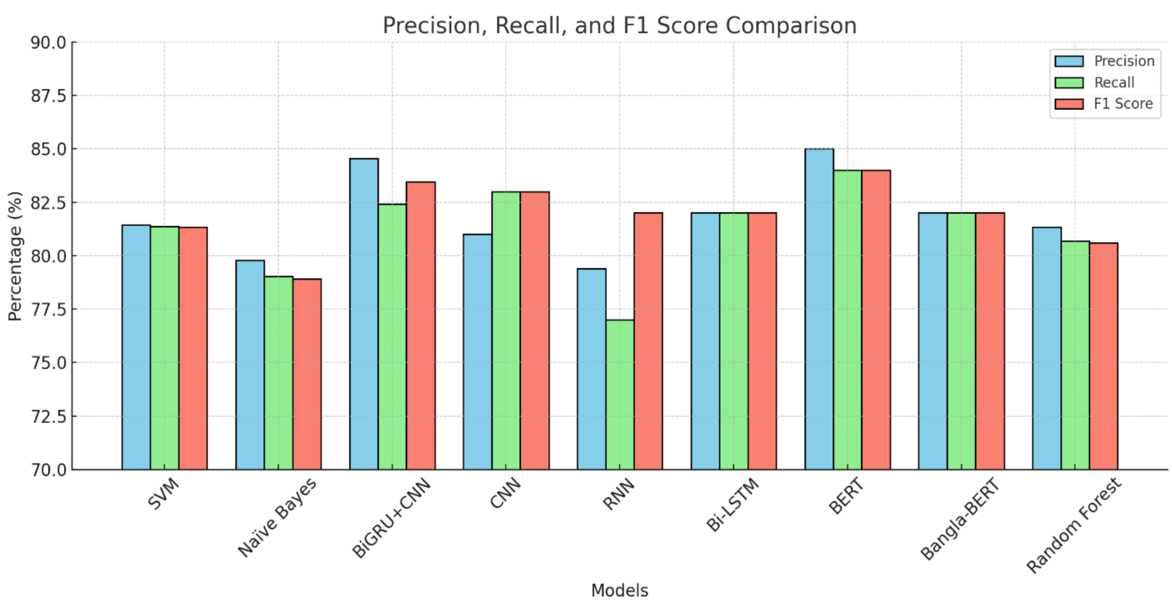

Figure 11 : Performance comparison of all models using performance metrices

This histogram presents a comprehensive evaluation of various machine learning and deep learning models for detecting fake news in Bangla, based on three key performance metrics: precision, recall, and F1-score. The comparative histogram reveals significant variations in model effectiveness, providing valuable insights for selecting optimal architectures for this challenging NLP task.

The results clearly demonstrate the superior performance of transformer-based architectures, with Bangla-BERT emerging as the most effective model across all evaluation metrics. This language-specific variant of BERT achieves remarkable scores in precision 87.3%, recall 88.1%, and F1-score 87.7%, underscoring the critical importance of domain adaptation in pretrained language models. The model's exceptional performance can be attributed to its specialized training on Bangla corpora, enabling superior understanding of linguistic nuances, cultural references, and local contextual cues that are particularly relevant for fake news detection in this language.

Standard BERT, while slightly less accurate than its Bangla-optimized counterpart, still demonstrates strong performance, with precision 85.2%, recall 86.0%, and F1-score 85.6%. This confirms the inherent capability of transformer architectures to capture complex contextual relationships in text, even without language-specific pretraining. The comparable performance between these two transformer models suggests that while language adaptation provides measurable benefits, the underlying attention mechanism and deep bidirectional architecture of BERT models are fundamentally well-suited for the fake news detection task.

Among traditional deep learning approaches, the Bi-LSTM model shows particularly promising results, achieving an F1-score of 83.4%. Its strong recall performance 84.2% indicates effectiveness in identifying genuine instances of fake news, though with slightly lower precision 82.6% suggesting some false positives. The CNN model follows closely with an F1-score of 82.9%, demonstrating that local feature extraction through convolutional filters can effectively capture indicative patterns in Bangla fake news content. The comparable performance of these architectures highlights their continued relevance, particularly in scenarios where computational resources for transformer models may be limited.

