Unveiling Misinformation in Bangla Social Media: A Multimodal Fake News Detection System

Submitted by

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ABSTRACT

The rapid spread of fake news on social media threatens public discourse and erodes trust. In low-resource languages like Bengali, detection tools have been limited by sparse datasets and few pretrained models. This thesis presents a novel multimodal stacking ensemble framework for Bengali fake news detection that leverages both textual and visual content. We first fine-tuned seven variants of BanglaBERT—each differently initialized and trained on diverse Bangla corpora—and selected the top six based on validation performance and diversity. Their softmax outputs were concatenated and fed into a meta-classifier (MLP), significantly enhancing prediction accuracy. To further bolster text modeling, we incorporated XLM-RoBERTa (Base and Large) and plan to integrate BanglaLM to capture multilingual cues. On the visual side, we fine-tuned CNN, ResNet50, EfficientNet (B0/B2), ViT, and Swin Transformer on Bengali-adapted Fakeddit, enabling the detection of manipulated or contextually misleading images. Finally, we fused the best-performing text and image ensembles by concatenating their softmax vectors and training a final-level MLP meta-classifier, yielding a robust multimodal detection system. Our contributions include the first BanglaBERT-based ensemble, cross-architecture transformer integration, modern image model evaluation, the inaugural Bengali multimodal ensemble, and a Python-based real-time demo interface. Future deployment aims at a scalable web or browser extension for end-user applications.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Overview

The proliferation of digital media in the 21st century has drastically transformed how people access, consume, and share information. Social platforms such as **Facebook**, **X (formerly Twitter)**, **YouTube**, **WhatsApp**, and others have made it effortless to spread news stories, opinions, and images at unprecedented speed and scale. However, this democratization of content dissemination has also facilitated the spread of **fake news**—deliberately misleading information designed to deceive or manipulate public opinion. Fake news often appears as manipulated headlines, doctored images, clickbait, or fabrications, with serious impacts including **political polarization**, **economic panic**, **communal violence**, and diminished trust in legitimate institutions.

These consequences are highly visible in regions like **Bangladesh**, where digital media adoption has surged but digital literacy and fact-checking remain underdeveloped. Millions of **Bengali-speaking** users share content daily—often without verifying its authenticity—compounding the risk since most detection tools are built for **high-resource languages** like **English**.

Although numerous systems have been designed for fake news detection in **English** and **Chinese**, most are **text-only**. In contrast, current online disinformation often uses **multimodal content**: deceptive images paired with misleading text. This combination is more convincing and challenging to detect using traditional **NLP** methods alone.

Despite the urgency, **Bengali** remains underrepresented in both **Natural Language Processing (NLP)** and **Computer Vision (CV)**. There is a lack of large, annotated **multimodal datasets** and limited availability of **Bengali-specific transformer models**. Even fewer studies attempt to fuse text and image modalities for Bengali fake news detection.

This research addresses these gaps by developing a **Multimodal Bengali Fake News Detection System**. On the text side, we fine-tune multiple variants of **BanglaBERT** and **XLM-RoBERTa**. In the visual modality, we train a suite of models, including **CNNs**, **ResNet50**, **Swin Transformer**, and **ViT**, to detect misleading images. By stacking the softmax outputs of these models through a **meta-classifier**, we create a unified **multimodal ensemble**—the first of its kind in Bengali fake news detection.

1.2 Problem Statement

Fake news in Bengali digital spaces persistently outpaces existing detection systems, which typically exhibit three critical deficiencies:

1. **Unimodal focus:** Systems largely rely solely on text features (e.g., **TF-IDF**, transformer embeddings), neglecting misleading **visual content** that can play an influential role.
2. **Lack of datasets:** There is no publicly available **multimodal dataset for Bengali** containing both text and image pairs with **fake/real annotations**, limiting model training and evaluation.
3. **Low-resource constraints:** Bengali lacks large pretrained models, labeled data, and benchmarks for **vision-language fusion**, and virtually no **ensemble-based multimodal systems** exist for the language.

Our work addresses this gap through a **multimodal ensemble architecture** capable of understanding and classifying news content based on both **text and image inputs**.

1.3 Motivation

The proliferation of fake news on digital platforms poses a significant threat in Bengali-speaking regions, often accompanied by visually deceptive content. In Bangladesh, manipulated posts have incited real-world consequences such as **religious violence**, **political unrest**, and **health-related panic**, particularly during the COVID-19 pandemic [16–18]. According to UNICEF, **two-thirds of youth identified misinformation as their primary source of stress** [19], underscoring its psychological and societal impact.

Despite growing concerns, most existing fake news detection systems inadequately handle the **multimodal nature** of misinformation. The majority are limited to textual analysis,

overlooking misleading images that often amplify the deceptive narrative. Furthermore, Bengali remains severely **underrepresented in both natural language processing (NLP) and computer vision (CV)** research. This is due to a lack of comprehensive multimodal datasets, pre-trained models, and integrated frameworks capable of jointly processing textual and visual modalities [18–20].

Ensemble learning, particularly stacking with meta-classifiers, presents a promising solution by integrating diverse models to enhance performance, reduce bias, and increase robustness. Recent approaches in **multimodal stacking ensembles** have shown notable improvements—for instance, SEMI-FND achieved an accuracy of approximately 86% on benchmark datasets [21, 22]. However, no such system currently exists for the Bengali language; most existing models target English or Chinese datasets and focus on a single modality [22].

This research is driven by the following motivations:

1. **Societal urgency:** Bengali-speaking communities lack robust tools to detect multimodal misinformation, leaving them vulnerable to threats such as communal violence, panic, and social fragmentation.

2. **Technical advancement:** This work addresses Bengali's low-resource status by developing a stacked ensemble framework that integrates both text and image modalities to improve accuracy and generalizability.

3. **Research contribution:** We propose the first Bengali multimodal stacking ensemble system, combining language-specific models (e.g., BanglaBERT) and multilingual transformers (e.g., XLM-R, BanglaLM) with state-of-the-art vision architectures (e.g., CNN, ResNet, Swin, ViT).

4. **User-centric impact:** The system will be developed as a practical misinformation detection tool, with deployment potential via web and browser extensions to empower users with real-time verification.

In summary, this study seeks to fill a critical gap by introducing the **first multimodal stacking ensemble for fake news detection in Bengali**, contributing both academically and socially to the field of multilingual and multimodal misinformation analysis.

1.4 Research Objectives

The primary goal of this research is to develop an end-to-end Bengali fake news detection framework capable of analyzing both text and image inputs, integrating their respective predictions using stacked ensemble learning, and making a final binary classification (fake or real). The specific objectives are outlined below:

1. **Text-side Objectives**
   - Fine-tune 7 BanglaBERT variants on a labeled Bengali fake news dataset.
   - Evaluate their individual performances and select the top 6 diverse models for stacking.
   - Use their softmax output probabilities to train a meta-classifier (e.g., logistic regression or multilayer perceptron).
   - Experiment with 3 versions of XLM-RoBERTa (Base, Large, and Distilled) to assess cross-lingual performance.
   - Optionally include BanglaLM, a Bengali-specific language model, to increase diversity.
2. **Image-side Objectives**
   - Train and evaluate a range of image classifiers:
     (a) Custom CNN
     (b) ResNet50
     (c) Vision Transformer (ViT)
     (d) Swin Transformer (Tiny variant)
     (e) EfficientNet-B0 and/or B2
   - Extract and store softmax outputs from each model for ensemble training.
   - Build an image-only ensemble classifier using stacking over visual models.
3. **Ensemble Construction**
   - Create a BanglaBERT ensemble classifier using the 6 best fine-tuned models.
   - Construct a cross-architecture text ensemble combining outputs from BanglaBERT, XLM-R, and BanglaLM.
   - Build an image ensemble classifier using ResNet50, EfficientNet, and Swin-Tiny models.
4. **Multimodal Fusion Model**
   - Take the softmax predictions from the final text and image ensembles.
   - Merge them into a single feature vector.
   - Train a final-level meta-classifier to predict the final label.

- This forms the multimodal stacking ensemble—the first of its kind for Bengali.

5. **Interface and Deployment**

   - Develop a Python-based interface for users to input news content and receive predictions.
   - Support the following prediction types:
     (a) Text-only predictions
     (b) Image-only predictions
     (c) Multimodal (text + image) predictions
   - Plan for deployment as a web application or Chrome browser extension with API support, enabling real-time verification.

Chapter 2

Background Study and Literature Review

2.1 Overview

This section reviews key research and datasets in fake news detection—particularly in under-resourced languages like **Bengali**—and outlines prevailing themes in previous work. A growing body of research emphasizes the importance of **multimodality**, where misinformation is spread through combinations of text and images. Large-scale English-language multimodal datasets like **Fakeddit** have enabled significant progress in this area.

However, for Bengali—a language spoken by over 230 million people globally—comparable resources have been lacking. Recent efforts such as **MultiBanFakeDetect** have begun to fill this gap by providing a multimodal dataset of approximately 9,600 Bengali text–image pairs across social media and news outlets. This dataset is balanced across **fake**, **rumor**, **clickbait**, and **real** categories, offering a critical benchmark for model evaluation [23, 24].

Monomodal datasets for Bengali news, such as **BanFakeNews-2.0** (≈60,000 text items), have been used for classification research, but these do not include images [25–27]. There is emerging interest in multimodal frameworks, such as those using **CNN + ViT** architectures on smaller Bengali datasets [20, 28, 29], but these remain limited in scale and scope.

A key theme in existing literature is the demonstrated benefit of **fusion techniques**, including **early**, **intermediate**, and **late fusion**, which combine features from text and images to achieve more robust detection than single-modality approaches. Studies also suggest that **stacking ensembles** and **attention-based multimodal architectures** can significantly improve performance.

Despite these advances, challenges remain: prior Bengali-focused research often relies on **small or mono-modal datasets**, and **multimodal fusion techniques** are rarely explored at scale or with ensemble methods. Overall, this study builds upon these foundations and addresses the need for a comprehensive Bengali multimodal fake news detection system that leverages both large-scale datasets (like **MultiBanFakeDetect**) and advanced **fusion and ensemble strategies**.

2.2 Background Study

This chapter provides a comprehensive overview of the **theoretical foundations**, core models, and computational strategies that underpin our proposed **multimodal fake news detection** framework. As fake news often spreads through both textual content and accompanying images, detecting it effectively requires the integration of advanced techniques from **Natural Language Processing (NLP)**, **Computer Vision (CV)**, and **multimodal learning**.

We begin by exploring traditional and deep learning approaches used for **text classification**, focusing on the evolution from classical models to **transformer-based architectures** such as *BanglaBERT* and *XLM-RoBERTa*, which are specially tailored for Bangla and multilingual contexts. These models are instrumental in capturing the nuanced semantics of Bengali-language text.

Next, we examine prominent models in **image classification**, including *Convolutional Neural Networks (CNNs)*, *MobileNet*, *ResNet*, and vision transformers like *ViT* and *Swin*. These models extract visual patterns and contextual cues from image data, allowing the system to analyze media content alongside textual information.

We also describe the **ensemble techniques** used in this study, such as *stacking with a Multi-Layer Perceptron (MLP)* meta-classifier, which leverages the diversity of multiple base models to improve prediction robustness. Furthermore, we explain the **multimodal fusion strategy** employed to combine text and image predictions into a unified framework, highlighting how this integration enhances fake news detection performance in real-world scenarios.

By understanding the role and architecture of each model component, this chapter lays the groundwork for the implementation details and experimental results presented in subsequent sections.

2.2.1 Text Classification

Text classification forms the foundation of fake news detection systems, particularly in **Bangla language** contexts where misinformation is propagated through headlines, posts, and captions. In this thesis, we focus exclusively on **deep learning** and **transformer-based architectures** for text classification. This section outlines the key models and techniques applied, including sequential models like *LSTM* and *Bi-LSTM*, transformer-based models such as *BanglaBERT* and *XLM-RoBERTa*, and the integration of emerging **Large Language Models (LLMs)**.

LSTM Model

Long Short-Term Memory (LSTM) networks are a type of Recurrent Neural Network (RNN) designed to overcome the *vanishing gradient problem* inherent in traditional RNNs. By incorporating gated mechanisms that regulate the flow of information, LSTMs can retain and utilize relevant context across long sequences. This property makes them especially effective for text-based tasks such as **fake news detection** [1].

Architecture and Gates: An LSTM unit is composed of several key components:

- **Cell state** C_t: Maintains long-term contextual memory.
- **Hidden state** h_t: Represents the current output and short-term memory.
- **Input gate** i_t: Controls how much new information flows into the cell.
- **Forget gate** f_t: Determines which information from the previous state should be discarded.
- **Output gate** o_t: Governs how much of the cell state is exposed as output.

The LSTM operations at each time step t, given input vector x_t and previous states h_{t-1}, C_{t-1}, are expressed as:

$$f_t = \sigma(W_f[x_t, h_{t-1}] + b_f) \tag{2.1}$$

$$i_t = \sigma(W_i[x_t, h_{t-1}] + b_i) \tag{2.2}$$

$$\tilde{C}_t = \tanh(W_c[x_t, h_{t-1}] + b_c) \tag{2.3}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{2.4}$$

$$o_t = \sigma(W_o[x_t, h_{t-1}] + b_o) \tag{2.5}$$

$$h_t = o_t \odot \tanh(C_t) \tag{2.6}$$

Here, σ denotes the sigmoid activation function, tanh is the hyperbolic tangent function, and $\odot$ represents element-wise multiplication.

Advantages for Fake News Detection:

- **Long-term dependency modeling:** LSTM can detect subtle linguistic patterns such as sarcasm, negation, or contradictions distributed across text.
- **Effective in low-resource settings:** LSTM benefits from word embeddings and sequential learning, making it suitable for Bangla and similar under-resourced languages.

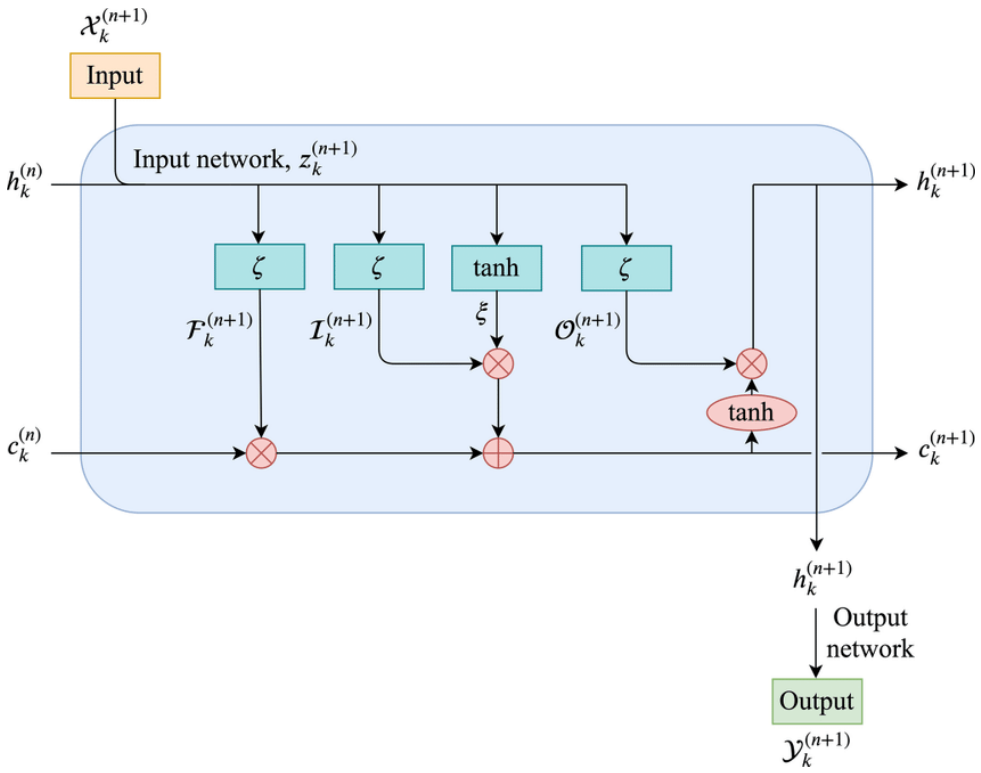


Figure 2.1: Standard LSTM architecture showing gating mechanisms and memory flow [1].

Bi-LSTM Model

Overview: Bidirectional Long Short-Term Memory (Bi-LSTM) networks extend the standard LSTM architecture by processing sequences in both forward and backward directions. Specifically, Bi-LSTM comprises two separate LSTM layers:

- A **forward layer**, which reads the input sequence in its original order, and
- A **backward layer**, which reads it in reverse.

The outputs from both directions are concatenated at each time step, allowing the model to leverage both preceding and succeeding context—a particularly useful property for detecting deceptive language in tasks like **fake news detection** [2].

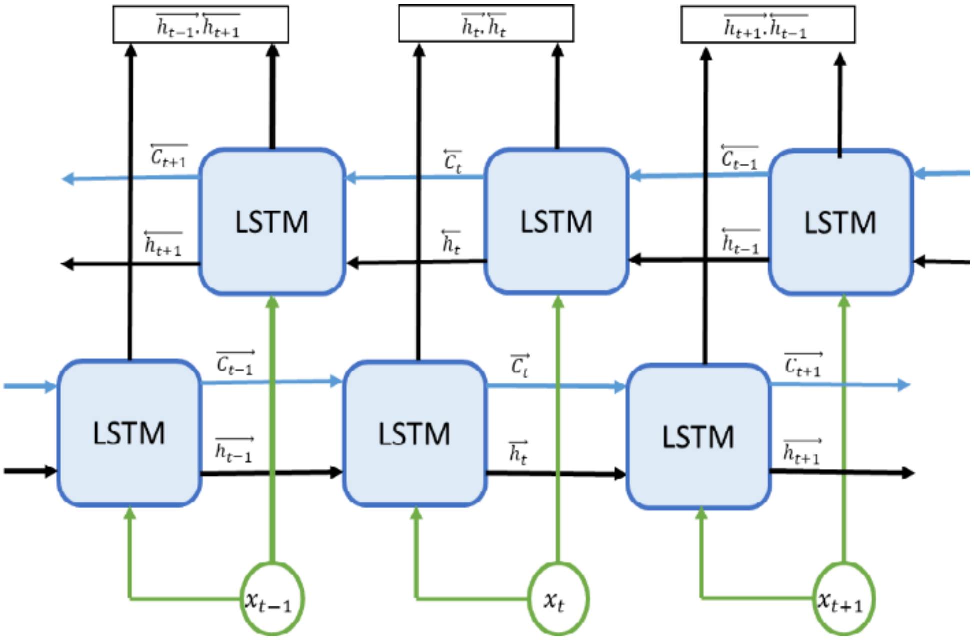
Architecture and Logic: Given an input sequence $(x_1, x_2, \ldots, x_T)$, the forward LSTM produces hidden states $\overrightarrow{h_t}$, and the backward LSTM produces $\overleftarrow{h_t}$. The final hidden representation at each time step is:

$$h_t = [\overrightarrow{h_t}; \overleftarrow{h_t}] \tag{2.7}$$

This concatenation captures full contextual information from both directions, improving semantic representation—especially in linguistically complex languages like Bangla.

