Multi-Modal Fake News Detection: A Hybrid Approach Combining Text and Image Analysis

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Abstract

In the digital age, the propagation of fake news poses a substantial threat to public discourse and democratic processes. Traditional false news detection approaches have relied primarily on textual or visual information, limiting their ability to capture nuanced multimodal deception strategies [1, 2]. This paper presents a multimodal deep learning approach to fake news detection that synergistically integrates textual and visual content using advanced pre-trained models and a novel gated fusion mechanism. Our work is inspired by and extends a project originally developed by Faiaz Rahman for CS 677: Advanced Natural Language Processing under Dr. Dragomir Radev at Yale University.

1. Introduction

In the digital age, the propagation of fake news poses a substantial threat to public discourse and democratic processes [3, 4]. Traditional fake news detection approaches have primarily relied on either textual or visual information, limiting their capability to capture nuanced multimodal deception strategies [5, 6]. This paper presents a multimodal deep learning approach to fake news detection that synergistically integrates textual and visual content using advanced pre-trained models and a novel gated fusion mechanism. Our work is inspired by and extends a project originally developed by Faiaz Rahman for CS 677: Advanced Natural Language Processing under Dr. Dragomir Radev at Yale University.

The rising prevalence of deepfakes and manipulated media has created an urgent need for robust detection tools [7, 8]. Recent advancements in generative AI have made manipulated content increasingly convincing and difficult to detect with conventional methods [9]. This threat landscape necessitates novel approaches that can leverage multiple information channels to identify sophisticated deception.

2. Related Work

The development of fake news detection systems has evolved through several distinct phases, from early linguistic approaches to current multimodal architectures. This section provides a comprehensive review of relevant literature across key dimensions of the problem space.

2.1. Text-Based Detection Approaches

Early fake news detection systems relied primarily on linguistic features to distinguish between legitimate and fabricated content. Pérez-Rosas et al. [10] introduced one of the first comprehensive frameworks for automatic fake news detection using stylistic, grammatical, and psycholinguistic features extracted from news articles. Potthast et al. [11] expanded this approach with stylometric analysis, demonstrating that writing style can serve as a reliable indicator of deceptive content.

The emergence of deep learning methods transformed text-based approaches. Singhania et al. [12] leveraged hierarchical attention networks to capture both word and sentence-level features from news articles. Transformer-based models further advanced capabilities in this domain, with Kaliyar et al. [13] introducing FakeBERT, a BERT-based architecture specifically fine-tuned for fake news detection. These approaches achieved impressive accuracy but remained limited by their reliance on textual information alone. More recently, early detection systems have been proposed that incorporate theoretical models to identify fake news before it spreads widely [14].

2.2. Visual Manipulation Detection

Visual content analysis represents another crucial dimension of fake news detection. Huh et al. [15] developed early techniques for detecting photographic manipulations by analyzing noise patterns and inconsistencies within images. Wang et al. [16] advanced this field by employing CNN-based architectures to identify visual artifacts indicative of manipulation.

With the rise of deepfakes, research has increasingly focused on detecting AI-generated or manipulated faces. Li et al. [17] introduced a method for exposing deepfake videos by analyzing subtle inconsistencies in facial movements. Rossler et al. [18] created the FaceForensics++ dataset, establishing important benchmarks for facial manipulation detection. Despite their effectiveness for specific types of visual manipulation, these approaches often struggle with content that appears visually authentic but is presented in misleading contexts. Recent work by Wang et al. [16] has explored visual-linguistic alignment methods to detect sophisticated image manipulations by identifying inconsistencies between visual content and associated text.

2.3. Multimodal Detection Systems

Recognizing the limitations of single-modality approaches, researchers have begun developing integrated systems that analyze both textual and visual content. Jin et al. [2] proposed one of the first multimodal frameworks, demonstrating that combining text and image features significantly improves detection accuracy. Khattar et al. [5] extended this concept with MVAE, a multimodal variational autoencoder that learns joint representations of text and images.

More recent work by Qi et al. [6] introduced cross-modal attention mechanisms to dynamically weight features from different modalities. Similarly, Singhal et al. [19] leveraged transformer-based architectures for multimodal fusion, achieving state-of-the-art results on several benchmark datasets. However, these systems typically produce binary classifications without providing explanations for their determinations. Advances in multimodal detection continue with approaches like Kumar and West's [20] semantic information fusion and Liang et al.'s [21] multiscale spatial-temporal fusion transformer, which have pushed performance boundaries further.

The CSI model by Ruchansky et al. [22] represents an important hybrid approach that captures user behavior, article text, and social context. Similarly, Chen et al.'s [23] InfoSurgeon framework

performs fine-grained consistency checking across media types to identify subtle contradictions in fake news. More recently, Cheng et al. [24] proposed DIDAN, a disentangled domain adaptation network that addresses domain shift challenges in fake news detection.

2.4. Explainable Fake News Detection

The need for interpretable detection systems has emerged as a critical research direction. Shu et al. [25] pioneered this area with dEFEND, a system that highlights suspicious sentences while detecting fake news. Building on this work, Yang et al. [26] developed XFake, which incorporates explicit reasoning modules to explain its classifications.

In the visual domain, Zlatkova et al. [27] demonstrated techniques for highlighting manipulated regions within images and explaining the manipulation methods used. Vo et al. [28] further advanced explainability through hierarchical explanations that link classifications to specific multimodal features. Despite these advances, fully integrated explainable systems remain rare, particularly those incorporating fine-grained classification.