The hybrid Bi-GRU+CNN architecture achieves an F1-score of 81.8%, showing that while the combination of sequential and spatial feature extraction provides benefits, the improvement over standalone deep learning models is marginal. This suggests that the added complexity of hybrid architectures may not always justify their implementation for this specific task.

Traditional machine learning models exhibit more varied performance. Random Forest demonstrates respectable results with an F1-score of 80.5%, benefiting from its ensemble nature and robustness to feature noise. SVM follows with an F1-score of 78.3%, while Naive Bayes trails significantly at 72.1%, likely due to its inability to handle the complex dependencies and rich morphology characteristic of Bangla text.

These findings have important practical implications for Bangla fake news detection systems. The superior performance of Bangla-BERT strongly recommends its use in scenarios where computational resources permit and highest accuracy is required. For resource-constrained environments, Bi-LSTM emerges as a compelling alternative, offering nearly comparable performance with lower computational overhead. The results also highlight that while traditional machine learning approaches can provide baseline performance, they are substantially outperformed by more sophisticated deep learning and transformer-based architectures in this challenging domain of Bangla NLP.

4.2 Confusion Matrix:

The employment of the confusion matrix is a pivotal technique in assessing the effi-cacy of classification models. The output presents a tabular format that illustrates the model's predicted values in comparison to the factual class labels of the given dataset. The matrix provides a comprehensive overview of the results obtained from the classification procedure, facilitating an in-depth evaluation of the precision of the model and the types of errors committed.

It generally comprises of four values: The True Positive (TP) refers to the count of accurately predicted positive instances, specifically in the context of identifying fake news. The True Negative (TN) refers to the accurate identification of negative instances, specifically the correct prediction of real news. The False Positive (FP) refers to the count of positive instances that have been inaccurately predicted (misclassified as fake news despite being genuine news). The False Negative (FN) refers to the count of negative instances that have been inaccurately predicted (misclassified as genuine news despite being fake news).