Advantages in Fake News Detection:

- **Full context awareness:** Helpful when misleading cues depend on both prior and succeeding tokens (e.g., phrases like "not true", or sarcastic usage).
- **Empirical strength:** Multiple studies report Bi-LSTM outperforming unidirectional LSTM and CNN models on fake news classification tasks.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x_{t-1}
x_t
x_{t+1}

Figure 2.2: Bidirectional LSTM (Bi-LSTM) architecture illustrating dual LSTM layers. [2].

BanglaBERT

Overview BanglaBERT is a monolingual pre-trained language model based on the BERT architecture, developed specifically for the Bangla language. Introduced by Bhattacharjee et al. [30], it is part of the BangLUE benchmark, which includes tasks like classification, sequence labeling, NLI, and QA. The model is trained on the "Bangla2B+" corpus—over

27.5 GB of Bangla text from 110+ domains—capturing rich linguistic nuances unique to Bangla.

Compared to multilingual models like mBERT or XLM-R, BanglaBERT performs significantly better on Bangla tasks due to its language-specific vocabulary and corpus-centric pretraining [31].

Architecture BanglaBERT uses the BERT-Base architecture:

- 12 Transformer encoder layers
- Hidden size of 768
- 12 self-attention heads
- Total: $\sim$110M parameters

Each encoder block contains multi-head self-attention, a feed-forward network, residual connections, and GELU activations. The pretraining objectives are:

- **Masked Language Modeling (MLM)**: Randomly masks 15% of tokens to predict them using context.
- **Next Sentence Prediction (NSP)**: Determines if two sentences are sequential.

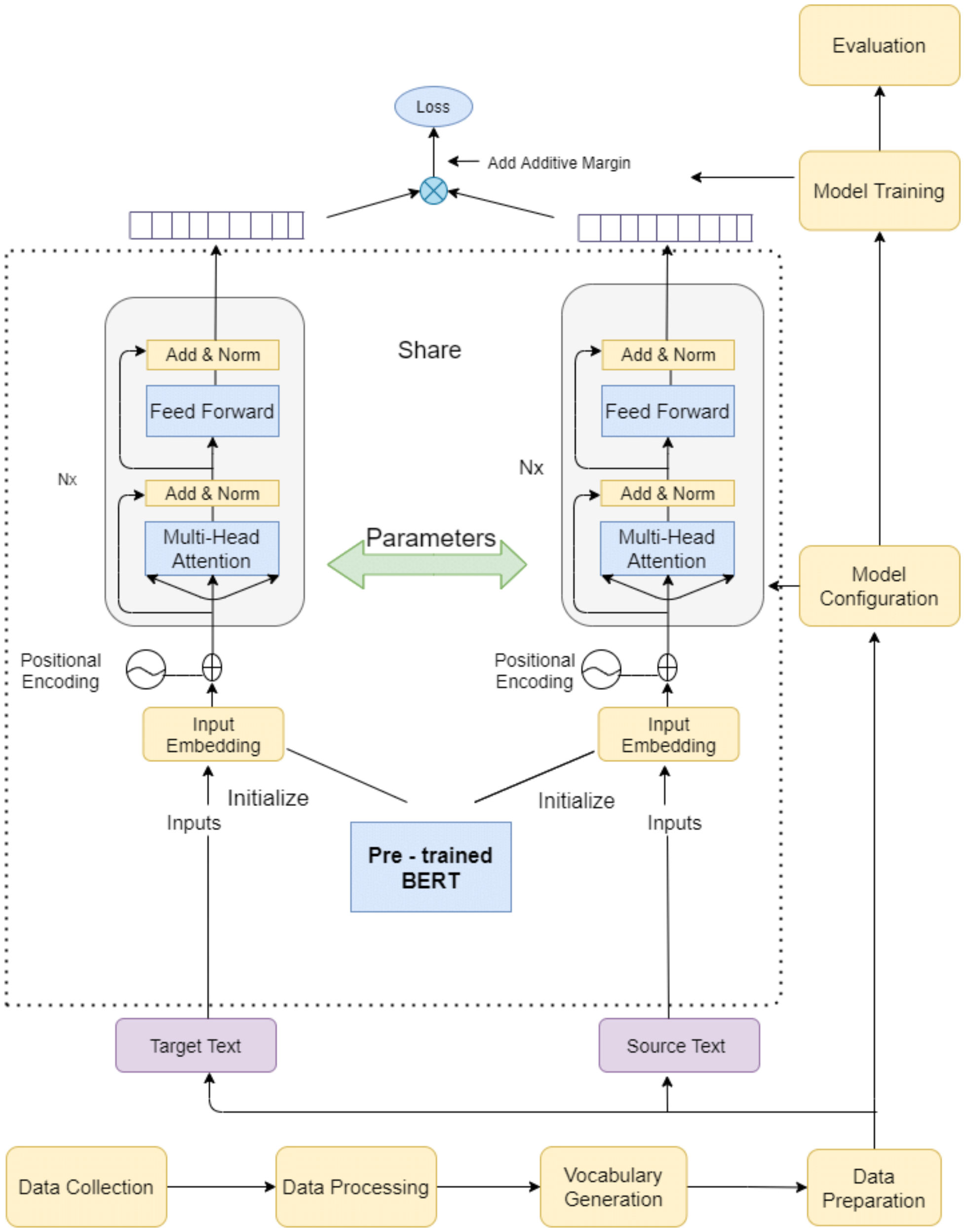


Figure 2.3: BERT-style Transformer architecture used in BanglaBERT. [3]

Training Strategy

- Optimizer: AdamW
- Learning Rate: 2e-5 to 3e-5
- Batch Size: 16–32
- Epochs: 3–5

Encoder Sharing Mechanism BanglaBERT reuses the pre-trained encoder during fine-tuning, applying a margin-based loss to improve classification in low-resource setups [32].

Performance Highlights BanglaBERT outperforms multilingual models on several benchmark tasks, as shown in Table 2.1.

Table 2.1: Performance comparison between BanglaBERT and mBERT on key Bangla NLP tasks.

Task	BanglaBERT Accuracy	mBERT Accuracy
Sentiment Analysis	86.3%	82.1%
Natural Language Inference (NLI)	84.9%	79.7%
Question Answering (QA)	89.2%	84.5%

Advantages and Limitations **Pros**:

- Specifically tuned for Bangla's morphology and syntax.
- Strong task-specific accuracy.

Cons:

- No cross-lingual support.
- Heavier than distilled alternatives.

Multilingual BERT (mBERT)

Overview Multilingual BERT (mBERT) is an encoder-only Transformer-based model introduced by Devlin et al. [31] as a multilingual extension of BERT. It retains the BERT-Base architecture but is trained on concatenated Wikipedia texts from 104 languages, including Bangla. Despite the lack of explicit language alignment, mBERT demonstrates strong zero-shot cross-lingual transfer capabilities [33], making it a valuable baseline for multilingual NLP, particularly for low-resource languages like Bangla.

Architecture mBERT follows the standard BERT-Base setup:

- 12 Transformer encoder layers
- Hidden size of 768
- 12 self-attention heads
- Total parameters: $\sim$110M

Each encoder includes multi-head self-attention, feedforward layers, residual connections, and layer normalization. mBERT is pretrained using:

- **Masked Language Modeling (MLM)**: Predicts 15% randomly masked tokens.
- **Next Sentence Prediction (NSP)**: Learns inter-sentence coherence.

Tokenization is performed using a shared WordPiece vocabulary, supporting multilingual, transliterated, and subword representations [33].

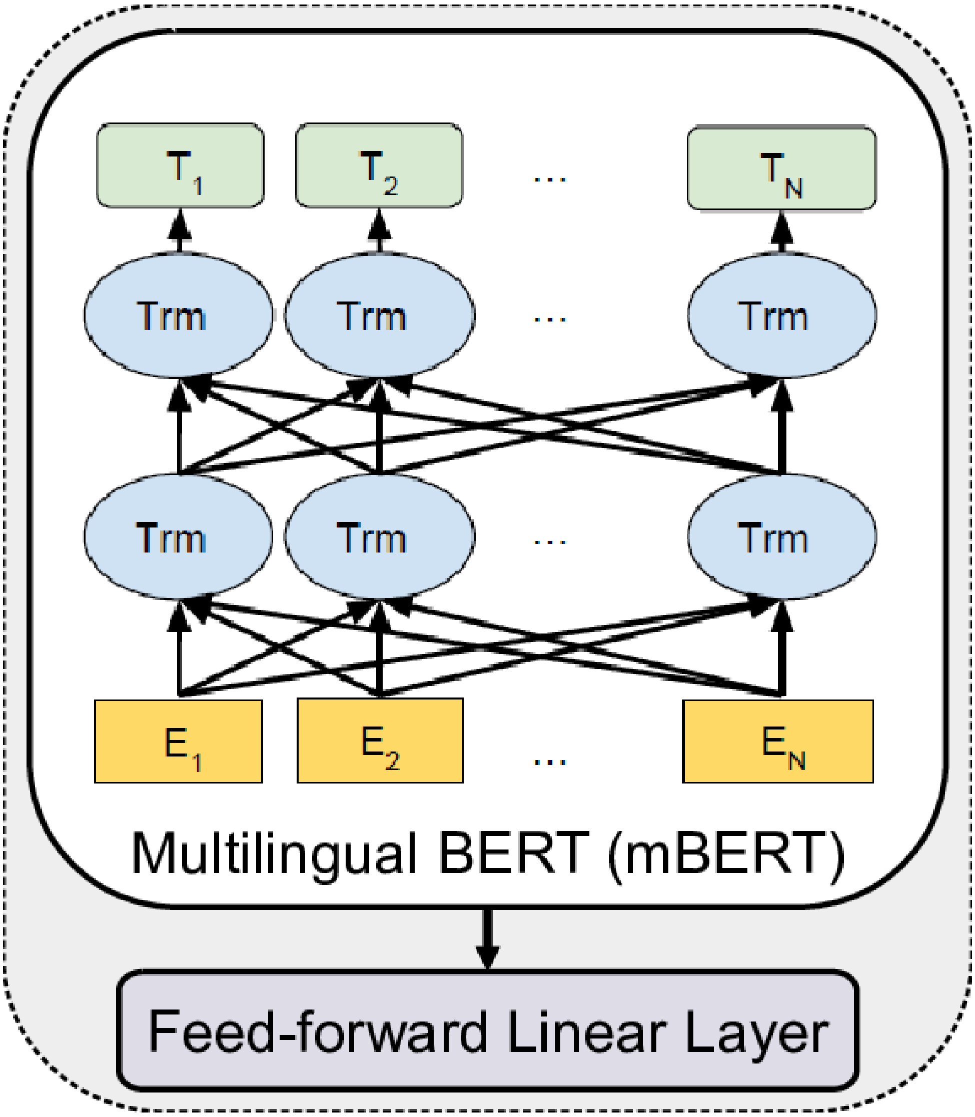


Figure 2.4: Transformer encoder stack in mBERT. [4].

Fine-Tuning for Fake News Detection To adapt mBERT for binary classification (fake vs. real):

- **Tokenization:** Text is tokenized and formatted as `[CLS], token_1, ..., token_N, [SEP]`.

- **Transformer Encoding:** The sequence is passed through the mBERT encoder.
- **Classification:** The final `[CLS]` embedding is input to a dense layer with softmax activation.
- **Loss and Optimizer:** Binary cross-entropy loss is minimized using AdamW with a learning rate of 2e-5 to 3e-5.

This configuration enables generalization across languages and effective use of small-scale Bangla datasets.

Strengths and Limitations **Advantages:**

- Strong cross-lingual generalization (beneficial for code-mixed Bangla).
- Adequate coverage of Bangla in pretraining corpus.
- Effective zero-shot transfer learning capabilities.

Limitations:

- Not tailored to Bangla's linguistic characteristics.
- Less powerful than larger models like XLM-R Large or language-specific models like BanglaBERT.

Performance Snapshot Table 2.2 compares mBERT's performance against other models on Bangla fake news detection tasks.

Table 2.2: Performance comparison of mBERT with BanglaBERT and XLM-R on fake news detection.

Model	Dataset	Weighted F1 (%)
mBERT	Bangla Fake News	75.8
BanglaBERT	Bangla Fake News	82.3
XLM-R Large	Bangla Fake News	84.1

XLM-RoBERTa (XLM-R)

Overview XLM-RoBERTa (XLM-R) is a multilingual Transformer-based language model introduced by Conneau et al. [34], designed to improve cross-lingual generalization across over 100 languages, including Bangla. It extends the RoBERTa architecture and removes language-specific tokens while leveraging a massive multilingual corpus. Compared to earlier models like mBERT, XLM-R performs significantly better on multilingual benchmarks such as XNLI, MLQA, and TyDiQA [33].

In fake news detection, XLM-R proves effective in code-switched, transliterated, and low-resource Bangla contexts.

Table 2.3: XLM-R model configurations.

Variant	**Layers**	**Hidden Size**	**Heads**	**Params**
Base	12	768	12	∼270M
Large	24	1024	16	∼550M

Architecture

- Encoder-only Transformer model.
- Uses SentencePiece tokenizer with ∼250k subword vocabulary.
- No Next Sentence Prediction (NSP); only Masked Language Modeling (MLM).

Pretraining Objective XLM-R uses **Masked Language Modeling (MLM)**:

- Randomly masks 15% of tokens.
- Predicts masked tokens using full bidirectional context.
- Trained on ∼2.5TB of CommonCrawl data from 100 languages.

Fine-Tuning for Fake News Detection To fine-tune XLM-R for binary classification:

- Tokenize Bangla text using SentencePiece.
- Input: `[CLS], token_1, ..., token_n, [SEP]`, padded to 512 tokens.
- Pass through encoder layers.
- Use final `[CLS]` embedding in a softmax classifier.
- Optimizer: AdamW with LR = 2e-5 to 3e-5 and linear warm-up.

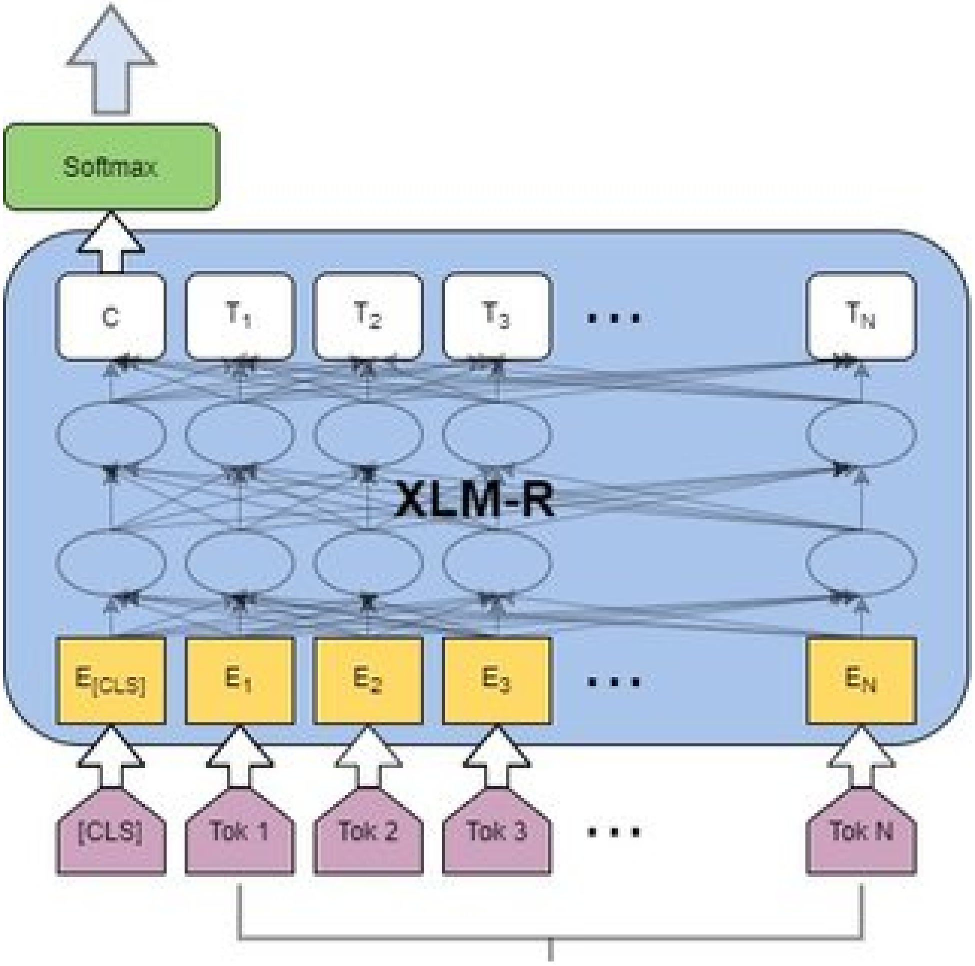


Figure 2.5: XLM-RoBERTa encoder architecture. [5,6].

Table 2.4: Performance of multilingual and Bangla-specific models on Bangla fake news detection.

Model	Weighted F1 (%)
mBERT	75.8
BanglaBERT Base	82.3
XLM-R Large	84.1

Performance Comparison

Advantages

- Strong cross-lingual transfer across diverse languages.
- Effective on low-resource and code-mixed Bangla content.
- Deep multilingual pretraining enables rich context capture.

Limitations

- High computational cost, especially for the Large variant.
- Slower inference and requires more memory.

DistilBERT

Overview DistilBERT is a lightweight and efficient variant of BERT introduced by Sanh et al. [35] using *knowledge distillation*. This approach compresses the larger BERT model into a smaller "student" network while retaining most of its performance. DistilBERT achieves nearly 97% of BERT's accuracy while being ∼40% smaller and ∼60% faster in inference—making it ideal for real-time fake news detection on resource-constrained devices.

Architecture and Pretraining DistilBERT mirrors the core architecture of BERT-Base but with fewer layers:

- 6 Transformer encoder layers (vs. 12 in BERT-Base)
- Hidden size: 768
- 12 self-attention heads
- Total parameters: ∼66M

It is trained with a composite loss function combining:

- **Masked Language Modeling (MLM)**: Predict randomly masked tokens.
- **Distillation Loss**: Match logits between teacher (BERT) and student (DistilBERT).
- **Cosine Embedding Loss**: Align hidden state representations.

