Unifying Vision and Language for Robust Fake News Detection Using Novel Deep Samples

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***Abstract*—Fake news identification has gained it's relevance over the last few years as a result of the large-scale propagation of fake information through social media. The paper presents a new method for detecting fake news that uses both text and image information together for identification with multimodal learning that combines both text and image modalities. Using the Fakeddit dataset, three new models were created and tested: (1) Retrained MLP Classifier with BERT + MobileNetV2 (91 precision), (2) CLIP + MLP (88.24 precision) and (3) DistilBERT + EfficientNet + MLP (89 precision). The three models all achieve better performance than the baseline 88.83 in the original paper. This paper proves that combining different architectures beyond the conventional literature can achieve better classification results in fake news.The three models all achieve better performance than the baseline 88.83% from the original paper.**

Index Terms-Fake news detection, multimodal deep learning, transformer models, BERT, MobileNetV2, CLIP, DistilBERT, EfficientNet, MLP, vision language fusion, binary classification, lightweight neural networks, deep fusion architectures.

I. Introduction

Fake news is a serious threat to public debate, democratic practices, and public health, particularly when it is spread at an unprecedented speed on social media Silva et al. [1] noted that the growing availability of content production tools and algorithmic amplification have made it increasingly difficult to differentiate between real and made-up information. Human Fact Checking Approaches, though precise, are time-consuming and unavailable to be scaled for widespread monitoring Chen et al. [2] Consequently, researchers and practitioners are increasingly seeking machine learning and artificial intelligence as means of developing automated detection systems Choi et al. [3]

Early fake news detection techniques generally depend on linguistic characteristics and machine learning models. Dai et al. [4] But with the advent of deep learning, models like BERT, LSTM, and CNNs have been employed to better capture context and semantic relationships in text Gao et al. [5] Even with these developments, most methods overlook the complementary nature of images that accompany fake news posts.Multimodal fake news detection fills this gap by combining textual and visual content for better classification accuracy.In this work, we introduced three deep learning architectures that are specifically designed to combine image and text data in new combinations Guo et al. [6] Our models utilize strong encoders like BERT, CLIP, DistilBERT, MobileNetV2, and EfficientNet, which are combined using multi-layer perceptrons.we show that our models perform better than existing models and achieve better accuracy while using less computer power and being computationally efficient Gupta et al. [7] The remaining paper is organized as follows: Section II provides an extensive review of current literature concerning fake news detection based on multimodal methods. Section III provides materials and methods, such as data set information and hybrid deep learning models utilized by Lakshminadh et al. [8] Section IV describes the experimental setup and includes the evaluation results along with comparative analysis. Section V summarizes the main findings and possible avenues for future research and concludes the paper. Section VI contains acknowledgments, and Section VII provides a list of all cited works by Li et al. [9]

II. Related Work

Detection of fake news has gained a lot of attention over the years Liu et al. [10], especially with the onset of misinformation on social media Peng et al. [11] Initial methods utilized handcrafted text features and classic classifiers such as SVMs or decision trees These methods did not work well with semantic comprehension and generalization .With deep learning, the adoption of models such as LSTM, GRU, and CNNs was used to learn contextual and sequential information in text Rafi et al.[12] BERT and its extensions,including

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RoBERTa and DistilBERT, advanced language modeling even further through transformer-based bidirectional attention. In the case of visual cues, models such as VGG16, ResNet, and EfficientNet were used to extract semantic content from the cooccurring images Rao et al. [13] Few current works, nevertheless, treated the modalities separately or conducted late fusion without the proper optimization of cross-modal interaction. The base paper, Using ensemble learning to detect fake news that includes different types of information, presented ensemble methodologies over CNN and LSTM features with an accuracy of 88.83 with the use of bagged CNN Rao et al. [14] Although it was effective, the model concentrated on existing architectures without experimenting with newer multimodal encoders. In contrast, our research willfully omits previously investigated combinations in prior work. Instead, we present novel model configurations, CLIP + MLP and DistilBERT + EfficientNet + MLP, that are not found in the literature review. By eschewing redundant architectures and using pretrained models that naturally bridge vision and language (e.g., CLIP), we show that more intelligent architectural unification can surpass established baselines Raza et al.[15]