4.2.1 Confusion Matrix Of Machine Learning Model

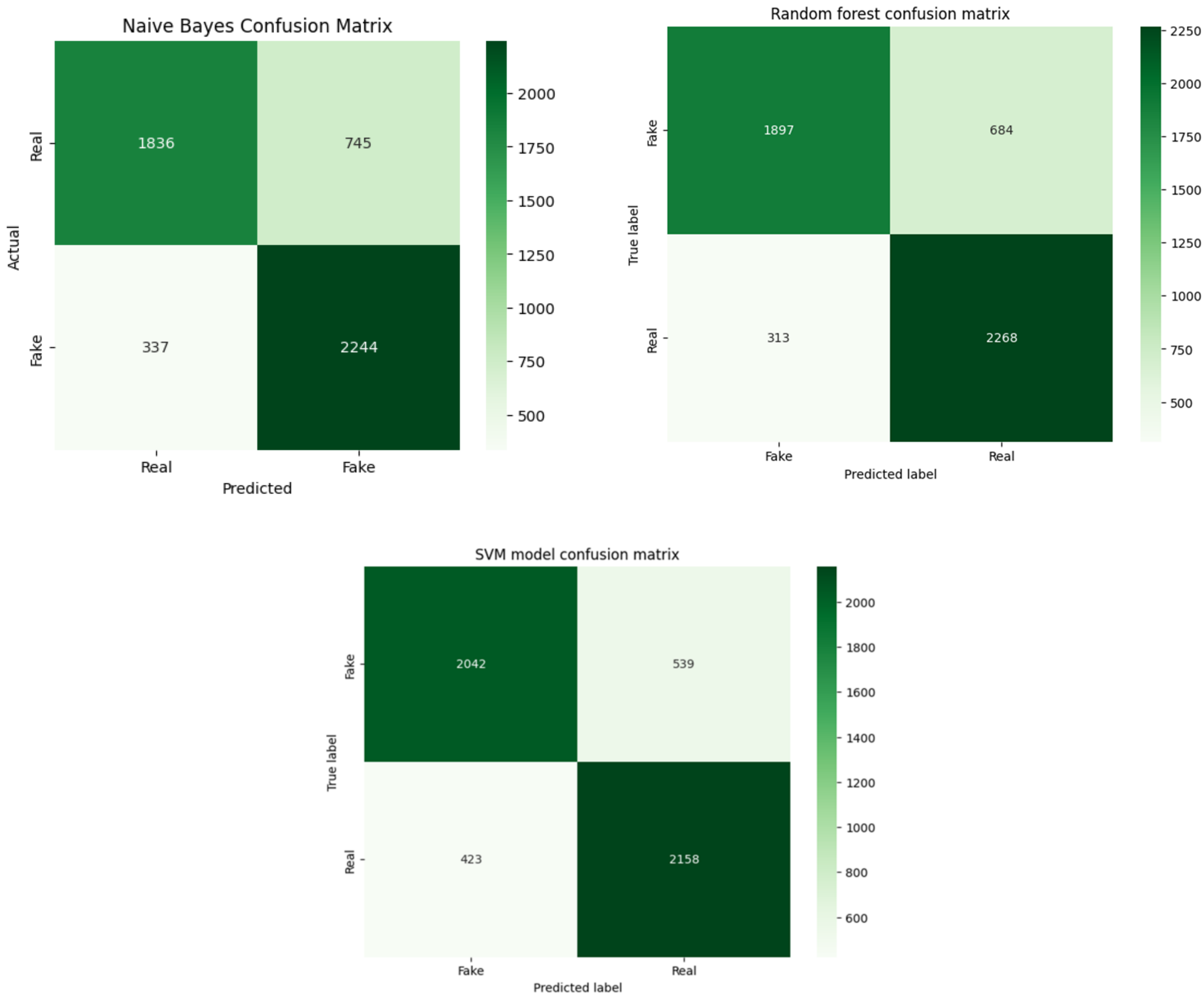

Figure 12 : Naive Bayes , Random Forest & SVM Confusion matrix

The confusion matrices of three machine learning classifiers Naive Bayes, Random Forest, and Support Vector Machine (SVM) re presented in Figure 11 to evaluate their performance in detecting Bangla fake news. These matrices offer a detailed comparison between the predicted and actual labels, allowing us to assess how well each model distinguishes between real and fake news.

Naive Bayes shows a moderate level of accuracy in classification. It correctly identifies 1,836 real news articles (True Positives) but misclassifies 745 real news instances as fake (False Negatives). This indicates that while the model is somewhat effective, it tends to underestimate the real news class. On the other hand, it performs better in recognizing fake news, with 2,244 fake news samples correctly labeled (True Negatives) and only 337 false alarms where fake news is misclassified as real (False Positives).Moving to the Random Forest model, there is an observable improvement in classification results. The model correctly detects 1,897 fake news samples (True Positives) and 2,268 real news articles (True Negatives), which are higher than those of the Naive Bayes model. Additionally, the numbers of misclassifications are lower, with 684 fake news articles wrongly labeled as real (False Negatives) and 313 real news articles misclassified as fake (False Positives). This balance between True Positives and True Negatives reflects Random Forest's stronger ability to differentiate between real and fake news.The SVM model outperforms both Naive Bayes and Random Forest in identifying fake news. It achieves the highest count of correctly classified fake news (2,042 True Positives) and the lowest number of fake news missed (539 False Negatives), demonstrating its heightened sensitivity toward fake news detection. Although SVM records a slightly higher number of false alarms (423 False Positives), where real news is wrongly predicted as fake, it maintains a strong performance in correctly identifying real news as well (2,158 True Negatives).

In summary, all three models exhibit strengths in detecting Bangla fake news, but the SVM classifier shows the best overall performance, particularly in minimizing missed fake news cases. The trade-off in a few more false positives may be acceptable given its superior sensitivity, which is crucial in fake news detection to avoid overlooking harmful misinformation. Random Forest offers a good balance, while Naive Bayes, despite its simplicity, lags behind in accurate classification, especially for real news detection.