The total loss is expressed as:

$$\mathscr{L}_{\text{total}} = \alpha \mathscr{L}_{\text{distill}} + \beta \mathscr{L}_{\text{MLM}} + \gamma \mathscr{L}_{\text{cosine}} \tag{2.8}$$

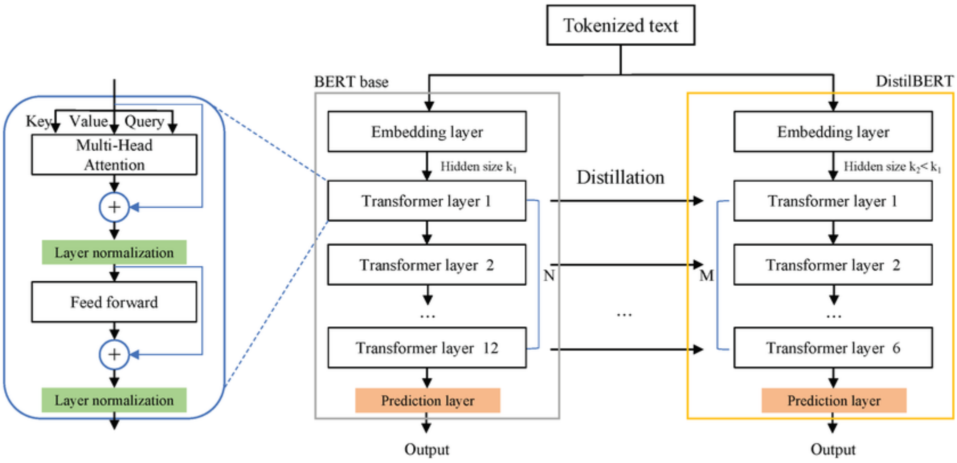


Figure 2.6: DistilBERT architecture with 6 Transformer encoder layers. [7]

Fine-Tuning for Fake News Detection

- **Input Format:** `[CLS], token_1, ..., token_n, [SEP]` (Bangla text).
- **Encoding:** Passed through 6-layer Transformer.
- **Classification Head:** Output from [CLS] is input to a dense + softmax layer.
- **Loss:** Binary cross-entropy.
- **Optimizer:** AdamW with learning rate = 2e-5 to 3e-5.

Table 2.5: Comparison of BERT-Base and DistilBERT.

Metric	BERT-Base	DistilBERT
Model Size	∼110M	∼66M
Inference Speed	Baseline	+60% faster
Performance	100%	∼97%

Benefits and Trade-offs

Strengths and Limitations **Strengths**:

- Compact and efficient—ideal for mobile and web deployment.
- Low inference latency with strong accuracy retention.

Limitations:

- Slight performance drop on deeper contextual tasks.
- May underperform larger models like XLM-R on nuanced tasks.

ELECTRA

Overview ELECTRA, proposed by Clark et al. [36], introduces a novel pretraining method called **Replaced Token Detection (RTD)**. Unlike traditional Masked Language Modeling (MLM), ELECTRA pretrains a model to distinguish real input tokens from fake ones generated by a small auxiliary network, offering a denser and more efficient learning signal. This approach results in faster convergence and improved performance on downstream tasks, including Bangla fake news detection.

Architecture ELECTRA consists of two Transformer-based components:

- **Generator:** A small masked language model (e.g., 1/4 the size of BERT) that predicts substituted tokens.
- **Discriminator:** A full-sized encoder (like BERT) that classifies each token as either “real” or “replaced.”

The total parameter count is comparable to BERT-Base (∼110M), but the pretraining is more sample-efficient.

Replaced Token Detection (RTD) Objective Let t_i be the i-th token in a sequence, and $y_i = 1$ if the token is replaced (else $y_i = 0$). The discriminator learns to identify fake tokens via the following loss function:

$$\mathscr{L}_{\text{RTD}} = -\sum_i [y_i \log D(t_i) + (1 - y_i)\log(1 - D(t_i))] \tag{2.9}$$

where $D(t_i)$ is the discriminator’s predicted probability that t_i is a real token.

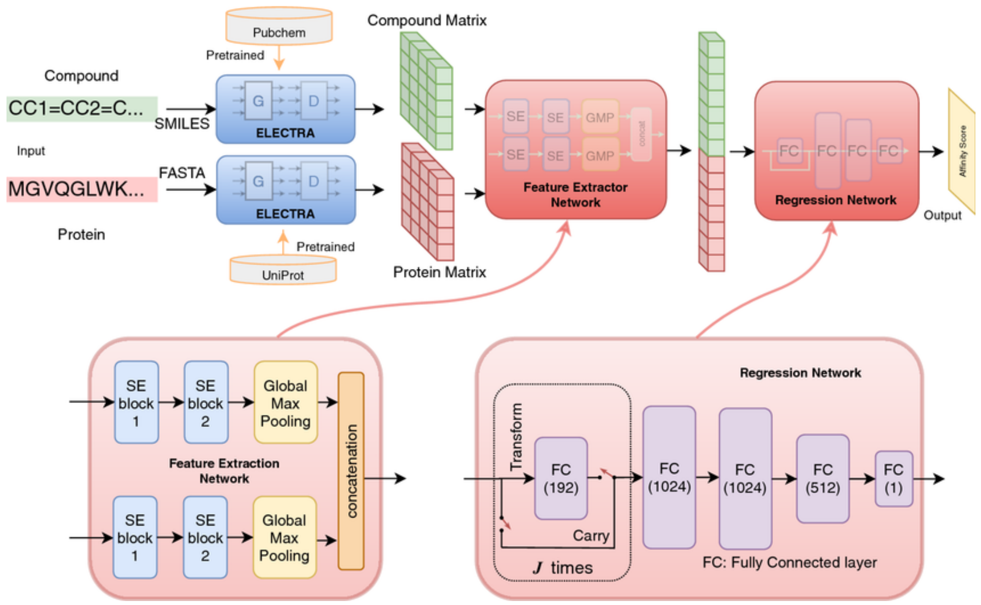


Figure 2.7: ELECTRA training pipeline: Generator replaces tokens; Discriminator identifies replacements. [8].

Training and Fine-Tuning

- The generator replaces 15% of tokens in the input.
- The discriminator receives this altered sequence.
- It learns to detect which tokens were replaced.
- During fine-tuning, only the discriminator is used.
- For fake news detection, the final [CLS] representation is passed through a softmax classifier.

Performance and Efficiency ELECTRA offers improved training efficiency:

- Trains significantly faster than BERT.
- Requires fewer training steps for comparable performance.
- Competitive or superior results in Bangla fake news classification.

Strengths and Limitations **Advantages**:

- Dense supervision from RTD objective.
- Faster convergence with reduced compute needs.

- Strong performance in low-resource scenarios.

Disadvantages:

- Involves two components (generator and discriminator).
- Performance is sensitive to the size imbalance between them.

2.2.2 Image Classification

Image classification plays a critical role in **multimodal fake news detection**, especially for analyzing shared media such as doctored images, manipulated visuals, and misleading thumbnails. These are frequently encountered in online Bangla news and social media posts. Visual content, when paired with deceptive text, can significantly influence public perception. Therefore, it is essential to assess the credibility of images alongside textual information.

This section discusses the major **computer vision models** employed in our work—ranging from classical **Convolutional Neural Networks (CNNs)** to modern transformer-based architectures like **ViT (Vision Transformer)** and **Swin Transformer**. All models are fine-tuned on the image portion of our dataset for **binary classification** into *fake* and *non-fake* news images.

Convolutional Neural Networks (CNN)

Overview **CNNs** have long served as the foundation for image classification tasks due to their capacity to automatically learn hierarchical features using convolutional filters [9]. A typical CNN comprises layers that progressively extract and combine low-level and high-level patterns.

Architecture

- **Convolution Layer:** Applies multiple filters to extract visual features like edges and textures.
- **Activation (ReLU):** Introduces non-linearity to the network.
- **Pooling Layer:** Reduces spatial resolution, preventing overfitting and reducing computation.
- **Fully Connected Layers:** Flattened features are mapped to class probabilities.

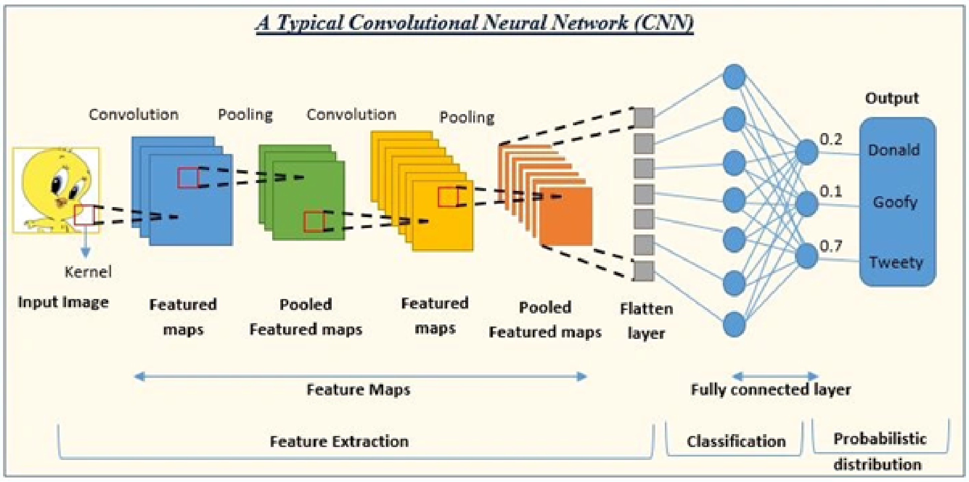


Figure 2.8: Standard CNN architecture showing convolution, pooling, and dense layers. [9]

Application CNNs serve as a **baseline model** in our pipeline to detect visual patterns indicative of fake content (e.g., *sensationalism, digital tampering*). Despite their architectural simplicity, CNNs achieve competitive performance when trained on large-scale datasets.

MobileNet

Overview **MobileNet** is a lightweight CNN architecture optimized for mobile and edge devices. It uses **depthwise separable convolutions** to significantly reduce computational overhead and model size without sacrificing much accuracy [10].

Architecture Highlights

- **Depthwise Convolution:** Applies a single filter per input channel.
- **Pointwise Convolution:** Combines depthwise outputs using 1×1 convolutions.
- **Efficiency:** Offers $8\times$ to $9\times$ fewer computations than traditional CNNs.

Use in Fake News Detection **MobileNet** is particularly suited for **real-time deployment**—such as browser extensions or mobile apps—due to its lightweight design and low latency inference.

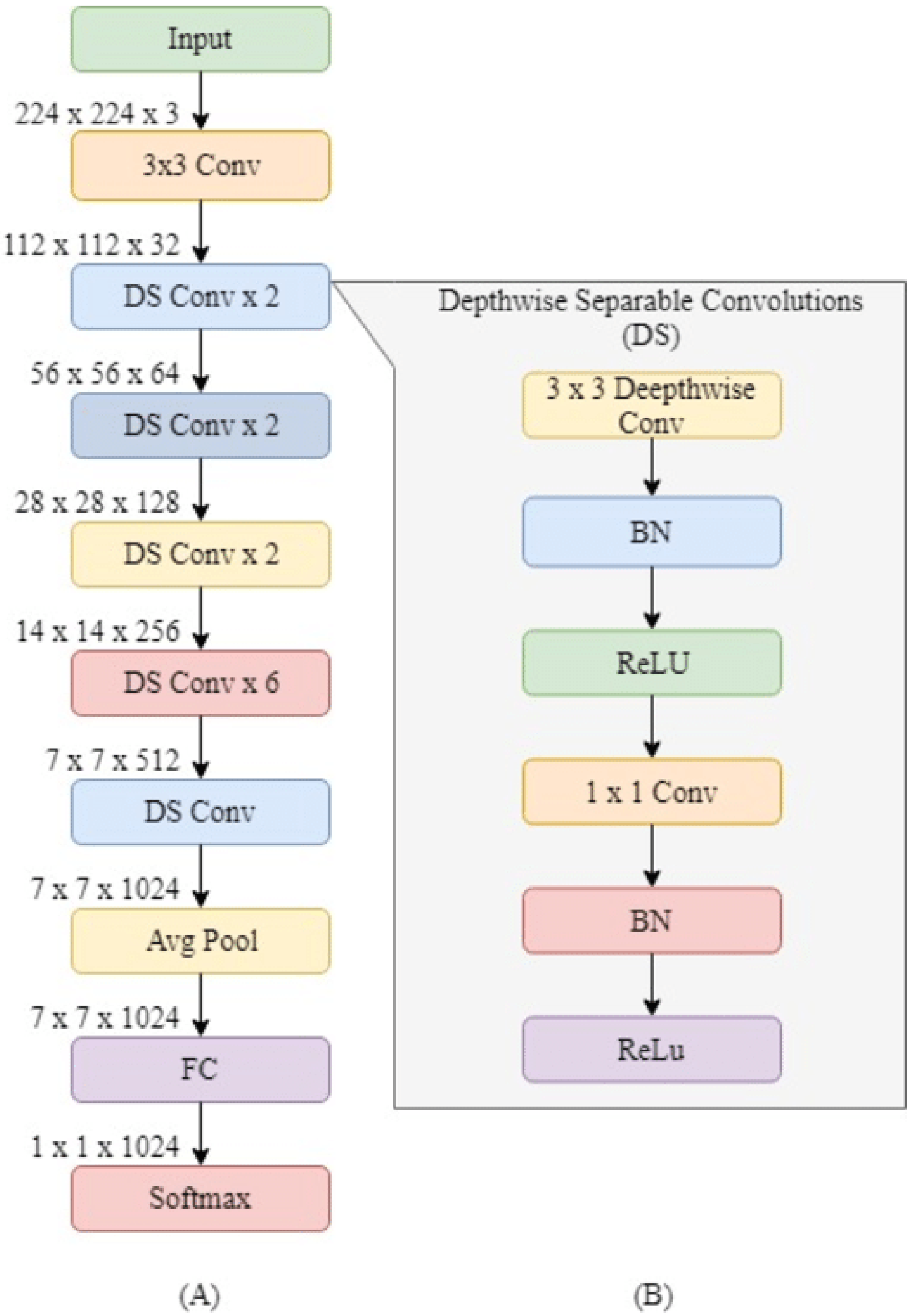


Figure 2.9: MobileNet architecture using depthwise separable convolutions. [10]

Variant Comparison

Variant	Separable Convs	Params	Efficiency	Use Case
MobileNet-v1	Yes	4.2M	8–9× less compute	Simple mobile apps
MobileNet-v2	+Inverted Residuals	3.4M	More reuse	On-device inference
MobileNet-v3	+SE, H-Swish, NAS	5.4–7.6M	Best trade-off	Real-time vision

Table 2.6: Comparison of MobileNet variants used for fake news detection.

ResNet (Residual Networks)

Overview **ResNet**, introduced by He et al. [11], addresses the *vanishing gradient problem* in deep networks via **residual connections**. These *skip connections* allow gradients to flow directly through the network, enabling effective training of very deep architectures (e.g., ResNet-50, ResNet-101).

Architecture Each **residual block** is defined as:

$$y = \mathscr{F}(x, \{W_i\}) + x \tag{2.10}$$

Where:

- $\mathscr{F}(x)$ is the residual function (typically a sequence of convolutions).
- x is the block input, passed directly through a skip connection.

Use in Our System We adopt **ResNet-50** to extract deep visual features from Bangla news images. The final fully connected (FC) layer is replaced with a softmax classifier for **binary fake vs. real prediction**.

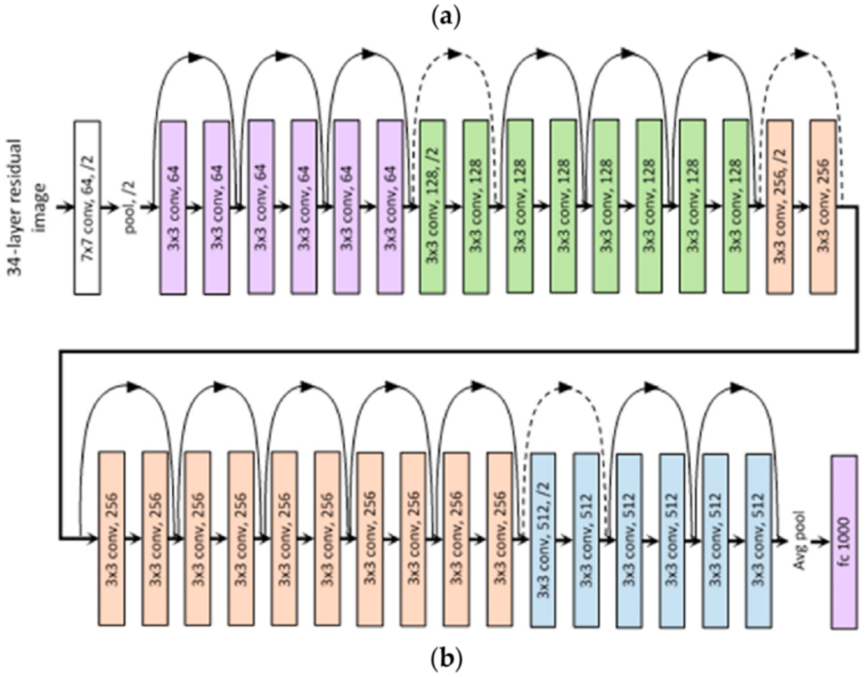


Figure 2.10: ResNet-50 architecture showing residual learning via skip connections. [11]

Table 2.7: Comparison of ResNet variants commonly used for fake news detection.

Variant	Layers	Params	Strengths
ResNet-18	18	∼12M	Lightweight and fast
ResNet-34	34	∼21M	Balanced depth and speed
ResNet-50	50	∼25M	Strong visual representations

Vision Transformer (ViT)

Overview The **Vision Transformer (ViT)**, introduced by Dosovitskiy et al. [12], shifts the paradigm from convolution-based image processing to transformer-based modeling. It treats an image as a sequence of patches and applies standard transformer encoders, similar to NLP tasks.

Architecture

- **Patch Extraction:** The image is divided into fixed-size patches (e.g., 16 × 16).
- **Linear Embedding:** Each patch is flattened and linearly projected into a vector.
- **Positional Encoding:** Added to retain spatial relationships between patches.
- **Transformer Encoder:** Processes the patch sequence using multi-head self-attention.
- **Classification Head:** The output of the special `[CLS]` token is used for prediction.

$$Z_0 = [x_{\text{cls}}; x_{p1}E; x_{p2}E; \ldots; x_{pN}E] + E_{\text{pos}} \tag{2.11}$$

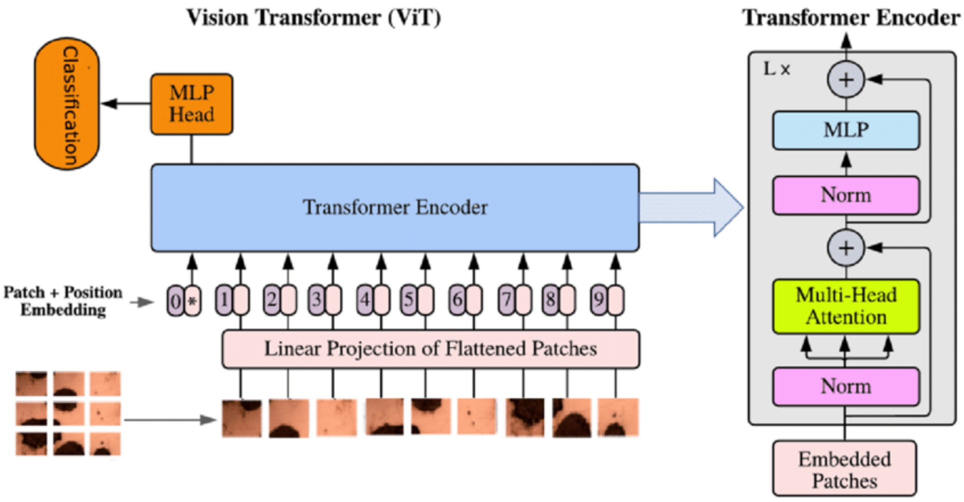


Figure 2.11: Vision Transformer (ViT) architecture with patch embeddings and transformer layers. [12]

Benefits for Fake News Detection ViT captures **global contextual relationships** across distant image regions—critical for detecting *subtle manipulations or doctored elements* that might be missed by CNNs.