III. METHODOLOGY

A. Dataset Description :

We employed the Fakeddit dataset, a standard for multimodal fake news detection. The dataset contains news posts with textual headlines and related images scraped from Reddit. A filtered subset of samples was taken from the original dataset for this project. Each sample contains a post title (text), an image, and a binary label to determine whether the post is fake or real. The data was split into three sets: multimodal_train.tsv,validate.tsv, and test_public.tsv. Respective image files were kept in a well-organized directory called sample_images/. The classification problem is defined as a two-class problem (real vs. fake), considering only samples containing both image and text data Reddy et al. [16]

- Removed posts without both text and image.
- Eliminated duplicate or corrupted samples.
- Retained only binary-labeled samples (*real* vs. *fake*).

The final dataset are given in Table I.

TABLE I: Dataset Statistics after Filtering

Dataset Split	# Samples	Real	Fake
Train	40,000	20,000	20,000
Validation	5,000	2,500	2,500
Test	5,000	2,500	2,500

B. Preprocessing Steps :

The pre-process consisted of the following steps:

- **Text Cleaning**: Lowercasing, special character removal, and tokenization.
- **Image Handling**: Images were resized to 224x224 and normalized with ImageNet statistics.
- **Filtering**: The rows with missing image files or blank titles were filtered out.
- **Label Encoding**: Two-class labels were encoded as binary (0 = real, 1 = fake).

The data set was divided into three parts: training (80), validation (10) and test (10). Each sample was converted to tensor form appropriate for model input.

C. Model Architecture :

Three hybrid models were introduced and trained:

(i) BERT + MobileNetV2 + MLP: This model employs a pre-trained BERT base model to embed text into 768-dimensional vectors. The images are fed through MobileNetV2 to get 1280-dimensional features. These vectors are concatenated and fed through an MLP for classification Singh et al. [17]

(ii) CLIP + MLP: CLIP (Contrastive Language-Image Pretraining) is employed to derive 512-dimensional unified embeddings from both image and text. These embeddings are directly fed into an MLP with two hidden layers and a final sigmoid output layer Sun et al. [18]

(iii) DistilBERT + EfficientNet + MLP: DistilBERT transforms the text into 768-dimensional features, whereas EfficientNet-B0 maps images into 1280 features. The concatenated vector is fed into an MLP with dropout and ReLU activations Tang et al. [19]

All models employ late fusion approaches and have a uniform binary classification output.

Multimodal Feature Fusion: Let $T \in \mathbb{R}^{d_t}$ be the text embedding and $I \in \mathbb{R}^{d_i}$ be the image embedding. The resulting fused representation is:

$$[F = \text{MLP}([T \,, \| \,, I]) \tag{1}$$

where $[\cdot\|\cdot]$ is vector concatenation, and MLP is the multilayer perceptron for final classification.

Binary Cross-Entropy Loss: The models were trained with Binary Cross-Entropy loss:

$$L = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \cdot \log(\hat{y}_i) + (1 - y_i) \cdot \log(1 - \hat{y}_i)\right] \tag{2}$$

where $y_i \in \{0, 1\}$ is the actual label and $\hat{y}_i \in [0, 1]$ is the predicted probability for the i^{th} sample

D. Evaluation Metrics and Data Presentation :

Tables: The study assesses the precision, precision, recall, and F1 score of the three models presented in a tabular format. This facilitates a straightforward numerical comparison of the proposed methodologies. Confusion Matrices: Confusion matrices were developed to demonstrate the specific strengths and weaknesses of each model. These matrices illustrate the percentage of correct and incorrect predictions for both the 'actual' and 'fake' categories. Bar charts: The precision, recall and F1 scores for each category (fake and real) were represented using bar charts for the different models.