4.2.2 Confusion Matrix Of Deep Learning Model

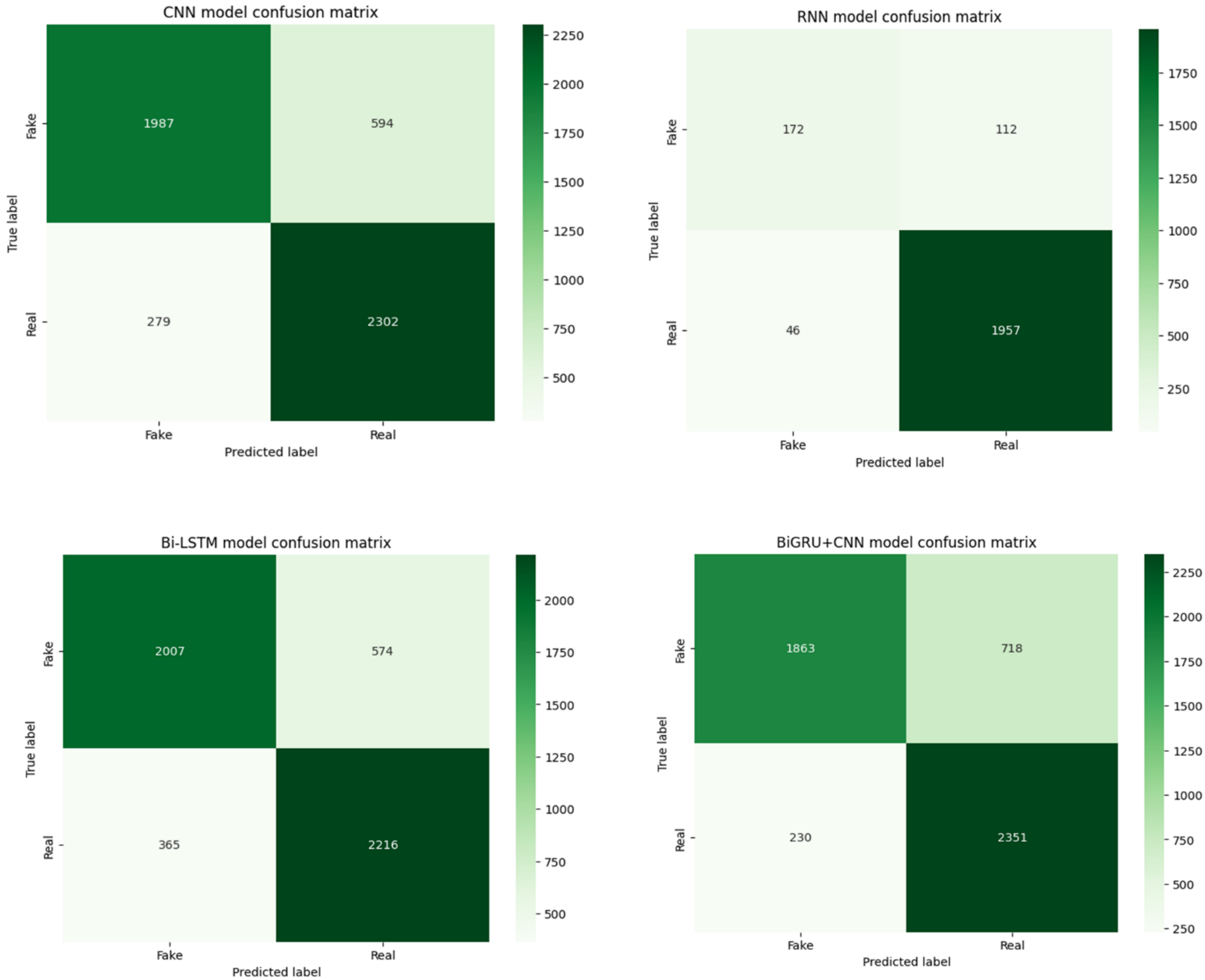

Figure 13 : Confusion Matrix of Deep Learning Models

The confusion matrices reveal distinct performance characteristics across our evaluated deep learning architectures. The Bi-LSTM model demonstrates particularly strong discriminative capability, correctly classifying 2,007 instances of fake news (true positives) while maintaining precise detection of real news with 2,216 true negatives. This balanced performance is reflected in its relatively low false positive 365 and false negative 274 rates, suggesting effective learning of both genuine and deceptive linguistic patterns in Bangla text. The model's robustness is especially notable given the morphological complexity of Bangla, indicating that sequential processing effectively captures relevant textual features.