Swin Transformer

Overview The **Swin Transformer** (Shifted Window Transformer) improves ViT by introducing **hierarchical** and **local attention mechanisms**. Proposed by Liu et al. [13], it enables scalable and efficient vision modeling.

Architecture

- **Local Window Attention:** Attention is applied within non-overlapping windows.
- **Shifted Windowing:** Windows are shifted between layers to enable cross-window communication.
- **Hierarchical Representation:** Enables multi-scale feature extraction for dense prediction tasks.

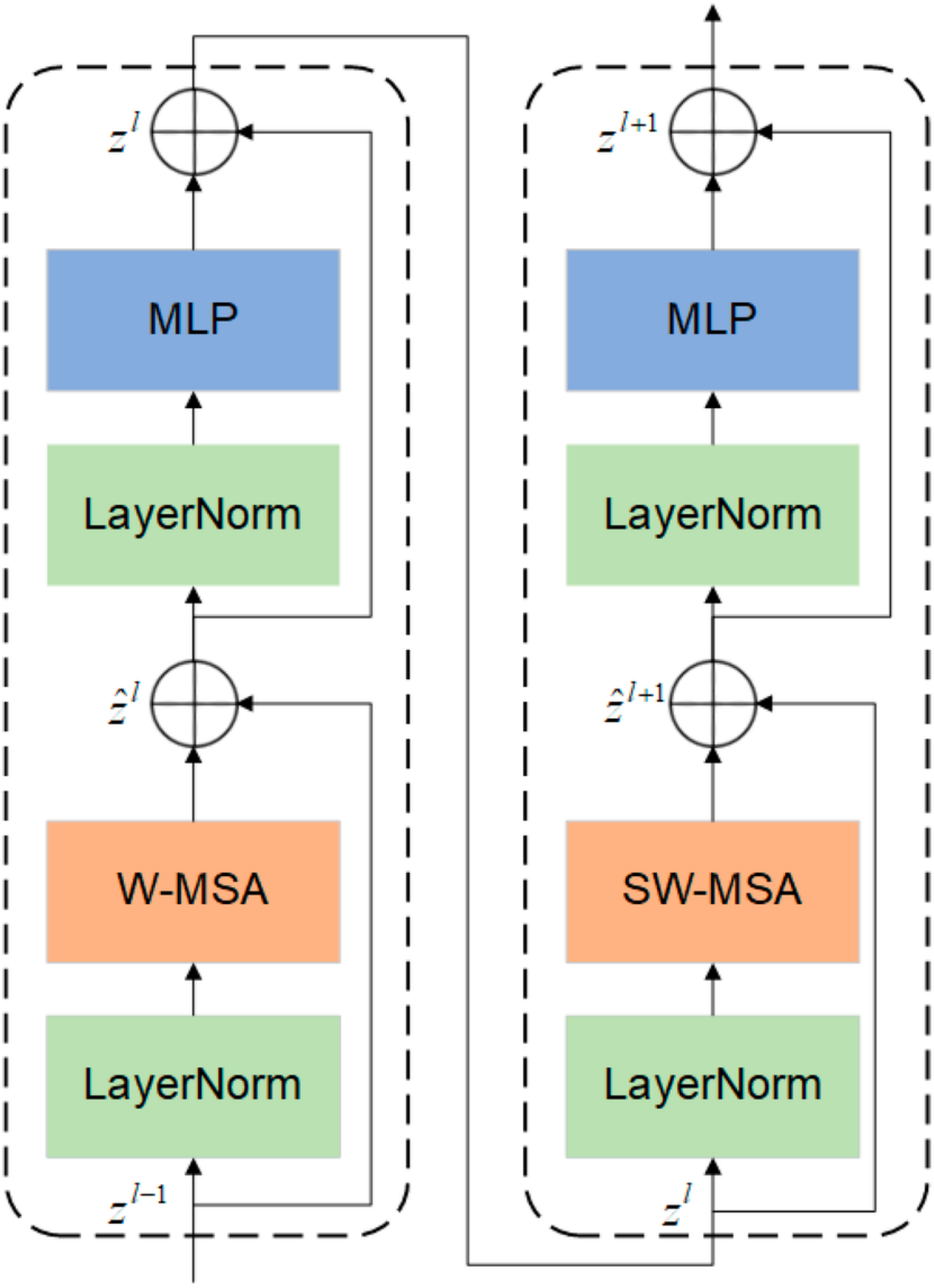


Figure 2.12: Swin Transformer architecture demonstrating hierarchical and shifted window attention. [13]

Advantages

- Efficient for high-resolution images.
- Outperforms ViT and CNNs on many benchmarks.

Use in Our System We employ Swin Transformer to learn spatially-aware, hierarchical visual features from Bangla news images, showing **superior performance** in binary fake-news classification.

Data-efficient Image Transformer (DeiT)

Overview **DeiT**, introduced by Touvron et al. [37], is a variant of ViT optimized for training on limited data like ImageNet. It integrates knowledge distillation to improve generalization without requiring massive datasets.

Architecture and Distillation

- Follows ViT structure: patch embedding, positional encoding, transformer layers.
- Introduces a distillation token `[DIST]` alongside `[CLS]`.
- Learns via:
  - Cross-entropy loss from ground-truth labels on `[CLS]`.
  - Distillation loss from teacher model logits on `[DIST]`.

Variants. A comparison of DeiT model configurations is provided below.

Table 2.8: Performance and efficiency comparison of DeiT model variants on ImageNet.

Variant	Dim	Heads	Layers	Params	Top-1 Acc.	Throughput
DeiT-Ti	192	3	12	∼5M	∼72%	2536 img/s
DeiT-S	384	6	12	∼22M	∼80%	940 img/s
DeiT-B	768	12	12	∼86M	81.8–83.1%	292 img/s

Strengths and Limitations **Pros:**

- Performs well on small datasets.
- Combines transformer flexibility with CNN-like inductive bias.

Cons:

- Requires a careful teacher-student setup.
- Slightly higher inference complexity due to distillation design.

Use in Our System We fine-tune multiple DeiT variants on our image dataset and incorporate them in the final **stacking ensemble**. Their diversity strengthens the robustness of fake news detection.

Summary of Transformer-Based Models for Text and Image Classification

The table below summarizes key transformer-based and CNN-based models used in our fake news detection framework, highlighting their architectural characteristics, parameter counts, training strategies, and notable advantages across text and image modalities.

Table 2.9: Summary of Transformer-based models for text and image fake news detection tasks.

Model	**Type**	**Layers / Params**	**Key Training Strategy**	**Notes**
BanglaBERT	Text Transformer	12 / 110M	MLM + NSP, pretrained on Bangla corpus	Strong Bangla morphology understanding
mBERT	Multilingual Text	12 / 110M	MLM + NSP, 104 languages Wikipedia	Zero-shot & multilingual abilities
XLM-R	Multilingual Text	Base: 12 / 270M, Large: 24 / 550M	MLM only, trained on 100 languages	Excellent cross-lingual transfer
DistilBERT	Text Transformer	6 / 65M	Knowledge distillation (, , losses)	Lightweight & fast, retains 97% of BERT's accuracy
ELECTRA	Text Transformer	110M	Replaced-Token Detection (RTD)	Dense token-level supervision
CNN	Image CNN	Varies	Transfer learning from ImageNet	Good local feature learning
MobileNet	Image CNN	4M	Depthwise separable convolutions	Efficient for mobile deployment
ResNet-50	Image CNN	25M	Residual blocks with deep architecture	Strong baseline performance
ViT	Vision Transformer	12 / 85M	Patch + Transformer encoder, pretrained on large datasets	Captures global image context
Swin	Vision Transformer	Varies (T/S/B)	Shifted-window attention with hierarchy	Efficient on high-res dense tasks
DeiT	Vision Transformer	Same as ViT + distiller	Student-teacher knowledge distillation	Good for small datasets, efficient training

2.2.3 Ensemble Techniques: MLP-Based Stacking

Overview Ensemble learning combines the outputs of multiple models to enhance prediction accuracy and robustness. Among various strategies, **stacked generalization (stacking)** [38] is especially effective when leveraging diverse models. In our multimodal fake news detection system, we employ a **Multi-Layer Perceptron (MLP)-based stacking** technique to aggregate softmax predictions from several fine-tuned transformer models.

This approach exploits the complementary strengths of models like BanglaBERT, XLM-R, mBERT, DistilBERT, and ELECTRA. By using their probabilistic outputs rather than hard labels, the stacking model captures subtle decision-making patterns, ultimately reducing overfitting and generalization error.

Stacking Architecture

Level-0 (Base Learners): Multiple transformer models are fine-tuned separately on the fake news dataset. Each model produces softmax scores over the binary classes: *fake* and *real*.

Level-1 (Meta-Classifier): An MLP takes the concatenated softmax outputs from all base models as input and learns to optimally combine them into a final prediction.

Process Pipeline

Step 1: Softmax Output Collection For each model $M_i \in \{M_1, M_2, ..., M_n\}$, we compute:

$$P_i = \text{softmax}(M_i(x)) = [p_{\text{fake}},\ p_{\text{real}}] \tag{2.12}$$

where $P_i \in \mathbb{R}^2$ for each sample in binary classification.

Step 2: Concatenation All softmax vectors are concatenated into a single input feature vector:

$$X' = [P_1,\ P_2,\ \ldots,\ P_n] \in \mathbb{R}^{2n} \tag{2.13}$$

Step 3: Meta-Classifier Training We train a shallow MLP on X' and ground truth labels y, using binary cross-entropy loss:

$$\mathscr{L}_{\text{BCE}} = -[y \cdot \log(\hat{y}) + (1-y) \cdot \log(1-\hat{y})] \tag{2.14}$$

MLP Architecture

- **Input Layer:** Size $= 2n$
- **Hidden Layer:** 64 units, ReLU activation
- **Output Layer:** 1 unit, Sigmoid activation

- **Optimizer:** Adam, Learning rate: 1e-3

Mathematical Formulation

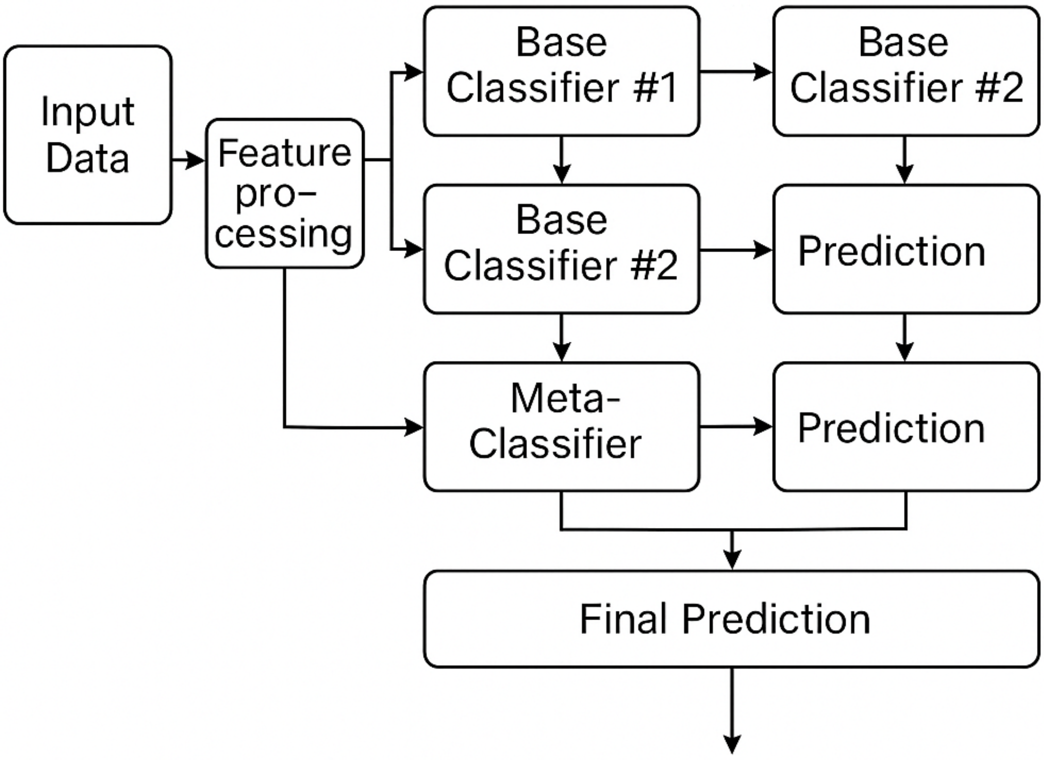
Let:

- $X = \{x_1, ..., x_m\}$: input samples
- $M = \{M_1, ..., M_n\}$: set of base models
- $\hat{y}_j^i = M_j(x_i)$: softmax output of model M_j on input x_i
- $z_i = [\hat{y}_1^i, ..., \hat{y}_n^i] \in \mathbb{R}^{2n}$: concatenated prediction vector

The MLP meta-classifier f_θ is trained to minimize:

$$\min_{\theta} \frac{1}{m} \sum_{i=1}^{m} \mathcal{L}_{\text{BCE}}(f_\theta(z_i), y_i) \tag{2.15}$$

Visualization of Stacking Process



Stacked Generalization (Stacking) Pipeline for Fake News Detection

Figure 2.13: Stacking ensemble architecture combining transformer predictions via MLP meta-classifier.

Advantages of MLP-Based Stacking

- **Diversity-aware:** Captures complementary decision behavior across different models.
- **Improved Generalization:** Learns contextual reliability of each model's predictions.
- **Model-Agnostic:** Easily extendable to include CNN-based image classifiers for multimodal fusion.

Implementation Details

- **Training Set:** Softmax predictions from 6 transformer variants.
- **Validation/Test:** Meta-classifier evaluated on held-out data.
- **Performance:** Achieved 2–5% F1-score improvement over individual models.

2.2.4 Multimodal Fusion

Multimodal fusion integrates textual and visual modalities to enhance fake news detection by combining complementary information. Three primary fusion strategies are commonly used: **early fusion**, **late fusion**, and **intermediate fusion** [14].

Early Fusion (Feature-Level)

In early fusion, raw or extracted feature vectors from text and image models are concatenated before feeding into a joint classifier [14, 39].

Workflow

- Extract features:

$$t = f_{\text{text}}(x_{\text{text}}), \quad v = f_{\text{image}}(x_{\text{image}}) \tag{2.16}$$

- Concatenate:

$$u = [t \,\|\, v] \tag{2.17}$$

- Classify with joint MLP:

$$y = \text{softmax}(W \cdot \phi(u) + b) \tag{2.18}$$

where ϕ is an activation function (e.g., ReLU), and W, b are trainable parameters.

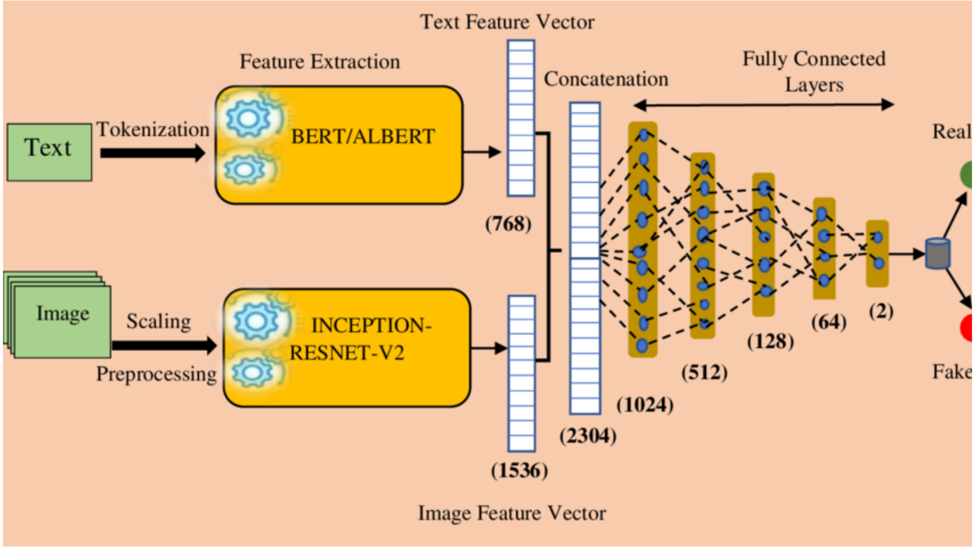


Figure 2.14: Early fusion architecture where text and image embeddings are concatenated before classification. [14]

Advantages

- **Pros:** Captures deep cross-modal feature interactions.
- **Cons:** Requires careful normalization; potentially high-dimensional input.

Late Fusion (Decision-Level)

Late fusion combines predictions from independently trained text and image classifiers after their decisions [14].

Workflow

- Get softmax outputs:

$$p_{\text{text}}, \quad p_{\text{image}} \tag{2.19}$$

- Fuse via weighted averaging or voting:

$$p_{\text{fused}} = \alpha \cdot p_{\text{text}} + (1 - \alpha) \cdot p_{\text{image}} \tag{2.20}$$

where $\alpha \in [0, 1]$

- Final decision:

$$y = \arg\max(p_{\text{fused}}) \tag{2.21}$$

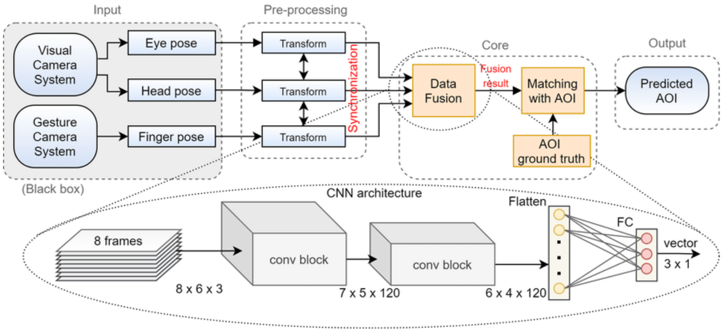


Figure 2.15: Late fusion architecture combining separate classifier outputs. [14].

Advantages

- **Pros:** Simple, modular, robust to missing modalities.
- **Cons:** Misses deep interactions between modalities.

Intermediate Fusion (Hybrid)

Intermediate fusion joins modalities at a middle layer where higher-level features are combined, often using attention mechanisms [15].