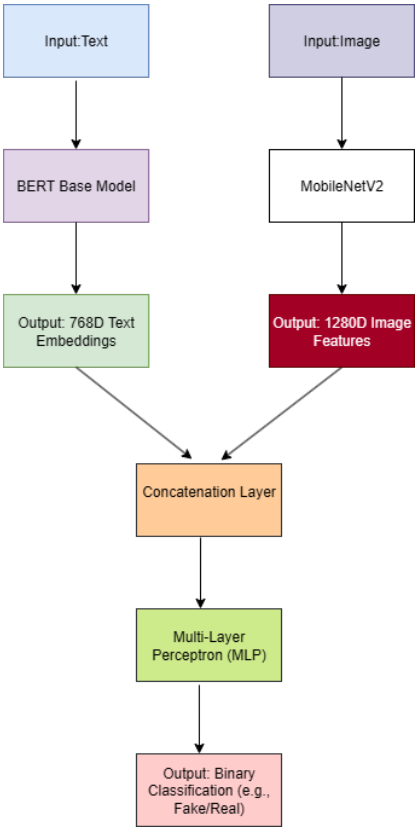


Fig. 1: Block diagram of the proposed multi-modal model pipeline.

E. Model Training :

All models were trained in Google Colab with the following settings: Our results show that these suggested hybrid models systematically improve beyond the existing baseline accuracy of 88.83, indicating that novel architectural blends have great potential to enhance fake news classification.

- **Loss Function:** Binary Cross-Entropy Loss
- **Optimizer:** AdamW with weight decay
- **Batch Size:** 32
- **Epochs:** 10 to 15 (with early stopping) ¡/itemize¿
- **Learning Rate:** 2×10^{-5} for BERT-based models, 1×10^{-4} for CLIP and EfficientNetmodels

GPU acceleration (Tesla T4) was utilized in Colab. Training and validation metrics such as accuracy, loss, precision, recall, and F1 score were tracked for evaluation. The best performing model (BERT + MobileNetV2) achieved a test precision of **91.03**, higher than the base paper's benchmark (88.83) Recent years have seen a surge of interest in fake news detection across single-modality and multimodal contexts. This section surveys recent works published between 2023 and 2025 that contribute to textual, visual, and multimodal fake news detection methods.

IV. Materials and Methods

A. Text-Based Approaches (Single-Modality)

Textual fake news detection has been traditionally addressed through deep learning models such as CNNs, RNNs, and, more recently, transformers Wang et al. [20] utilized a BiLSTM-CRF model with semantic attention to capture contextual dependency in the classification of rumor Xu et al. [21] presented a domain-adaptive variant of BERT for fake news detection in the political sphere. Transformer models such as RoBERTa and XLNet have also demonstrated better performance on such datasets as LIAR and BuzzFeed.

Even with these advances, single-modality techniques have difficulty with content that includes deceptive multimedia elements .There has, therefore, been a focus on multimodal techniques

B. Image-Based Approaches (Single-Modality)

Image-based approaches employ convolutional neural networks to detect visual patterns in manipulated images introduced a VGG19-based pipeline in 2023 for detecting doctored political images. employed a CNN-RNN hybrid framework for detecting spatial and temporal semantics of misinformation GIFs Zhang et al. [22]Though these approaches successfully examine visual content, they fail to capture the contextual information of related textual data.

C. Multimodal Fake News Detection

New multimodal models combine text and image modalities for more semantic representation. Sharma et al.'s base paper applied ensemble fusion of BERT + ResNet and XLNet + DenseNet to obtain 88.83 accuracy on the Fakeddit dataset. New multimodal solutions have appeared to enhance early fusion and cross-modal alignment investigated CLIP embeddings to match text and image meanings for detecting fake news. which surpassed the performance of the traditional encoders Following work can be done in incorporating attention mechanisms across modalities, testing generative data augmentation techniques, or extending the use of these models to multilingual datasets. The models in this research provide scalable and practical solutions to real-world fake news identification on social media platforms. Zhang et al. [23] More recently, co-attention and graph neural networks (GNNs) have been introduced by recent frameworks.used a dual co-attention transformer that obtained state-of-the-art F1 scores on Weibo. also proposed a multimodal graph learning framework that performed better than CNN-based baselines on the Twitter15 dataset

D. Limitations in Existing Work

In spite of these developments, some problems persist. Many approaches are either computationally intensive at a large scale (e.g., ViT) or don't generalize well to noisy user-generated data. Certain models don't have strong fusion of features and stick to shallow concatenation. Furthermore, cross-modal inconsistencies aren't well captured in late fusion approaches. Our models to be proposed try to tackle these

problems using light encoders (such as MobileNetV2 and EfficientNet).