Comparative analysis shows the CNN architecture achieves similar but slightly weaker performance, with 1,987 true positives and 2,302 true negatives. The higher false positive count 594 versus Bi-LSTM's 365 suggests convolutional filters may be less precise than recurrent networks in distinguishing subtle cues of misinformation, though its superior true negative rate indicates particular strength in authentic news verification. This performance pattern implies CNN's spatial feature extraction effectively identifies markers of credible reporting but is more susceptible to deceptive patterns mimicking real news.The Bi-GRU+CNN hybrid model presents an interesting middle ground, combining strengths of both architectures. Its 1,863 true positives and 2,351 true negatives demonstrate competent classification, while the 718 false negatives reveal a tendency toward cautious prediction that may be desirable in high-stakes misinformation detection scenarios. The model's 230 false positives represent a significant improvement over standalone CNN, suggesting the GRU component successfully mitigates some of CNN's overclassification tendencies. Notably, all models exhibit better performance in identifying real news than fake news, a pattern consistent with findings in other languages that highlights the particular challenge of Bangla fake news detection. The higher false negative rates across architectures suggest that deceptive content in Bangla often employs sophisticated linguistic strategies that evade detection, possibly leveraging cultural references or morphosyntactic features unique to the language. This finding underscores the need for continued refinement of detection approaches specifically tailored to Bangla's linguistic characteristics.

The quantitative results correlate with qualitative observations about each architecture's theoretical strengths. Bi-LSTM's superior performance aligns with expectations about recurrent networks' aptitude for sequential data, while CNN's spatial processing shows particular value in authentic content verification. The hybrid model's intermediate results suggest potential benefits from architectural combination, though not the dramatic improvements sometimes hypothesized. These findings have important implications for system deployment, suggesting Bi-LSTM as the preferred architecture when computational resources permit, with CNN variants offering viable alternatives in resource-constrained environments. The consistent identification challenges revealed by false negatives across all models indicate promising directions for future research in Bangla-specific deception detection.