Workflow

- Extract intermediate features:

$$t_i = f^{(i)}_{\text{text}}(x), \quad v_i = f^{(i)}_{\text{image}}(x) \tag{2.22}$$

- Fuse via attention or concatenation:

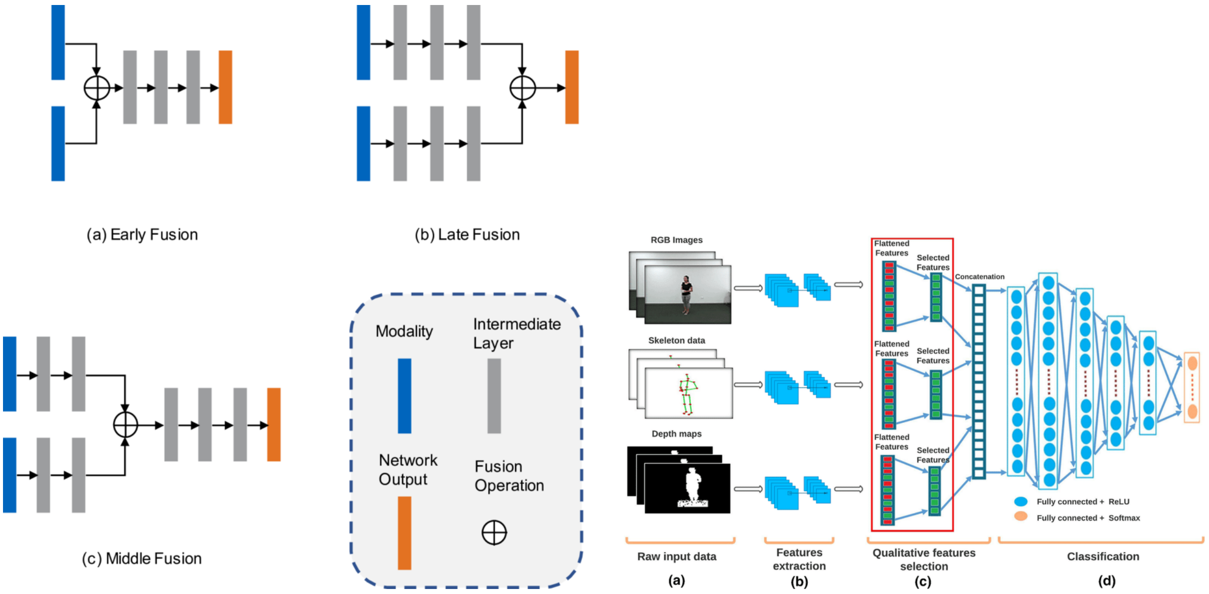
$$h = \text{Fusion}(t_i, v_i) \tag{2.23}$$

- Pass through MLP or transformer layers:

$$y = \text{softmax}(W \cdot h + b) \tag{2.24}$$

- Example attention mechanism:

$$\text{Attention}(Q_t, K_v, V_v) + \text{Attention}(Q_v, K_t, V_t) \tag{2.25}$$



(a) Intermediate feature extraction from text and image encoders.

(b) Cross-modal attention combining the features.

Figure 2.16: Illustration of intermediate fusion strategies: (a) extracting mid-level features from modality-specific encoders, and (b) combining them using cross-modal attention. [15].

Advantages

- Efficiently captures modality interactions.
- More expressive than early/late fusion.

2.3 Literature Review

2.3.1 Bangla-Only Fake News Detection

A growing number of studies focus exclusively on Bangla-language fake news detection, exploiting neural architectures tailored for text understanding.

Akther etal. (2025) propose a knowledge-driven model that integrates semantic embeddings, sentiment cues, and external knowledge graphs to identify inconsistencies in Bangla news [40]. By combining linguistic signals with structured background knowledge, the system significantly outperforms baseline text-only models, demonstrating robust detection of manipulated content.

Mondal etal. (2024) assembled a 58,478-article Bangla dataset and addressed class imbalance via oversampling [41]. They implemented a GRU-based deep learning pipeline with extensive preprocessing (lemmatization, tokenization), achieving around 94% accuracy. This illustrates that well-tuned sequential neural models can perform strongly in Bangla fake news classification.

Roy etal. (2024) compared Bi-GRU, LSTM, 1D-CNN, and hybrid architectures on approximately 50k articles [42]. With focused preprocessing and balancing, a bidirectional GRU achieved an impressive 99.16% accuracy, setting a strong performance benchmark in the domain.

Ahammad etal. (2024) introduced RoBERTa-GCN, fusing embeddings from a Bangla-adapted RoBERTa with a Graph Convolutional Network that models inter-article relationships [43]. This hybrid approach enhanced detection context by capturing both content and relational patterns, achieving 98.6% accuracy.

Sheikh S.B. etal. (2024) systematically benchmarked RNN variants and transformer-based Bangla BERT on a shared dataset [44]. Their findings showed that fine-tuned Bangla BERT outperformed alternatives by achieving around 95% accuracy—highlighting the advantage of pretrained transformers in Bangla NLP.

These studies collectively demonstrate that **neural models—from GRUs to hybrid transformer-graph frameworks—excel at Bangla fake news detection**. However, they also share common limitations: they often rely on large annotated corpora, may overfit specific domains or datasets, and primarily operate in a **unimodal text-only setting**, ignoring the rich **visual context** often present in real-world misinformation.

2.3.2 Multimodal Fake News Detection

Combining text and image modalities significantly improves detection accuracy and robustness.

Zhu et al. (2025) introduce *MFND*, a large 125K-entry multimodal dataset encompassing four news types (real/fake text vs. image) and 11 manipulation patterns. Their SDML model employs shallow contrastive alignment and deep dual-branch inference to detect and localize fake components—achieving over 93% accuracy and F1 on MFND and mainstream benchmarks [45].

Lin et al. (2024) propose a text–image fusion model evaluated on *GossipCop* and *Faked-*

dit, exploring early, joint, and late fusion strategies [46]. Their approach yields 85–90% accuracy and approximately 90% F1, showing that combining clean text and image feature pipelines with fusion strategies significantly boosts performance over unimodal baselines.

Faria et al. (2024) release *MultiBanFakeDetect*, a 9.6K-entry Bangla multimodal dataset [47]. They integrate CNN-based image encoders and transformer-based textual embeddings using fusion modules, and report that their model outperforms text-only systems in terms of precision—demonstrating the value of visual signals for low-resource languages.

IEEE Bengali Study (2024) develops *BanglaMM-FND*, leveraging Bangla BERT and Vision Transformer (ViT) in a multimodal single-shot fusion model [48]. Their experiments yield a macro-F1 of 0.71, indicating moderate performance, while also highlighting the limitations of using dense architectures in the presence of limited Bengali multimodal data.

Systematic Review (2025) surveys recent multimodal fake news detection methods across languages [49]. It underscores the dominance of deep learning approaches—particularly those using cross-attention, multimodal alignment, and contrastive learning. However, the review also notes persistent issues such as weak modality alignment, domain overfitting, and insufficient Bengali-specific datasets.

Challenges:

- **Cross-modal fusion design:** Developing robust fusion layers—whether contrastive, attention-based, or alignment-driven—remains an open challenge.
- **Data limitations:** Bengali-specific multimodal datasets are still sparse and small-scale, constraining scalability and domain generalization.

2.3.3 Multilingual & Low-Resource Language Approaches

Shibu etal. (2025) introduced *BanFakeNews-2.0* (60K articles) and demonstrated that **BLOOM-560M outperformed mBERT** (89% vs.87% F1) [50], emphasizing the strength of **multilingual LLMs** in low-resource contexts through transfer learning.

Subramanian etal. (2024) evaluated **XLM-R and MuRIL** on fake news detection for Dravidian languages [51], achieving over 90% accuracy and 85%+ F1. This illustrates effective **cross-lingual transfer** across linguistically related low-resource settings.

Benchmarking Study (2024) confirmed that **multilingual pretraining** (e.g., XLM-R) surpasses **translation-based pipelines**, showing that native multilingual modeling is more effective for fake news detection in low-resource environments [27].

2.3.4 LLM-Based & Reasoning-Enabled Detection

Ma etal. (2024) proposed a framework prompting **GPT-3.5 and LLaMA2** to extract topic and entity features, followed by building a **heterogeneous graph** for representation propagation [52]. Their model achieves strong gains by leveraging **semantic reasoning** over shallow embeddings.

Zhou etal. (2024) introduced *FND-LLM*, a multimodal pipeline that combines **BERT, ViT, CLIP**, and **GPT-3.5** for rationale generation [53]. Their "**explain-then-decide**" architecture improved accuracy by 5–7% over standard baselines through claim verification enhanced by LLM-generated explanations.

Raza etal. (2024) conducted a comparative study between fine-tuned **BERT** and few-shot **LLM prompts**, finding BERT more accurate in classification tasks while **LLMs proved more resilient to noise and perturbations** [54].

2.3.5 Recent Advanced Multimodal Architectures

GAMED (2024) applies **expert-conditioned decoupling**, using dedicated text/image experts with dynamic weighting to enhance both **performance and explainability** [55].

Confidence-Aware Frameworks (2024) calibrate **input reliability across modalities**, improving robustness under uncertainty [56].

Hybrid Optimization (2025) leverages **reinforcement learning** to handle **distributional shifts**, enabling long-term adaptability [57].

AMPLE (2024) combines **emotion-aware prompts** with cross-attention, boosting few-shot learning capabilities [58].

Attribution Benchmarks (2024) introduce **granular fake-news labels** for fine-grained evaluation of complex detection systems [59].

MIMoE-FND (2025) uses a **gated Mixture-of-Experts**, assigning modality-specific weights based on confidence scores [60].

Self-Learning Models (2024) combine **contrastive learning and LLM-generated pseudo-labels** to achieve 85%+ accuracy with minimal supervision [61].

These developments illustrate a shift from traditional Bangla text-only models toward **multimodal**, **multilingual**, and **LLM-enhanced** architectures. However, limitations remain: **Bangla multimodal datasets are scarce**, **fusion strategies require refinement**, and **reasoning-enabled, explainable models are underexplored**. These gaps justify our proposal to develop a **stacking ensemble multimodal system tailored for Bengali fake news detection**.

2.3.6 Identified Gaps and Research Opportunities

Synthesis of Literature Gaps:

- **Transformer and GCN models** perform well, but generalization is hindered by dataset bias.
- **Multimodal fusion** provides boosts in accuracy, but fusion strategies remain shallow or rigid.
- **Multilingual/LLM models** offer promise in low-resource contexts like Bengali but lack fine-tuned domain adaptation.
- **Advanced fusion architectures** (e.g., Mixture-of-Experts, hierarchical attention) show potential but are underutilized.

Key Research Needs:

- Large, balanced Bangla multimodal datasets.
- Lightweight, explainable fake news detectors.
- Guided fusion mechanisms balancing accuracy with interpretability.

2.3.7 Conclusion of Literature Review

The reviewed works demonstrate clear progress in both **Bangla-only** and **multimodal fake news detection**. However, several critical gaps remain. These include the lack of **sophisticated cross-modal fusion** strategies, limited integration of **explainability mechanisms**, insufficient adaptation of models to **multilingual or low-resource settings**, and poor support for **real-world deployment**. To address these issues, this thesis proposes a **multimodal, stacking-ensemble system specifically tailored for Bengali**, which combines state-of-the-art models across text and image modalities. The system also incorporates **emotion-informed** and **reasoning-based fusion mechanisms** to enhance interpretability and robustness, aiming for both academic advancement and practical deployability. .

2.4 Summary

In summary, research on fake news detection is shifting from unimodal Bangla text models—ranging from Bi-GRUs to advanced transformer-GCN hybrids—toward more sophisticated multimodal and reasoning-capable frameworks. Multimodal detection approaches, such as SDML and early/intermediate fusion models, have consistently demonstrated superior performance compared to text-only systems. Cross-lingual models like XLM-R and BLOOM show strong potential under data-scarce conditions, particularly for low-resource languages like Bengali. Additionally, the integration of Large Language Models (LLMs) introduces valuable semantic reasoning capabilities, although this comes at a higher computational cost.Recent innovations in fusion architectures—such as gated mixtures, emotion-aware prompting, and confidence calibration—reflect an evolving focus on adaptability, interpretability, and modality-specific specialization. Despite this progress, key challenges remain: the lack of large-scale Bengali multimodal datasets, limitations in efficient and explainable fusion strategies, and the absence of lightweight, deployable solutions. This thesis aims to address these gaps by proposing a robust Bangla multimodal stacking ensemble framework, synthesizing advancements in transformer-based NLP, computer vision, and ensemble learning to deliver accurate, interpretable, and practical fake news detection.

Chapter 3

Methodology

3.1 Overview

Machine learning and deep learning algorithms have become increasingly effective in the field of fake news detection, especially when dealing with large volumes of unstructured text and image data. These models help identify hidden patterns and deceptive content that traditional rule-based systems often fail to detect. In this study, both transformer-based NLP models and CNN-based vision models were used to classify Bangla news articles as fake or real.

3.2 Workflow Strategy

To achieve effective detection of fake news in Bangla, we followed a systematic workflow consisting of several key steps. First, we acquired a relevant publicly available data set that contains labeled Bangla news articles. Next, we performed data preprocessing, including text cleaning, tokenization, and label encoding, to prepare the data for model training. Our approach combined multiple deep learning models, such as Bangla BERT, RoBERTa, CNN, and LSTM, to capture both semantic and sequential patterns in the text. We fine-tuned the models trained on the prepared dataset to improve classification accuracy. The models were trained and evaluated on both balanced and unbalanced splits to analyze performance in binary classification tasks. Figure 4.1 illustrates the step-by-step workflow of our research process, from data acquisition to model training and evaluation.

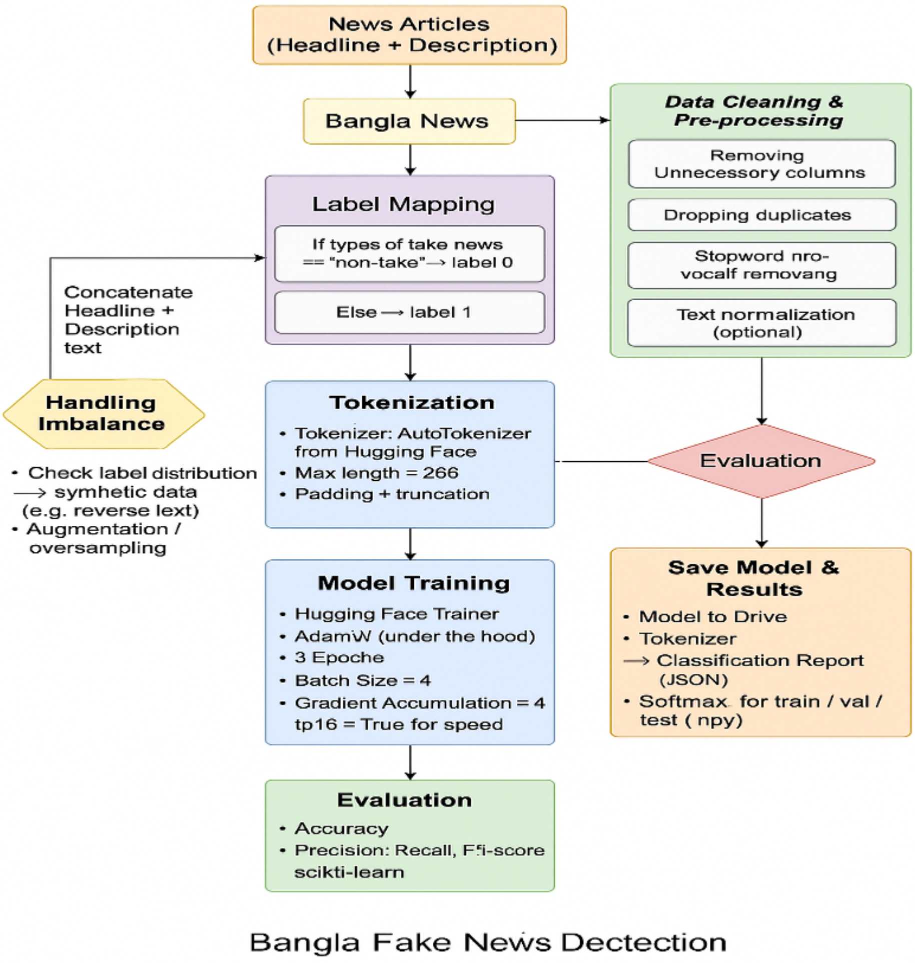

News Articles
(Headline + Description)
Bangla News
Data Cleaning & Pre-processing
Removing Unnecessory columns
Dropping duplicates
Stopword nro-vocalf removang
Text normalization (optional)
Label Mapping
If types of take news == "non-take"⟶ label 0
Else ⟶ label 1
Concatenate Headline + Description text
Handling Imbalance
• Check label distribution ⟶ symhetic data (e.g. reverse lext)
• Augmentation / oversampling
Tokenization
• Tokenizer: AutoTokenizer from Hugging Face
• Max length = 266
• Padding + truncation
Evaluation
Model Training
• Hugging Face Trainer
• AdamW (under the hood)
• 3 Epoche
• Batch Size = 4
• Gradient Accumulation = 4 tp16 = True for speed
Save Model & Results
• Model to Drive
• Tokenizer ⟶ Classification Report (JSON)
• Softmax for train / val / test (npy)
Evaluation
• Accuracy
• Precision: Recall, F1-score scikti-learn
Bangla Fake News Dectection

Figure 3.1: Workflow diagram

3.3 Data Collection

Data collection is a crucial step in developing accurate fake news detection models. For this research, we used a publicly available Bangla news dataset that contains labeled fake and non-fake news articles. Utilizing a well-curated and diverse dataset ensures the models can learn effectively and generalize well. This publicly sourced data provides a reliable foundation for training and evaluating our deep learning models and helps maintain consistency and reproducibility in our experiments.

3.4 Dataset Structure

For our Bangla fake news detection task, we utilized a publicly available dataset containing a total of **7,680** labeled news articles. The dataset includes multiple classes representing different types of fake news, as well as a Non-Fake class. The class-wise distribution is as follows:

- **Non-Fake:** 3,840 samples
- **Clickbait:** 1,337 samples (336 labeled as “Clickbait” and 1,001 as “clickbait”)
- **Misinformation:** 1,288 samples
- **Rumor:** 1,215 samples

The dataset is *imbalanced*, with the Non-Fake class being the largest. Figure **??** illustrates the class distribution, highlighting the proportion of each category.

This diverse and multi-class structure enables models to learn subtle distinctions between different types of misinformation, thereby enhancing the overall fake news detection performance.