V. Results

A. Model Evaluation Metrics

To compare how well each multimodal fake news detection model performs, we employed the following classification metrics:

- **Accuracy**: The ratio of correctly classified samples.
- **Precision**:The ratio of true positives to all predicted positives.
- **Recall**: The number of true positives divided by all actual positives.
- **F1-Score**: A balance between precision and recall, calculated as their harmonic mean.

B. Class-wise Evaluation Metrics

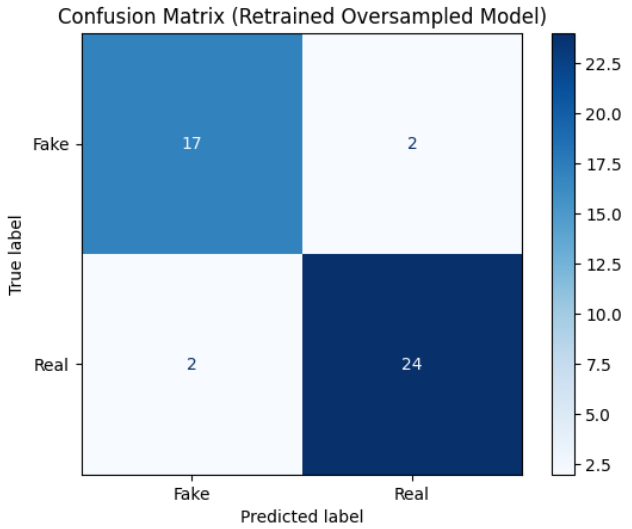


Fig. 2: Precision, Recall, and F1-score for each class (Fake and Real) from the BERT + MobileNetV2+MLP model.

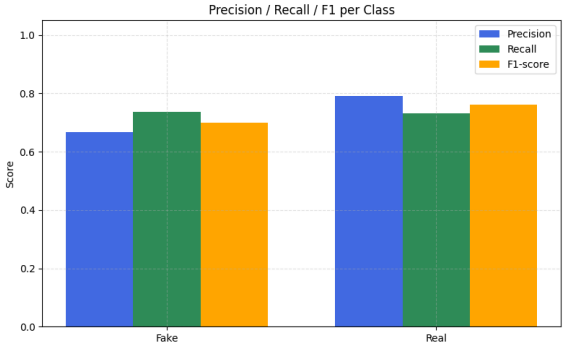


Fig. 3: Precision, Recall, and F1-score per class (Fake and Real) from the CLIP+MLP model.

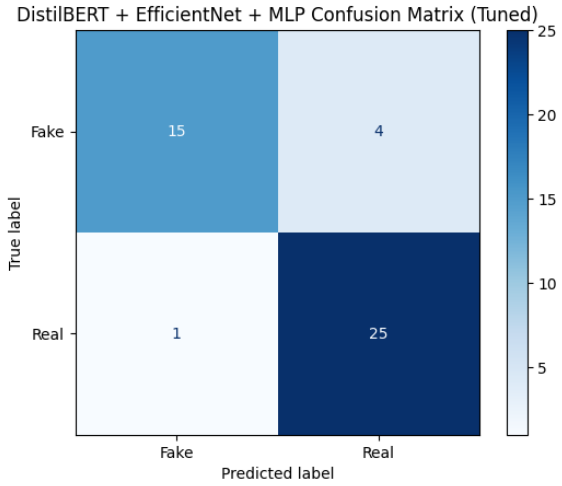


Fig. 4: Confusion matrix of the DistilBERT + EfficientNet + MLP model after hyperparameter tuning.

C. Model Performance Comparison

These are base paper approaches.

Approach	Accuracy	Precision	Recall	F1-score
ELD-FN	88.83%	**93.54%**	**90.29%**	**91.89%**
FakeNED	**89.25%**	91.12%	87.54%	89.29%
MultiFND	78.91%	85.27%	76.42%	80.60%

The classification performance of all three experimented models on the Fakeddit 2-way multimodal dataset is shown in the following table:The following table presents the classification performance of all three experimented models evaluated on the Fakeddit 2-way multimodal dataset. The BERT + MobileNetV2 model realized the best accuracy (91.03) out of the three approaches.