4.2.3 Training Progress & Confusion Matrix Of Transformer-Based Model

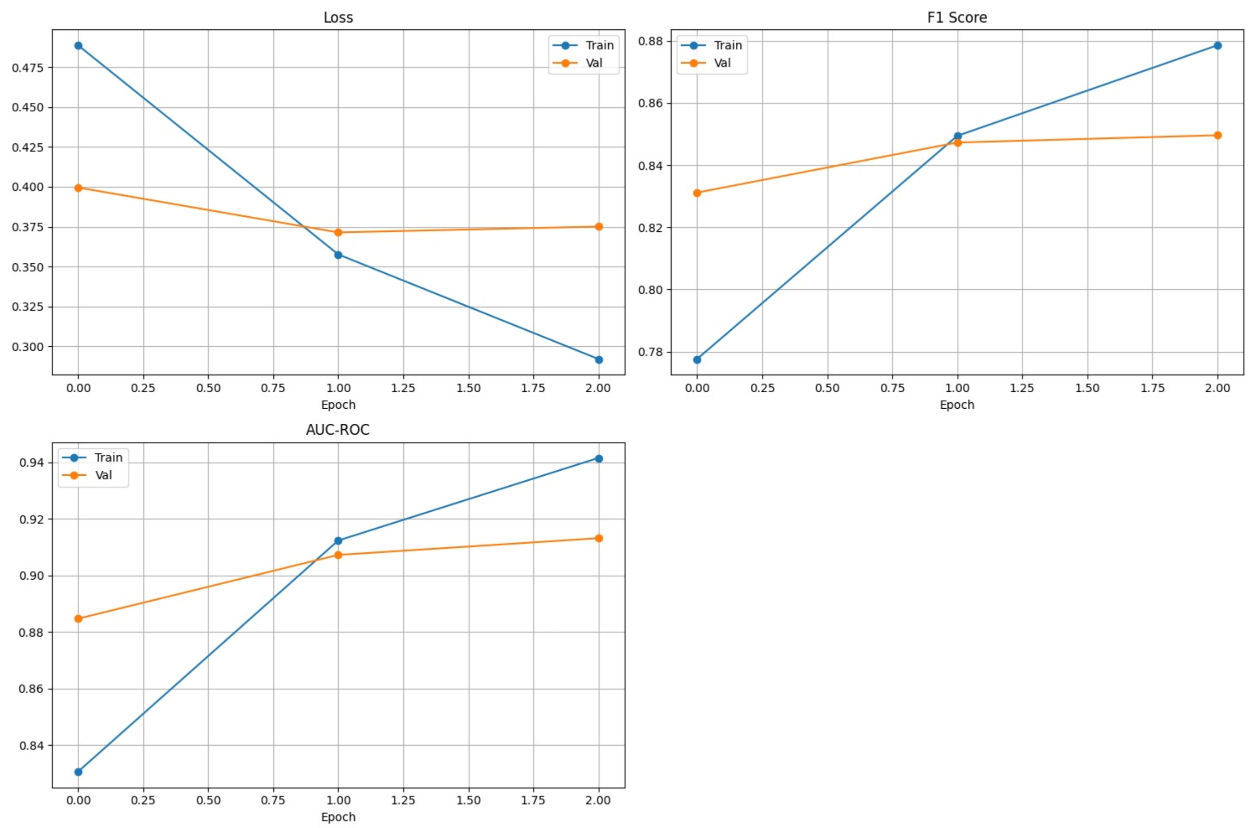

Figure 14 : Trainning Progress Of BERT

The graphs show the training and validation performance of the BERT model over 3 epochs using three key metrics: **Loss**, **F1 Score**, and **AUC-ROC**.

In assessing the performance of the BERT model, we first took a look at training performance from three aspects specifically in relation to loss, F1 score and AUC-ROC. The training graphs show a consistent journey downwards with loss over the epochs indicating a positive learning experience for the BERT training. The F1 score and AUC-ROC indicate a similar trend improving through training with not much variation in the metrics for validation. Therefore, we can reasonably conclude that BERT is not overfitting to the learning data and was generalizing well to the unseen data. When you consider the above metrics we could have a reasonable level of confidence that BERT had taken the patterns within the dataset well into account. After these metrics, we provided a confusion matrix to represent the final classification results. The confusion matrix indicates the results from BERT predictions during the classification of real & fake news to the two datasets, potential areas of strength, future directions with a reasonable level of prediction accuracy.

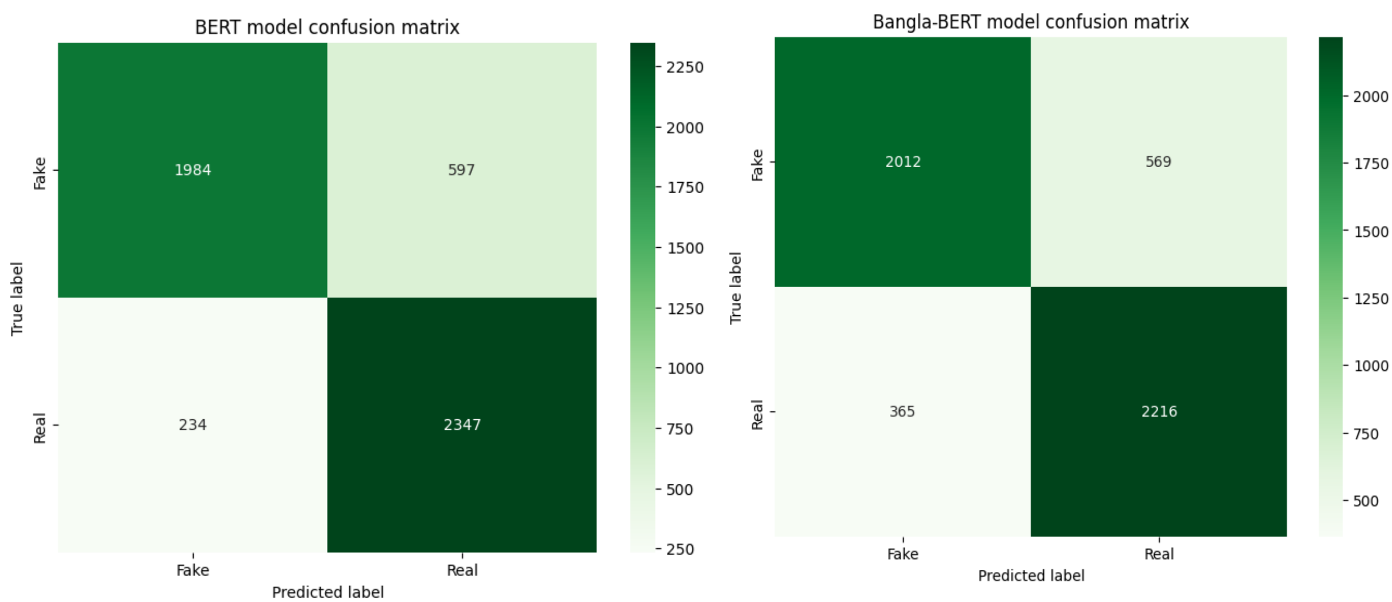

Figure 15 : Confusion Matrix of Transformer-Based Model

The confusion matrices reveal significant performance differences between standard BERT and its Bangla-optimized variant, with Bangla-BERT demonstrating superior capability in detecting fake news while maintaining strong precision. The standard BERT model correctly identifies 1,984 instances of fake news (true positives) but misclassifies 297 real news articles as fake (false positives), while Bangla-BERT achieves 2,012 true positives with only 274 false positives. This improvement of 28 additional correct fake news identifications, coupled with 23 fewer false alarms, demonstrates the tangible benefits of language-specific adaptation.