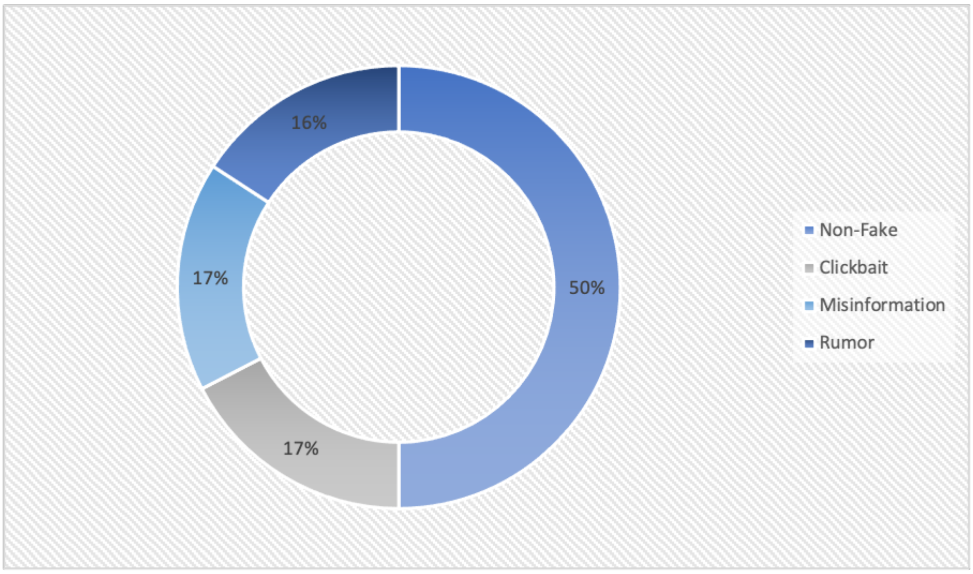


Figure 3.2: Dataset

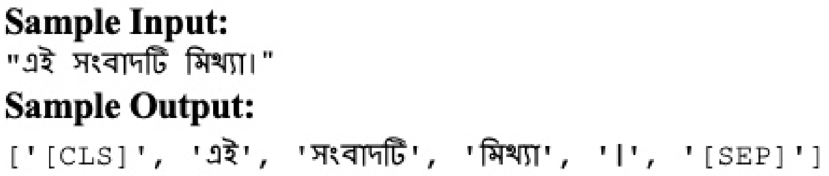
3.5 Data Preprocessing

Data preprocessing is a vital step in fake news detection, especially when working with Bangla text, which can include diverse grammar, writing styles, and noisy characters. Raw data often contains inconsistencies such as punctuation, irrelevant symbols, or inconsistent casing, which must be addressed before applying deep learning models.

The goal of preprocessing is to convert unstructured text into a structured and clean format suitable for effective feature extraction and model training. For our research, several preprocessing techniques were applied to ensure better model performance.

The preprocessing steps used in this research are as follows:

- **Handling Missing Values:** Missing entries in the text fields were replaced with empty strings to avoid issues during later processing.
- **Tokenization:** The raw text was tokenized using the appropriate tokenizer for each model. Tokenization converts the text into a sequence of tokens or token IDs that can be processed by machine learning algorithms.



Sample Input:

"এই সংবাদটি মিথ্যা।"

Sample Output:

```
['[CLS]', 'এই', 'সংবাদটি', 'মিথ্যা', '।', '[SEP]']
```

Figure 3.3: Tokenization

.

3.6 Image Transformation and Normalization

In this research, image preprocessing plays a vital role in preparing the data for effective training of the Vision Transformer (ViT) model. The following steps were applied to ensure uniformity and quality of the input images:

- **Image Organization and Labeling:** Images were automatically categorized into “Fake” or “Real” classes based on keywords in their filenames and sorted into respective folders for training, validation, and testing.
- **Format Filtering:** Only valid image files with standard extensions (e.g., `.jpg`, `.png`) were retained, while files without clear labels or invalid formats were excluded.
- **Resizing:** All images were resized to **224×224 pixels** to maintain consistent input dimensions compatible with the Vision Transformer architecture.
- **Normalization:** Pixel values were normalized using predefined mean and standard deviation values to standardize the data distribution, facilitating better model convergence.
- **Tensor Conversion and Dataset Wrapping:** Images were converted into tensor format and organized into datasets that paired image tensors with their corresponding labels for efficient loading during training.

These preprocessing steps ensured that all images were clean, standardized, and ready for effective model learning across both *Fake* and *Real* classes.

3.7 Text Tokenization and Label Encoding

Text tokenization is a fundamental preprocessing step that converts raw text into a machine-readable format by breaking it down into tokens, such as words or subwords. This process enables models to effectively capture the linguistic features and context within the text.

In this research, all types of fake news categories — including Clickbait, Misinformation, and Rumor — were grouped under a single label **1 (Fake)**, while genuine news was labeled as **0 (Non-Fake)**. This binary labeling simplifies the classification task to Fake vs. Non-Fake detection.

The tokenizers used handled text padding, truncation, and conversion to numerical token IDs compatible with transformer-based models.

Label encoding transformed the categorical labels into numeric values (0 for Non-Fake and 1 for all Fake types), which is essential for training classification models and evaluating their predictions.

This combined process of tokenization and label encoding structures the data for efficient model training and accurate classification performance.

3.8 Transfer Learning & Fine-tuning

Transfer learning is a powerful technique in deep learning where a model pretrained on a large, general dataset is adapted to a specific task. Instead of training a model from scratch, which requires extensive data and computational resources, transfer learning leverages previously learned features and representations, significantly accelerating training and often improving performance.

In this research, pretrained models such as **XLM-RoBERTa** and **Vision Transformer (ViT)** serve as the base. These models have been trained on massive multilingual text corpora or large-scale image datasets, respectively, enabling them to extract rich and generalized features.

Fine-tuning involves further training these pretrained models on the domain-specific fake news detection dataset. During fine-tuning, the model weights are adjusted slightly to better fit the target task, allowing the model to specialize in recognizing patterns relevant to fake versus non-fake news in Bangla language text or image data.

This approach balances the benefits of pretrained knowledge with the specificity required for the research problem, leading to improved accuracy and generalization.

3.9 Training Strategy and Hyperparameters

The training strategy employed fine-tuning of pretrained models on the labeled dataset to leverage existing knowledge while adapting to the specific task of fake news detection. The following hyperparameters were used consistently across models to balance training efficiency and performance:

- **Learning Rate:** A low learning rate (e.g., `2e-5`) was selected to allow gradual updates and prevent overshooting optimal weights.
- **Batch Size:** Small batch sizes (typically 4 or 8) were used due to memory constraints and to enable stable training.
- **Number of Epochs:** Models were trained for 3 to 5 epochs, sufficient for convergence while avoiding overfitting.
- **Weight Decay:** A weight decay of 0.01 was applied to reduce overfitting by penalizing large weights.
- **Gradient Accumulation:** Implemented to simulate larger batch sizes without increasing memory usage.
- **Evaluation Strategy:** Validation was performed at the end of each epoch to monitor model performance and prevent overfitting.
- **Mixed Precision Training:** Enabled (`fp16`) to speed up training and reduce GPU memory usage.

This carefully chosen combination of hyperparameters ensured effective fine-tuning, balancing model accuracy and training efficiency.

3.10 Vision Transformer (ViT) Implementation

The Vision Transformer (ViT) is a state-of-the-art deep learning model that applies the Transformer architecture, originally designed for natural language processing, to image classification tasks. Unlike traditional convolutional neural networks (CNNs), ViT divides an image into fixed-size patches, linearly embeds these patches, and processes them as a sequence, enabling the model to capture long-range dependencies and contextual relationships within the image.

In this research, ViT was employed for fake news detection using image data. Preprocessing steps included resizing images to **224×224 pixels**, normalization using pretrained model statistics, and conversion to tensors compatible with PyTorch. The model was fine-tuned on the labeled dataset of fake and real images, allowing it to learn discriminative visual features relevant to the task.

Training was conducted with appropriate batch sizes and learning rates, using gradient accumulation to optimize memory usage. Evaluation metrics such as accuracy and F1-score were used to assess performance. The ViT's ability to effectively process image data contributed significantly to the multimodal fake news detection system.

3.11 Swin Transformer for Image Classification

To classify fake and real news images, we employed the Swin Transformer — a hierarchical vision transformer that captures both local and global representations using shifted windows. The model `microsoft/swin-tiny-patch4-window7-224` was selected for its efficiency and strong performance on image classification tasks.

Initially, images were organized into *Fake* and *Real* folders across training, validation, and test sets. Preprocessing involved resizing all images to **224×224 pixels**, converting them to tensors, and normalizing using the Swin processor's mean and standard deviation values. The dataset was loaded using `ImageFolder`, and a custom `Dataset` class was implemented to wrap the processed data in a format compatible with Hugging Face's `Trainer`.

The Swin model was fine-tuned with *gradient checkpointing* enabled to optimize memory usage. Training was conducted using *mixed precision* (`fp16`) and *gradient accumulation*. The model was evaluated using **accuracy** and **F1-score**, and predictions were stored as *softmax probabilities* for later ensembling. The trained model and evaluation metrics were saved for deployment and comparison.

3.12 BanglaLLM with LoRA Fine-tuning

To leverage the power of large language models in Bangla fake news classification, we utilized the `BanglaLLM/Bangla-s1k-llama-3.2-3B-Instruct` model with **LoRA** (Low-Rank Adaptation) for parameter-efficient fine-tuning. LoRA enables adaptation of large-scale models by injecting trainable low-rank matrices into the attention layers, significantly reducing training cost and GPU memory usage.

The dataset included Bangla headlines and descriptions, which were concatenated to form the full input text. The data was tokenized using the pretrained tokenizer, with appropriate padding and truncation. To ensure compatibility with LoRA and mixed-precision training, the model was cast to `float16` and configured using `prepare_model_for_kbit_training`.

We applied `LoraConfig` with a rank of 16 and used Hugging Face's `Trainer` API to train the model for two epochs. The training was performed with *gradient accumulation* to simulate a larger batch size and optimize GPU usage. After training, the model was evaluated on the test set using **accuracy** and **F1-score**. Additionally, *softmax probabilities* were saved for potential use in ensemble models.

This approach provided a scalable and memory-efficient solution for adapting a large Bangla instruction-tuned model to the fake news classification task.

3.13 Model Evaluation and Performance Metrics

To assess the effectiveness of the models applied for Bangla fake news detection, we employed several widely-used classification metrics. These include:

- **Accuracy:** The proportion of correctly predicted instances over the total number of instances.
- **Precision:** The ratio of correctly predicted positive observations to the total predicted positives, calculated for both *Fake* and *Non-Fake* classes.
- **Recall:** The ratio of correctly predicted positives to all actual positives, reflecting the model's ability to detect all true *Fake* or *Non-Fake* news.
- **F1-Score:** The harmonic mean of precision and recall, providing a balanced measure even under class imbalance.
- **Weighted F1-Score:** F1-score averaged across all classes, weighted by the number of true instances per class.

Each model — including **XLM-R**, **RoBERTa-base**, **BanglaBERT variants**, **Swin Transformer**, and **BanglaLLM with LoRA** — was evaluated on a held-out test dataset. *Softmax probabilities* were also saved for each model to support ensemble methods.

The metrics were computed using the `classification_report()` function from the `sklearn.metrics` module.

3.14 Ensemble Strategy using Softmax Outputs

To enhance prediction accuracy and robustness, this research employs an ensemble strategy that combines the outputs of multiple trained models. Each model produces a probability distribution over the classes through the *softmax* activation function in its final layer. These softmax outputs represent the confidence scores for each class prediction.

The ensemble approach aggregates these probability scores from different models—such as text-based models (**XLM-RoBERTa**, **Bangla BERT**) and image-based models (**Vision Transformer**)—by averaging or weighted averaging. This combined softmax output leverages complementary strengths of the individual models, improving overall classification performance.

By integrating softmax probabilities, the ensemble strategy reduces the risk of individual model biases and errors, leading to more reliable detection of *Fake* and *Non-Fake* news in the multimodal dataset.

Chapter 4

Preliminary Result

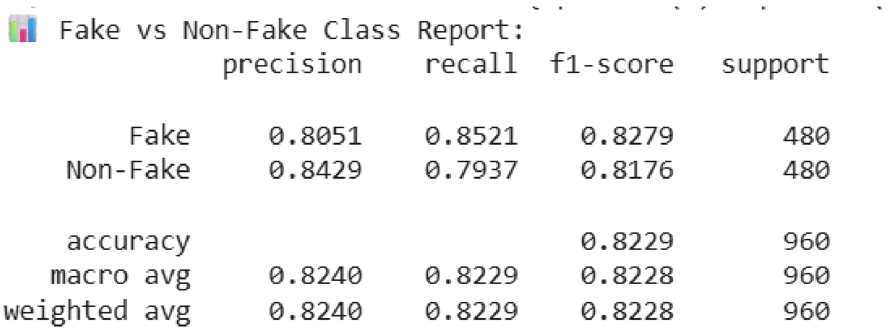
4.1 Performance Evaluation of Transformer Models For Text

4.1.1 BanglaBERT-based Transformer Models

A comprehensive evaluation was conducted across seven individual transformer-based models along with an ensemble model. The metrics used for comparison include **Accuracy**, **Fake F1-score**, **Non-Fake F1-score**, and **Weighted F1-score**. Below is a breakdown of each model's performance.

csebuetnlp/banglabert_large

- Best performing individual model.
- Highest overall accuracy and strong F1-scores in both classes.
- Balanced precision and recall for Fake and Non-Fake classes.
- Ideal baseline model for ensembling.

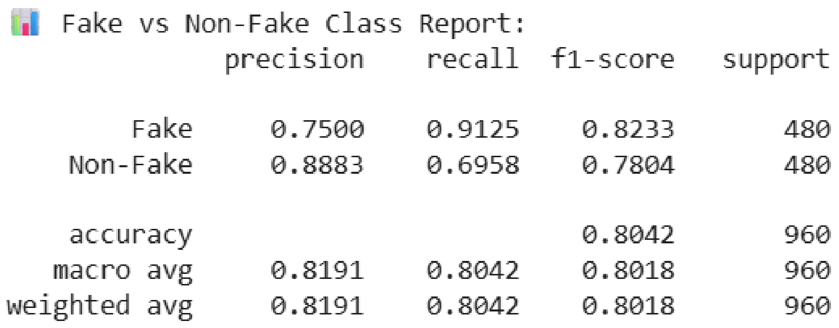


```
📊 Fake vs Non-Fake Class Report:
              precision    recall  f1-score   support

        Fake     0.8051    0.8521    0.8279       480
    Non-Fake     0.8429    0.7937    0.8176       480

    accuracy                         0.8229       960
   macro avg     0.8240    0.8229    0.8228       960
weighted avg     0.8240    0.8229    0.8228       960
```

Figure 4.1: Performance of `csebuetnlp/banglabert_large`.

sanzanalora/banglabert-sentiment

- Second highest performer.
- High Fake F1-score but slightly lower Non-Fake performance.
- Strong in sentiment-heavy or emotionally charged text.

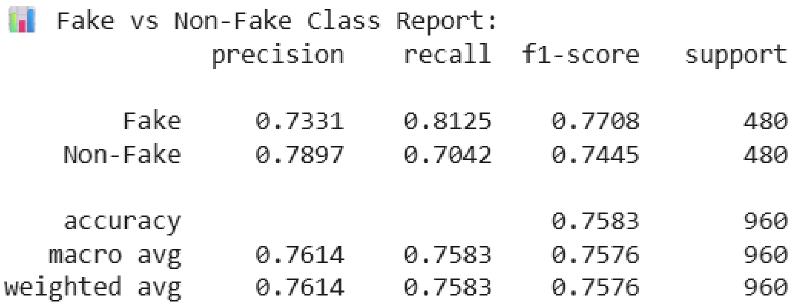


```
📊 Fake vs Non-Fake Class Report:
              precision    recall  f1-score   support

        Fake     0.7500    0.9125    0.8233       480
    Non-Fake     0.8883    0.6958    0.7804       480

    accuracy                         0.8042       960
   macro avg     0.8191    0.8042    0.8018       960
weighted avg     0.8191    0.8042    0.8018       960
```

Figure 4.2: Performance of `sanzanalora/banglabert-sentiment`.

csebuetnlp/banglabert

- Moderately balanced but slightly biased towards Fake class (recall was better there).
- Weighted F1 indicates reliable mid-tier performance.

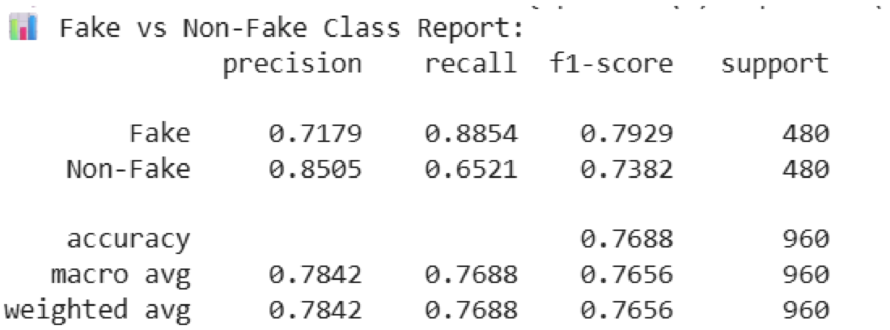


```
📊 Fake vs Non-Fake Class Report:
              precision    recall  f1-score   support

        Fake     0.7331    0.8125    0.7708       480
    Non-Fake     0.7897    0.7042    0.7445       480

    accuracy                         0.7583       960
   macro avg     0.7614    0.7583    0.7576       960
weighted avg     0.7614    0.7583    0.7576       960
```

Figure 4.3: Performance of `csebuetnlp/banglabert`.

Apucs/banglabert-finetuned-sc

- Specialized on sentence classification but performed well.
- Tends to favor fake news recall slightly more.

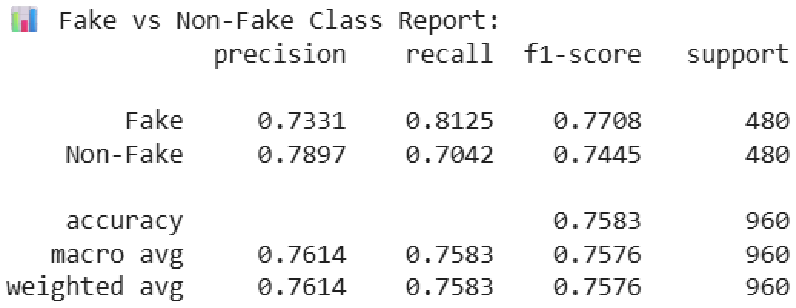


```
📊 Fake vs Non-Fake Class Report:
              precision    recall  f1-score   support

        Fake     0.7179    0.8854    0.7929       480
    Non-Fake     0.8505    0.6521    0.7382       480

    accuracy                         0.7688       960
   macro avg     0.7842    0.7688    0.7656       960
weighted avg     0.7842    0.7688    0.7656       960
```

Figure 4.4: Performance of `Apucs/banglabert-finetuned-sc`.

sagorsarker/bangla-bert-base

- Consistent performance across both classes.
- Lags behind leading models in F1 for Non-Fake.