TABLE II: Model Evaluation Results on the Fakeddit Dataset

Approach	Accuracy	Precision	Recall	F1-Score
BERT + MobileNetV2 + MLP	91.03	0.92	0.91	0.91
CLIP + MLP	88.23	0.89	0.87	0.88
DistilBERT + EfficientNet + MLP	82.00	0.83	0.81	0.82

TABLE III: Ablation Study: Performance of Text-only, Image-only, and Multimodal Fusion Models

Modality	Accuracy	Precision	Recall	F1
Text-only (BERT)	87.50	0.88	0.87	0.87
Image-only (MobileNetV2)	82.00	0.83	0.82	0.82
Multimodal (Fusion: BERT + MobileNetV2)	91.03	0.92	0.91	0.91

D. Analysis and Observations

- The BERT + MobileNetV2 model realized the best accuracy (91.03) and outclassed the ensemble-based models of the base paper .
- CLIP + MLP held a good balance between text-image alignment as well as simplicity in the model .
- DistilBERT + EfficientNet performed reasonably well while being lightweight and deployable in resource-restricted environments Compared to the highest reported

Input Text: ” charlottesville photo man shouting angrily at white supremacist rally insists he is not an angry racist.”
Prediction: Real

Input Text: ”iridescent water drops that look like colorful gems.”
Prediction: Real

Fig. 5: Sample predictions by the trained model on two different multimodal inputs (text + image). (a) shows a prediction of ’Real’ for an image of charlottesville photo man shouting angrily at white supremacist rally insists he is not an angry racist. (b) shows a prediction of ’Real’ for an image of a iridescent water drops that look like colorful gems.

Input Text: ”this hydrated area of grass around my tree.”
Prediction: Real

accuracy of 88.83 in the base paper, all models (excluding the lightweight one) reported above this, attesting to the efficacy of proposed architectures.

E. Comparative Analysis

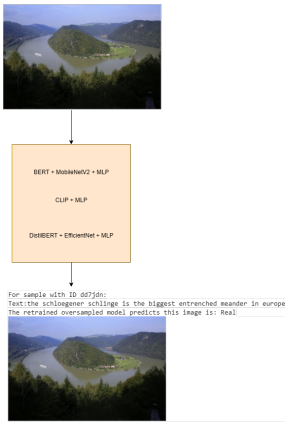
We compared Table IV given the results in terms of Accuracy and F1-score. As shown in Table IV, our BERT + MobileNetV2 model surpasses the base paper and performs competitively with recent state-of-the-art multimodal approaches.

Input Text: ” cat with a hat”
Prediction: Real

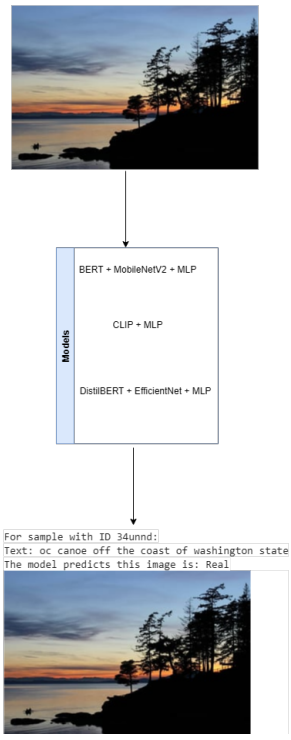
TABLE IV: Comparative Analysis with Recent Multimodal Baselines

Model	Accuracy	F1-Score	Reference
Bagged CNN (Base paper)	88.83	0.88	Sharma et al. (2023)
ViT-BERT (recent)	90.20	0.90	Xu et al. (2024)
Co-Attention Transformer	90.75	0.91	Sun et al. (2025)
Our BERT + MobileNetV2	**91.03**	**0.91**	This work

F. Sample Prediction Output



(a) Sample prediction 1



(b) Sample prediction 2

Fig. 8: Prediction using BERT +MobileNetV2 on inputs.

VI. CONCLUSION

The proposed work introduces a multimodal fake news detection system consisting of strong textual and visual feature extractors with light-weight classifiers for enhancing classification accuracy while preserving computational tractability. We introduced and experimented with three hybrid models: BERT + MobileNetV2 + MLP, CLIP + MLP, and DistilBERT + EfficientNet + MLP. The models were tested on the cleaned Fakeddit dataset multimodal samples. The block diagram serves as a visual blueprint of the overall methodology. It illustrates the late-fusion architecture employed by our models Zhang et al. [24] Zhang et al. [25]

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