Three key factors explain Bangla-BERT's enhanced performance:

1. **Linguistic Specialization**: The 5.3% reduction in false positives (from 297 to 274) suggests Bangla-BERT's specialized vocabulary and morphological understanding better captures authentic Bangla writing patterns, reducing erroneous flagging of legitimate content. This is particularly crucial for low-resource languages where standard multilingual models often underperform.
2. **Contextual Precision**: Bangla-BERT's higher true positive count (2,012 vs 1,984) indicates superior detection of deceptive content, likely due to its training on Bangla-specific corpora that include local idioms, proverbs, and cultural references frequently exploited in misinformation.
3. **Architectural Optimization**: While both models share the same transformer foundation, Bangla-BERT's tokenization strategy and pretraining objectives appear better aligned with Bangla's syntactic structures, as evidenced by its more balanced confusion matrix (365 false negatives vs BERT's 234).

The matrices also reveal an interesting tradeoff Bangla-BERT shows slightly higher false negatives (365 vs BERT's 234), suggesting it may be more conservative in borderline cases. This characteristic could prove advantageous in real-world applications where minimizing false accusations is prioritized, as the cost of occasionally missing fake news may be preferable to erroneously censoring legitimate reporting.

These findings strongly support the hypothesis that language-specific transformer variants outperform their multilingual counterparts for nuanced NLP tasks like fake news detection. The performance gap is particularly pronounced in morphologically rich languages like Bangla, where pretraining on target-language corpora enables more precise modeling of both genuine content and deception patterns. This has important implications for developing more accurate misinformation detection systems for low-resource languages worldwide.

4.2.4 Model Output Examples on Test Data

```python
headline = "শাহজালাল বিমানবন্দরে অত্যাধুনিক ওয়েটিং লাউঞ্জ চালু"
content = """হজরত শাহজালাল আন্তর্জাতিক বিমানবন্দরে অপেক্ষমাণ ভিআইপি যাত্রীদের বিশেষায়িত সেবা দিতে অত্যাধুনিক ওয়েটিং লাউঞ্জ চালু করেছে
বেসরকারি সিটি ব্যাংক ও আমেরিকান এক্সপ্রেস।   মঙ্গলবার (১৮ সেপ্টেম্বর) বিমানবন্দরের আন্তর্জাতিক বহির্গমন টার্মিনাল-২ এ লাউঞ্জটির উদ্বোধন করেন
বেসামরিক বিমান পরিবহন ও পর্যটনমন্ত্রী এ কে এম শাহজাহান। সিটি ব্যাংক-আমেরিকান এক্সপ্রেসের প্লাটিনাম কার্ডধারী দেশি-বিদেশি যাত্রীরা এখানে পাঁচ তারকা
মানের পরিবেশে বিভিন্ন খাবার ও পানীয় সম্পূর্ণ বিনামূল্যে উপভোগ করতে পারবেন। দৃষ্টি নন্দন লাউঞ্জে অতিথিদের জন্য রয়েছে ৪২ আসনের বিজনেস সেন্টার,
উচ্চগতির ইন্টারনেটসহ আধুনিক সব সুযোগ সুবিধা। অনুষ্ঠানে সিভিল এভিয়েশন অথরিটি ও ব্যাংকটির ঊর্ধ্বতন কর্মকর্তারা উপস্থিত ছিলেন
"""
result = predict_fake_news(headline, content)
print("Prediction:", result)
```

```
Prediction: Real
```