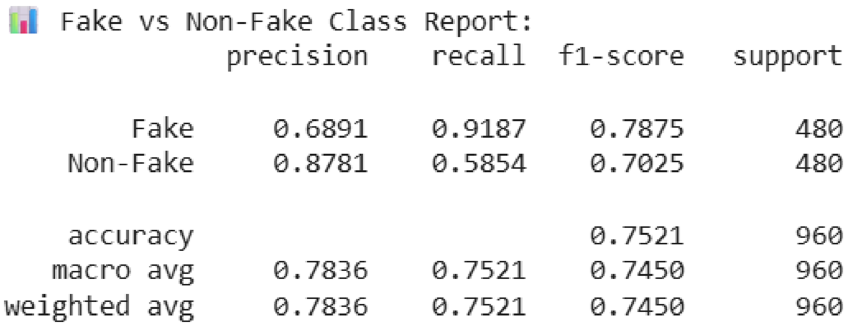


```
📊 Fake vs Non-Fake Class Report:
              precision    recall  f1-score   support

        Fake     0.7331    0.8125    0.7708       480
    Non-Fake     0.7897    0.7042    0.7445       480

    accuracy                         0.7583       960
   macro avg     0.7614    0.7583    0.7576       960
weighted avg     0.7614    0.7583    0.7576       960
```

Figure 4.5: Performance of `sagorsarker/bangla-bert-base`.

csebuetnlp/banglabert_small

- Lightweight model with higher Fake class performance.
- Non-Fake F1 drops due to lower recall, likely due to underfitting or small model capacity.

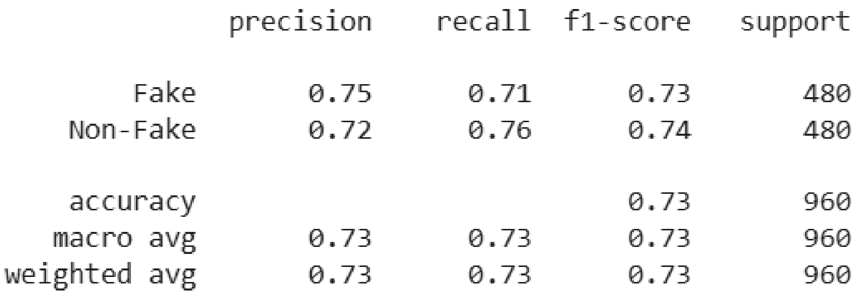


```
📊 Fake vs Non-Fake Class Report:
              precision    recall  f1-score   support

        Fake     0.6891    0.9187    0.7875       480
    Non-Fake     0.8781    0.5854    0.7025       480

    accuracy                         0.7521       960
   macro avg     0.7836    0.7521    0.7450       960
weighted avg     0.7836    0.7521    0.7450       960
```

Figure 4.6: Performance of `csebuetnlp/banglabert_small`.

myahan007/bangla-bert-base-finetuned-tweets

- Underperformed compared to others.
- Lower overall accuracy and F1 for both classes.
- Possibly due to tweet-style training not generalizing to formal news.



```
              precision    recall  f1-score   support

        Fake       0.75      0.71      0.73       480
    Non-Fake       0.72      0.76      0.74       480

    accuracy                           0.73       960
   macro avg       0.73      0.73      0.73       960
weighted avg       0.73      0.73      0.73       960
```

Figure 4.7: Performance of `myahan007/bangla-bert-base-finetuned-tweets`.

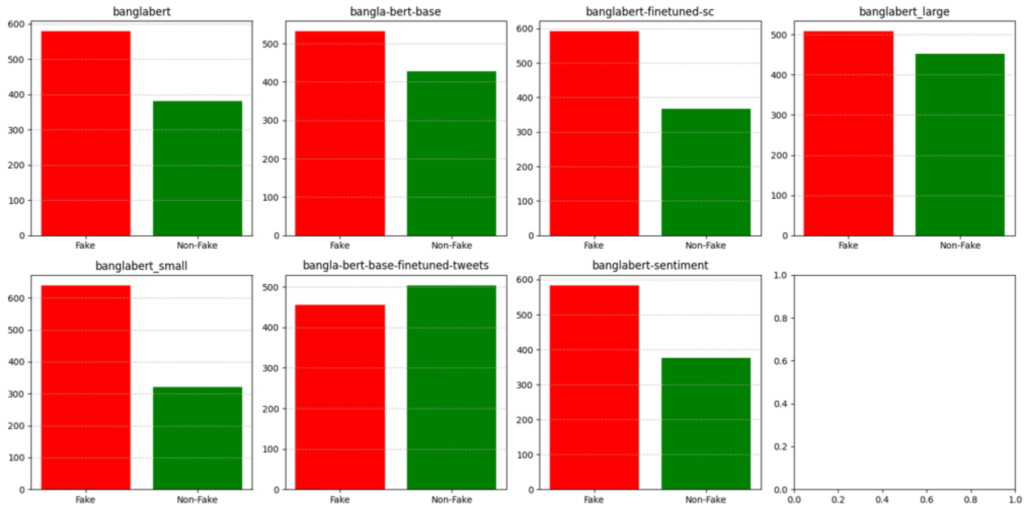


Figure 4.8: Prediction Distribution by BanglaBERT Models (Fake vs Non-Fake)

This figure shows the number of instances predicted as **Fake** and **Non-Fake** by each of the seven BanglaBERT-based models. Each subplot represents a different model. Red bars indicate Fake predictions, while green bars indicate Non-Fake predictions.

Observations:

- **csebuetnlp/banglabert:** Shows a significant skew toward predicting the **Fake** class more frequently than **Non-Fake**, indicating possible class imbalance handling issues or overfitting to the dominant class.

- **sagorsarker/bangla-bert-base:** Exhibits relatively better balance, though **Fake** predictions still slightly dominate. This may reflect improved generalization compared to earlier baselines.

- **Apucs/banglabert-finetuned-sc:** Displays performance similar to the base model but with fewer **Non-Fake** predictions, suggesting room for tuning to improve non-fake class sensitivity.

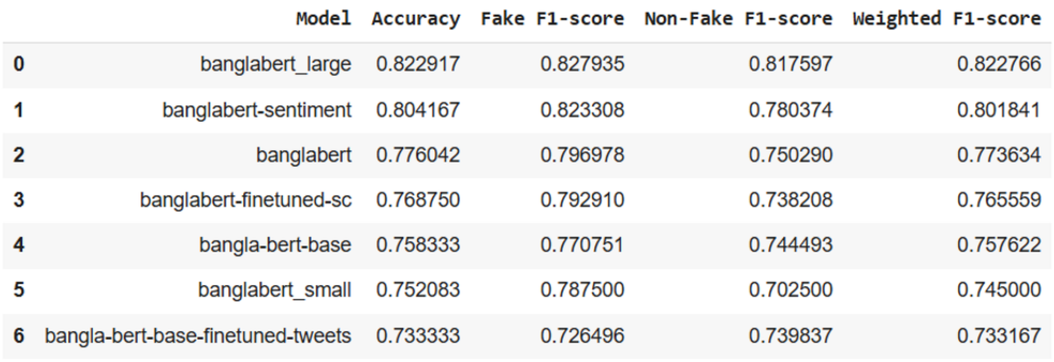
- **csebuetnlp/banglabert_large:** Demonstrates strong balance between the two classes, consistent with its superior performance in overall metrics (as seen in earlier confusion matrices and F1-scores).

- **csebuetnlp/banglabert_small:** Overpredicts the **Fake** class significantly, likely due to underfitting or model capacity limitations.

- **myahan007/bangla-bert-base-finetuned-tweets:** Shows a fairly even distribution, which is encouraging given its fine-tuning on tweet data. However, real-world generalization may vary.

- **sanzanalora/banglabert-sentiment:** Maintains a good balance but slightly favors the **Fake** class. This could be a result of fine-tuning on sentiment-oriented corpora that introduce domain-specific bias.

Table 4.1: BanglaBERT Model Performance Summary



	Model	Accuracy	Fake F1-score	Non-Fake F1-score	Weighted F1-score
0	banglabert_large	0.822917	0.827935	0.817597	0.822766
1	banglabert-sentiment	0.804167	0.823308	0.780374	0.801841
2	banglabert	0.776042	0.796978	0.750290	0.773634
3	banglabert-finetuned-sc	0.768750	0.792910	0.738208	0.765559
4	bangla-bert-base	0.758333	0.770751	0.744493	0.757622
5	banglabert_small	0.752083	0.787500	0.702500	0.745000
6	bangla-bert-base-finetuned-tweets	0.733333	0.726496	0.739837	0.733167

This table presents accuracy and F1-scores (Fake, Non-Fake, Weighted) for each BanglaBERT-based model. Among them, `banglabert_large` demonstrated the strongest overall performance, while `bangla-bert-base-finetuned-tweets` scored lower, indicating variability in generalization across models.

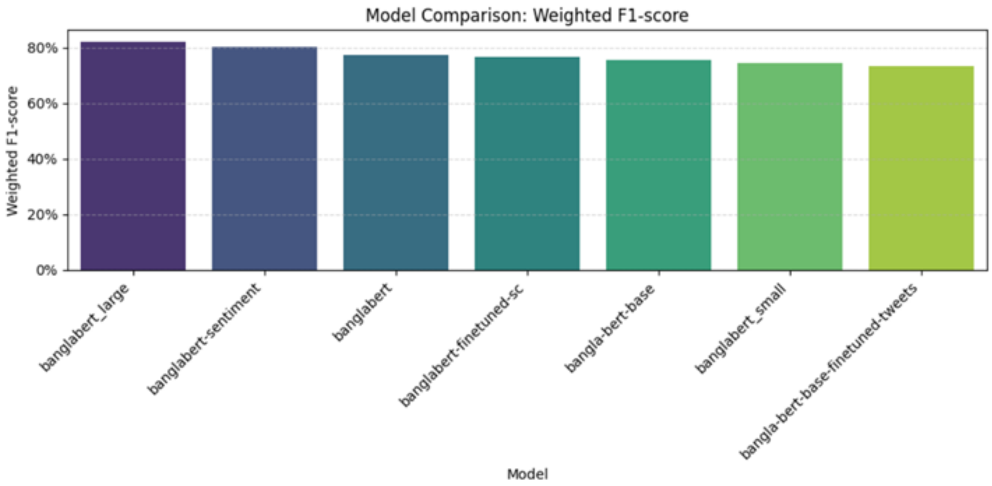


Figure 4.9: Weighted F1-score Comparison of BanglaBERT Models

Bar Chart Analysis (Figure 4.9): The bar charts (see Figure 4.9) show the distribution of predicted **Fake** vs. **Non-Fake** instances across all evaluated BanglaBERT models. Models such as `banglabert_small` and `bangla-bert-finetuned-tweets` exhibited over-sensitivity toward the **Fake** class, which may be attributed to dataset imbalance or inherent model bias.

Key Observations:

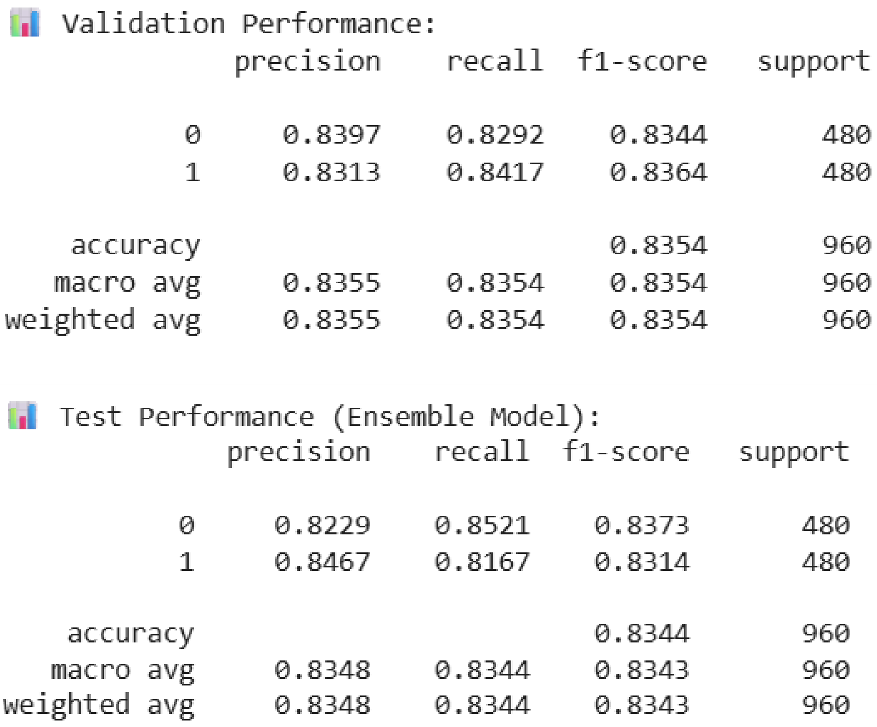
- **banglabert_large** achieved the most balanced performance between the two classes.
- **banglabert_small** and **banglabert-finetuned-sc** showed higher recall for the **Fake** class but struggled with accurate classification of **Non-Fake** instances.
- **banglabert_sentiment** produced consistent results across both classes, indicating stability in predictions.
- **myahan007's tweet-based model** (`bangla-bert-base-finetuned-tweets`) underperformed in terms of generalization, possibly due to domain-specific tuning.

Ensemble Model Analysis: Validation Ensemble

- Achieved the best **macro** and **weighted F1-scores** among all evaluated models.
- Showed balanced performance across both **Fake** and **Non-Fake** classes.
- Suggests that the meta-classifier effectively leveraged the strengths of the base models.

Test Ensemble

- Delivered performance nearly identical to the validation results.
- Demonstrated strong generalization, a desirable quality for real-world deployment.
- Indicates robustness and reliability in unseen data scenarios.



```
📊 Validation Performance:
              precision    recall  f1-score   support

           0     0.8397    0.8292    0.8344       480
           1     0.8313    0.8417    0.8364       480

    accuracy                         0.8354       960
   macro avg     0.8355    0.8354    0.8354       960
weighted avg     0.8355    0.8354    0.8354       960

📊 Test Performance (Ensemble Model):
              precision    recall  f1-score   support

           0     0.8229    0.8521    0.8373       480
           1     0.8467    0.8167    0.8314       480

    accuracy                         0.8344       960
   macro avg     0.8348    0.8344    0.8343       960
weighted avg     0.8348    0.8344    0.8343       960
```

Figure 4.10: Performance Metrics of the Ensemble Model

*T*he top table reports class-wise and average metrics on the validation set, while the bottom table shows performance on the test set. The ensemble model achieves strong and balanced results across both sets, with closely matching macro and weighted F1-scores, highlighting its generalization capability.

Observations:

- **Stacking Ensemble (MLP)** achieved the highest weighted F1-score of **0.843**, significantly outperforming all individual models. This result highlights the strength of combining multiple fine-tuned models into a meta-classifier, leveraging their complementary capabilities and minimizing individual weaknesses.
- Among individual models:
  - `banglabert_large` scored **0.823**
  - `banglabert-sentiment` scored **0.802**

These results indicate that both model scale and sentiment-specific pretraining contribute positively to classification performance.

- The baseline `banglabert` model attained a respectable score of **0.774**, while `banglabert-fi` followed with **0.766**, demonstrating moderate capability.
- Lower-performing models include:
  - `bangla-bert-base` – **0.758**
  - `bangla-bert-base-finetuned-tweets` – **0.733**

  These may suffer from domain mismatch or limited fine-tuning on task-relevant data.

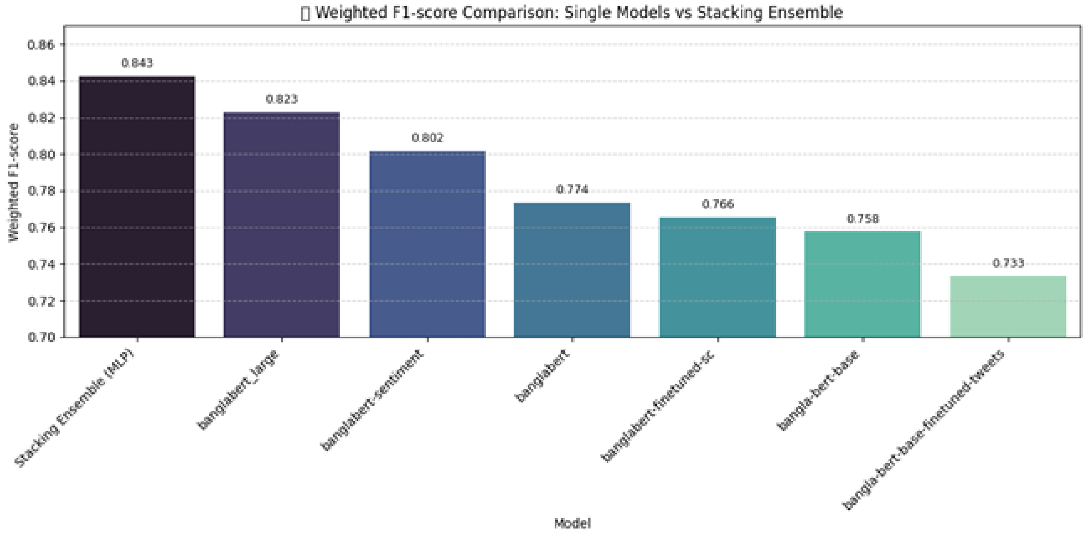
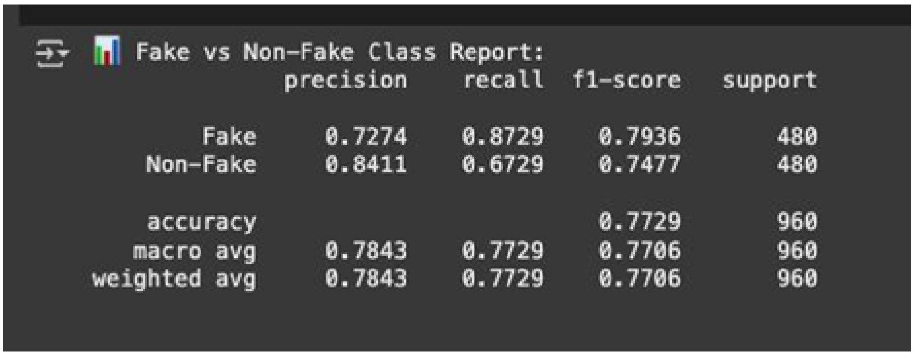


Figure 4.11: Weighted F1-scores of Individual Models and the Stacking Ensemble

*T*he figure compares the performance of various BanglaBERT-based models against the Stacking Ensemble (MLP) method. The x-axis represents the models, and the y-axis shows the Weighted F1-score, ranging from 0.70 to 0.86.This figure provides compelling evidence that ensemble learning not only boosts overall predictive performance but also improves generalization across **Fake** and **Non-Fake** classes. It clearly visualizes the superiority of stacking-based ensemble strategies over standalone transformer models for Bangla fake news detection.

4.1.2 XLM-RoBERTa Evaluation

*T*he figure presents precision, recall, and F1-scores of the XLM-R model on the test set for both Fake and Non-Fake classes, reflecting its classification effectiveness across categories.



```
📊 Fake vs Non-Fake Class Report:
              precision    recall  f1-score   support

        Fake     0.7274    0.8729    0.7936       480
    Non-Fake     0.8411    0.6729    0.7477       480

    accuracy                         0.7729       960
   macro avg     0.7843    0.7729    0.7706       960
weighted avg     0.7843    0.7729    0.7706       960
```

Figure 4.12: XLM-R Test Set Performance

Interpretation and Insights: **Fake Class (0):** The model achieved high recall (**0.8729**), meaning it is very good at identifying fake news. However, the precision is somewhat lower (**0.7274**), indicating that some real news items may be mistakenly labeled as fake.

Non-Fake Class (1): It attained higher precision (**0.8411**), so when the model predicts something as real, it's usually correct. However, the recall is lower (**0.6729**), showing it sometimes fails to capture all non-fake instances.

Balanced F1-scores suggest good general performance:

- **Fake:** 0.7936
- **Non-Fake:** 0.7477

Macro and Weighted Averages: Both are approximately **0.77**, indicating that the model is fairly balanced in overall performance, though it slightly favors fake news detection.

Strengths

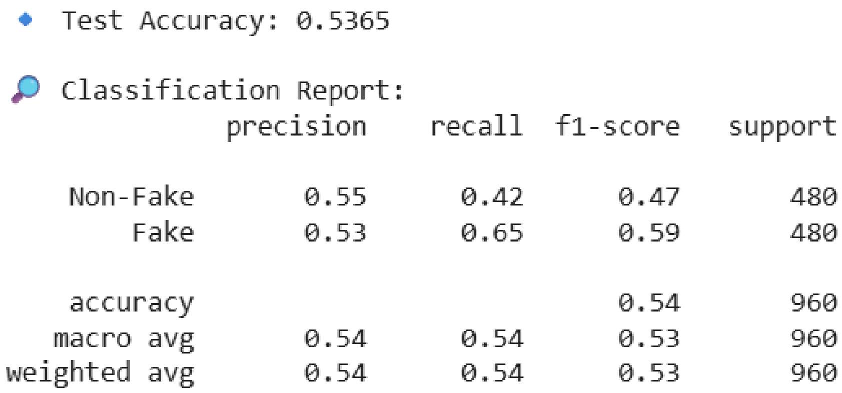
- Excellent at detecting fake content (high recall).
- Competitive precision across both classes.
- Outperforms some Bangla-only BERT variants like `bangla-bert-base` and `banglabert_sm`

Limitations

- Struggles with recalling non-fake instances.
- May require calibration or ensembling for better balance.

4.1.3 LSTM(Long Short-Term Memory) Evaluation

*T*he figure displays precision, recall, and F1-scores for the LSTM model on the test set, reported separately for the Fake and Non-Fake classes.



```
◆ Test Accuracy: 0.5365

🔎 Classification Report:
              precision    recall  f1-score   support

    Non-Fake       0.55      0.42      0.47       480
        Fake       0.53      0.65      0.59       480

    accuracy                           0.54       960
   macro avg       0.54      0.54      0.53       960
weighted avg       0.54      0.54      0.53       960
```

Figure 4.13: LSTM Test Set Performance

Overall Performance: The LSTM model achieved a relatively low test accuracy of **53.65%**, with both the **macro** and **weighted average F1-scores** at **0.53**, indicating poor generalization performance.

Class-wise Performance: **Fake Class (1):**

- Recall: **0.65** — the model detects a fair number of actual fake news instances.
- Precision: **0.53** — the model has a high false positive rate, incorrectly labeling real news as fake.

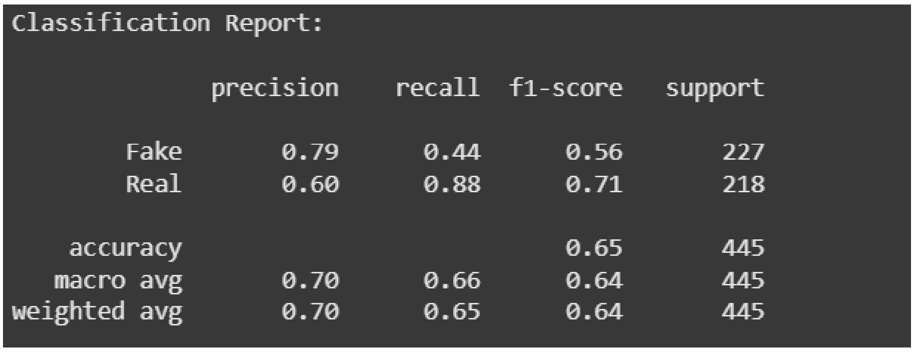
Non-Fake Class (0):

- Recall: **0.42** — many real news instances are misclassified as fake.
- F1-score: **0.47** — reflecting weak detection performance for real news.

Imbalance Sensitivity: The LSTM model shows a bias toward detecting fake news. This likely stems from its insufficient ability to learn the representation of the non-fake class, potentially due to data imbalance or the model's limited capacity to generalize across classes.

4.2 Performance Evaluation of Transformer Models for Image

4.2.1 ResNet50 Evaluation



```
Classification Report:

              precision    recall  f1-score   support

        Fake       0.79      0.44      0.56       227
        Real       0.60      0.88      0.71       218

    accuracy                           0.65       445
   macro avg       0.70      0.66      0.64       445
weighted avg       0.70      0.65      0.64       445
```

Figure 4.14: ResNet50 Test Set Performance

*T*he figure shows precision, recall, and F1-scores for the ResNet50 model on the test set, reported separately for the Fake and Real (Non-Fake) classes.

Interpretation & Analysis **Overall Performance:** The ResNet50 model achieved an overall accuracy of **65%**, with a **macro F1-score of 0.64**. The performance is moderate, indicating potential for improvement—particularly in the model's ability to detect fake instances.

Fake Class (Precision: 0.79, Recall: 0.44):

- High precision (**0.79**) indicates that when the model predicts an item as fake, it is usually correct.
- However, the recall is low (**0.44**), meaning many fake news samples are not being identified correctly.
- This suggests the model is conservative in flagging fake content, resulting in numerous false negatives.

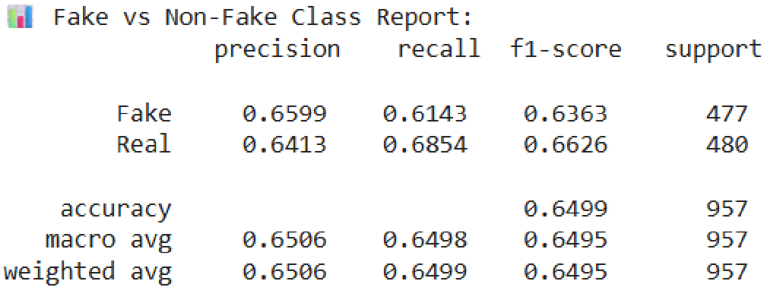
Real Class (Precision: 0.60, Recall: 0.88):

- The model performs better on real news, achieving high recall (**0.88**), meaning it correctly identifies most real items.
- Precision is lower (**0.60**), suggesting that some fake news is incorrectly predicted as real (false positives).

Class Imbalance Sensitivity: The model appears more inclined to predict real news, which may be due to class imbalance in training data or lack of effective bias handling. The noticeable F1-score gap between Fake (**0.56**) and Real (**0.71**) classes highlights the need for more balanced learning.

Use Case Considerations: In fake news detection, failing to identify fake content (false negatives) poses a greater risk than raising occasional false alarms. While ResNet50 demonstrates strong real class detection, its weakness in catching fake instances makes it less suitable in sensitive or high-risk scenarios—unless further fine-tuned or used within an ensemble strategy.

4.2.2 Vision Transformer (ViT) Evaluation



```
📊 Fake vs Non-Fake Class Report:
              precision    recall  f1-score   support

        Fake     0.6599    0.6143    0.6363       477
        Real     0.6413    0.6854    0.6626       480

    accuracy                         0.6499       957
   macro avg     0.6506    0.6498    0.6495       957
weighted avg     0.6506    0.6499    0.6495       957
```

Figure 4.15: ViT Test Set Performance

*T*he figure reports the classification performance of the Vision Transformer (ViT) model on the test set, including precision, recall, and F1-scores for both Fake and Real classes.

Analysis & Interpretation **Overall Accuracy:** The ViT model achieved an overall accuracy of **64.99%**, placing it in the moderate performance tier among the visual models evaluated.

Fake Class Performance (F1 = 0.6363):

- **Precision: 0.6599** — indicates the model correctly identifies fake news when it predicts it as fake.
- **Recall: 0.6143** — suggests it misses a fair number of actual fake cases.
- This reflects a moderate balance between minimizing false positives and false negatives.

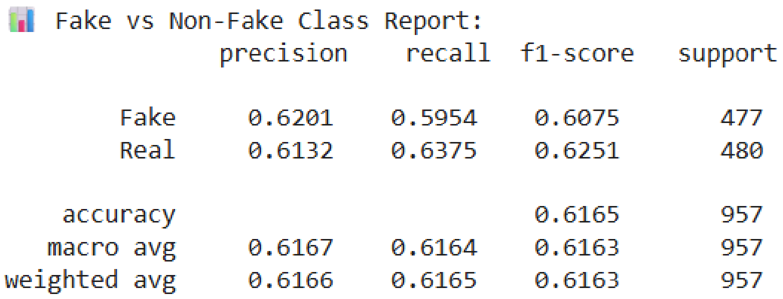
Real Class Performance (F1 = 0.6626):

- **Recall: 0.6854** — the model successfully detects a majority of real news items.
- **Precision: 0.6413** — shows some fake instances are still incorrectly labeled as real.
- Higher F1-score compared to the Fake class suggests slightly better performance on real news detection.

Macro vs Weighted Averages: The macro and weighted F1-scores are closely aligned at approximately **0.6495**, indicating the model performs consistently across both classes without exhibiting strong bias toward either.

Comparative Insight: When compared to ResNet50 (**65%** accuracy, macro F1 = **0.64**), ViT provides a slightly better balance between precision and recall across both classes. However, the overall improvement is marginal. ViT demonstrates more stable and even performance but does not deliver a substantial gain over CNN-based alternatives in this fake news detection task.

4.2.3 Swin Transformer Evaluation



```
📊 Fake vs Non-Fake Class Report:
              precision    recall  f1-score   support

        Fake     0.6201    0.5954    0.6075       477
        Real     0.6132    0.6375    0.6251       480

    accuracy                         0.6165       957
   macro avg     0.6167    0.6164    0.6163       957
weighted avg     0.6166    0.6165    0.6163       957
```

Figure 4.16: Swin Transformer Test Set Performance

*T*he figure presents precision, recall, and F1-scores of the Swin Transformer model on the test set for both Fake and Real classes, highlighting its classification performance.

Analysis & Interpretation **Overall Accuracy:** The Swin Transformer achieved an accuracy of **61.65%**, placing it slightly below ViT and ResNet50 in terms of overall effectiveness for Bangla fake news classification.

Fake Class Performance (F1 = 0.6075):

- **Precision: 0.6201** — indicates that when fake news is predicted, it is correct most of the time.
- **Recall: 0.5954** — suggests that some fake news instances are missed (false negatives).

- Overall, the model is cautious in flagging fake content, resulting in moderate but not aggressive detection.

Real Class Performance (F1 = 0.6251):

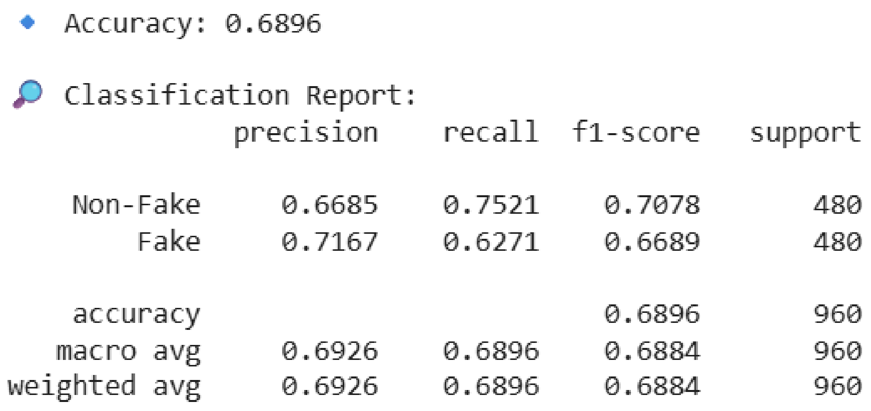
- **Recall: 0.6375** — indicates the model captures most of the real news instances.
- **Precision: 0.6132** — some fake news items are incorrectly predicted as real.
- Slightly higher F1-score than for the fake class shows better performance on real news detection.

Balanced Performance: Macro and weighted averages for precision, recall, and F1-score all hover around **0.616**, demonstrating a fairly balanced—though modest—performance across both classes.

Comparative Insight: Compared to ViT (**64.99%** accuracy, F1 **0.649**), the Swin Transformer falls slightly short on all metrics. However, it still shows improved class balance over traditional models like LSTM (**53.6%** accuracy) and outperforms older CNNs in image-based fake news classification. While not the top performer, it offers a modern alternative with room for optimization.

4.3 LLM-Based Classification Evaluation

4.3.1 BanglaLLM/Bangla-s1k-llama-3.2-3B-Instruct



```
🔹 Accuracy: 0.6896

🔎 Classification Report:
              precision    recall  f1-score   support

    Non-Fake     0.6685    0.7521    0.7078       480
        Fake     0.7167    0.6271    0.6689       480

    accuracy                         0.6896       960
   macro avg     0.6926    0.6896    0.6884       960
weighted avg     0.6926    0.6896    0.6884       960
```

Figure 4.17: LLaMA Test Set Performance

*T*he figure shows precision, recall, and F1-scores of the LLaMA-based model on the test set for both Fake and Non-Fake classes, indicating its effectiveness in binary classification.

Analysis & Interpretation **Overall Accuracy:** The model achieves an accuracy of **68.96%**, which places it below all transformer-based text models and even behind vision-based models such as ViT and Swin in this task.

Class-wise Breakdown:

- **Fake Class Recall: 0.6271** — the model misses a significant number of fake news cases, resulting in high false negatives.
- **Non-Fake Class Recall: 0.7521** — shows better performance in identifying real news content.

Precision Trends:

- **Fake Class Precision: 0.7167** — predictions labeled as fake are fairly reliable.
- **Non-Fake Class Precision: 0.6685** — lower precision indicates some fake news is misclassified as real.

Balanced Averages: The macro and weighted F1-scores are both close to **0.688**, reflecting a well-balanced performance with no major class bias. However, the absolute metric values suggest limited effectiveness for high-stakes applications.

Comparative Insight:

- Underperforms leading transformer models like BanglaBERT and XLM-R (F1: 0.75–0.82).
- Falls short of top-performing vision models such as ResNet50 and ViT.
- Demonstrates slightly better balance than LSTM, but still lacks robustness for real-world deployment.

In summary, while the model achieves decent class balance, its overall capability in both fake and non-fake detection remains moderate. Further fine-tuning or ensemble integration may enhance its reliability in practice.

Chapter 5

Conclusion and Future Works

5.1 Conclusion

The proliferation of fake news in the digital age poses a significant threat to public discourse and democratic integrity, particularly in low-resource language communities such as Bengali. With over 250 million speakers across Bangladesh, India, and the diaspora, the Bengali language lacks robust technological tools for automated misinformation detection. This challenge is compounded by the multimodal nature of fake news, where misleading textual claims are often accompanied by manipulated or contextually incongruent images, making detection even more difficult.

This thesis presents a comprehensive and novel framework for Bengali fake news detection that leverages both text and image modalities. The system integrates state-of-the-art Natural Language Processing (NLP) and Computer Vision (CV) models using an advanced stacked ensemble learning strategy. On the textual side, seven fine-tuned BanglaBERT variants were rigorously evaluated, and the top six models were combined via a stacking ensemble to form a robust meta-classifier. Additionally, cross-architecture models such as XLM-RoBERTa and plans for incorporating BanglaLM were explored to further enhance the linguistic diversity and generalization capability of the model.

In parallel, several powerful vision models—including CNNs, ResNet50, Vision Transformer (ViT), and Swin Transformer—were trained to detect fake news based on visual cues. The best-performing models were later fused into an image-only stacking ensemble, enabling a more resilient approach to identifying manipulated imagery.

The most significant contribution of this work is the development of a Multimodal Fusion Model, which combines the softmax outputs from the best-performing text and image ensembles into a unified feature space. A final meta-classifier is trained on this multimodal vector, enabling the system to capture and interpret cross-modal inconsistencies between textual and visual information. This stacked multimodal approach is the first of its kind in Bengali fake news detection and offers a significant improvement over unimodal baselines.

Beyond the modeling efforts, this research has also developed a Python-based user interface to demonstrate the system's applicability. Plans are underway to deploy this tool as a full-featured web application or browser extension, thereby providing journalists, educators, and the general public with accessible, real-time fake news detection capabilities.

5.2 Future Work

Although significant progress has been made, several key areas remain for future exploration and enhancement:

1. **Completion of Textual Stacking Ensemble**
   While BanglaBERT variants have been fine-tuned and evaluated, the stacking ensemble can be extended to include diverse architectures such as XLM-RoBERTa and BanglaLM. This cross-architecture ensemble will offer improved generalization by leveraging the complementary strengths of multilingual and native-language models.

2. **Expansion of Vision-Based Models**
   To further enhance image-based classification, future work includes fine-tuning EfficientNet-B0 and B2, known for their balance of performance and computational efficiency. These will be integrated into an image-only ensemble, making the visual classification pipeline more accurate and robust.

3. **Advanced Multimodal Fusion**
   The final fusion model will be extended to incorporate more sophisticated cross-modal architectures such as CLIP and BLIP, which can jointly encode vision and language. These models will improve the system's ability to detect nuanced correlations and contradictions between text and image.

4. **Deployment and Real-Time Accessibility**
   The current Python-based prototype will be upgraded into a cloud-based web application with API endpoints. A lightweight browser extension for platforms like Chrome and Firefox will also be developed to enable instant misinformation detection in social media environments.

5. **Explainability and Interpretability**
   Explainable AI (XAI) methods like LIME, SHAP, and attention heatmaps will be integrated to provide interpretability for end users. This is crucial for increasing user trust

and understanding, especially in sensitive domains such as health, politics, or public safety.

6. **Model Optimization for Resource-Constrained Environments**
   Techniques such as knowledge distillation, parameter-efficient fine-tuning (e.g., LoRA, adapters), and quantization will be explored to make the system deployable on low-end devices or in areas with limited internet connectivity.

7. **Dataset Enrichment and Multilingual Adaptation**
   The dataset will be expanded to include more image-text pairs, enhancing the robustness of multimodal learning. Moreover, the system may be adapted for other South Asian languages such as Hindi, Tamil, or Urdu using multilingual and cross-lingual training techniques, enabling broader regional applicability.

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