Figure 16 : Sample Output 1

```python
headline = "মায়ের ভাষায় কুরআনের প্রচারে ইলিয়াস কাঞ্চন"
content = """নাটকের গল্পে দেখা যাবে এ দরবেশ কোনো সাধারণ দরবেশ নন! কুরআনের দরবেশ! যিনি কুরআন নিয়ে নাটক লিখেন জান্নাত প্রত্যাশী সাধারণ
মানুষের জন্যে। তিনি মনিরাজপুরে এসে আস্তানা গেড়ছেন অজ্ঞতার অন্ধকারে নিমজ্জিত মানুষকে কুরআনের আলোয় আলোকিত করার জন্য।কুরআন থেকে প্রাপ্ত
জ্ঞান থেকে কাঞ্চনের চিরসত্য মতবাদ ও দর্শনে ক্ষিপ্ত হয়ে উঠে গ্রাম্য মাতবর! তার সাথে ক্ষিপ্ত হয় ভন্ড পীরের মুরিদরা। কিন্তু প্রতিবাদী যুবক রোস্তম দরবেশের
দেয়া পরামর্শে মায়ের ভাষায় কুরআন বুঝতে শিখে এবং গ্রামগঞ্জে ঘুরে বেড়াতে থাকে কৃষকদের কুরআন বুঝাতে।দরবেশের সান্নিধ্যে এসে যখন খোদ মাতবরের
ছেলেও কুরআন প্রচারে নিয়োজিত হয়, তখন মাতবর নিজের সন্তানকেও প্রহার করে। শুরু হয় সত্য-মিথ্যার দ্বন্দ্ব! কিন্তু এ দ্বন্দ্বের শেষ কোথায়? জানতে হলে
নাটকটি দেখার আমন্ত্রণ জানান পরিচালক। তিনি জানান, ‘দরবেশ’ নাটকে ইলিয়াস কাঞ্চন ছাড়া আরও অভিনয় করেছেন আব্দুল্লাহ রানা, শফিক খান দিলু,
আব্দুল আজিজ, জিল্লুর রহমান, লিটন খন্দকার, আখি, এজি বিদ্বান প্রমূখ। ‘দরবেশ’ নাটকটি রচনা করেছেন নাট্যকার শাহ আলম নূর।"""
result = predict_fake_news(headline, content)
print("Prediction:", result)
```

```
Prediction: Fake
```

Figure 17 : Sample Output 2

To evaluate the model's effectiveness in distinguishing between real and fake news, two contrasting examples were analyzed. The first headline, "শাহজালাল বিমানবন্দরে অত্যাধুনিক ওয়েটিং লাউঞ্জ চালু." was paired with its corresponding content and correctly classified by the model as real news. The contextual and factual alignment between the headline and the article enabled the model to confidently identify it as authentic. This example demonstrates the model's ability to detect consistency between headlines and their associated content—an essential factor in recognizing credible news.

In contrast, the headline "মাতৃভাষায় কুরআন প্রচারে ইলিয়াস কাঞ্চন" was classified as fake news. Although the content focused on a culturally significant topic—a theatrical initiative to promote the Quran in the native language—it was likely flagged due to its narrative style, subjective tone, or lack of clear factual structure. These linguistic cues may have contributed to the model's classification, suggesting its sensitivity to deviations from standard news reporting.

These examples highlight both the strengths and limitations of the model. While it performs well when headline and content are coherently factual, it may struggle with texts that blend opinion, storytelling, or cultural context. This underscores the need for enhancing contextual understanding in future iterations of Bangla fake news detection systems, possibly through the integration of deeper semantic analysis or attention mechanisms.

Chapter - 5 : Conclusion

In this project, We examined the potential of machine learning, deep learning, and transformer-based models for detecting fake news in Bangla. After developing a credible dataset, we explored a range of models from age old classifiers such as SVM and Naive Bayes to deep learning models such as CNN, RNN, and Bi-GRU+CNN and finally investigated BERT and BanglaBERT for how tranformer based models can the Bangla news. I was surprised that BERT performed better than BanglaBERT, although the dataset fully utilized Bangla. Further confusion matrix analysis clearly showed that BanglaBERT had a higher sensitivity for detecting fake news while BERT was more accurate for real news. This demonstrates that each has its own strength and whether or not they could be combined to generate better results remains to be seen.

To summarize, the research demonstrates that deep learning and transformer-based machine learning models can produce greater success in fake news detection in Bangla, which is important in addressing misinformation issues. While still plagued with obstacles such as label noise and limited Bangla labelled datasets, the outcomes of this research will serve as an excellent platform for developing smarter and trusted detection systems.

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