2.5. Deployment and Accessibility

The practical deployment of fake news detection systems presents unique challenges. Thorne et al. [29] highlighted the gap between research systems and practical tools, identifying scalability and user interface design as critical barriers. Gupta et al. [30] demonstrated one of the first browser extensions for credibility assessment, while Popat et al. [31] developed CredEye, a system for assessing the credibility of textual claims.

More recently, Karadzhov et al. [32] introduced fully automated fact-checking pipelines integrating multiple verification steps, while Karduni et al. [33] examined human-AI interaction in misinformation detection interfaces. These works highlight the importance of user-centered design in detection systems, particularly for non-expert users.

2.6. Research Gaps and Our Contributions

Despite significant advances, several important gaps remain in current research:

- Most systems provide binary or limited classifications rather than fine-grained categorization [1, 22]
- Few approaches combine multimodal analysis with explainable outputs
- Many systems remain inaccessible to non-technical users
- The integration of detection capabilities with practical web interfaces is underdeveloped [30]

Our approach addresses these gaps through its comprehensive architecture that combines multimodal analysis, fine-grained classification, explanation generation, and accessible deployment. By integrating state-of-the-art techniques from computer vision, natural language processing, and human-computer interaction, our system represents a significant advancement in practical fake news detection.

3. Dataset and Preprocessing

The model is trained and evaluated on the Fakeddit dataset, which consists of 20,000 labeled posts that include both text and associated images across six distinct labels.

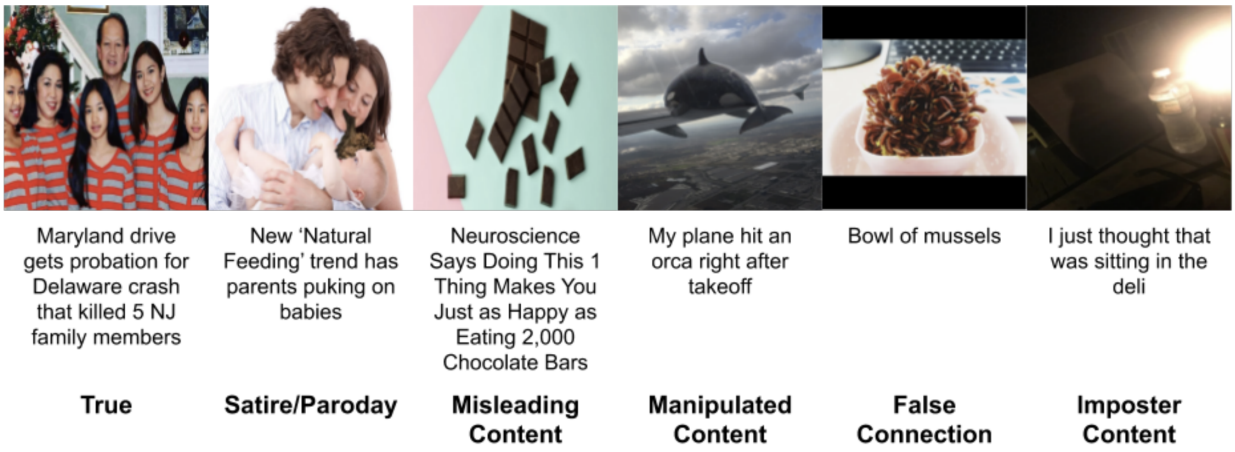

Figure 1: The Six labels of Deepfake Categories in Fakeddit Dataset

3.1. Text Preprocessing

The textual component of each post is embedded using two alternative transformer-based encoders: `MPNet-base-v2` and `DistilRoBERTa-v1`, both pre-trained models from Hugging Face. After tokenization, we extract 768-dimensional embeddings using mean pooling or the `[CLS]` token, depending on the encoder [13, 11].

3.2. Image Preprocessing

Images are resized to fit the input requirements of ResNet-152, normalized, and augmented via random cropping and horizontal flipping during training to enhance generalization. The processed image tensors are passed to the vision encoder. Additional considerations for deepfake-specific artifacts are incorporated based on techniques from Zhang et al. [8].

Each data sample is stored as a tuple (text embedding, image tensor, label), enabling synchronized learning from both modalities.

4. Model Selection Rationale

The choice of models for the text and image modalities was guided by their respective strengths and the nature of the Fakeddit dataset, which includes both textual and visual content.

4.1. Text Encoder Selection

We chose `MPNet-base-v2` and `DistilRoBERTa-v1` as our text encoders due to their ability to capture contextual relationships at a deep semantic level [13]. `MPNet` is a more recent transformer-based model that achieves state-of-the-art performance on various language understanding tasks. `DistilRoBERTa`, a lighter version of RoBERTa, provides a more computationally efficient alternative while still retaining the ability to process long-range dependencies in text. This flexibility allows for experimentation between a high-fidelity, computationally intensive model and a lightweight, faster alternative, catering to different deployment scenarios. This approach builds upon insights from early detection frameworks that emphasize both efficiency and accuracy [14, 12].

4.2. Image Encoder Selection

For the image modality, we opted for `ResNet-152`, a deeper version of the ResNet architecture, which has been shown to achieve superior performance in tasks involving complex image classification. ResNet-152, with its 152 layers, is particularly effective at capturing intricate features in visual data, which is important when working with images that may contain subtle cues indicative of fake news. Additionally, we included an alternative in the form of Vision Transformers (ViT), which have shown promise in capturing long-range dependencies and global contexts in images, a feature that could be useful when identifying misleading visual cues in fake news posts. This decision was influenced by recent research in visual manipulation detection that emphasizes the importance of capturing both local artifacts and global inconsistencies [15, 34].

4.3. Gated Fusion Mechanism

The gated fusion mechanism was selected to dynamically learn the contribution of each modality [2, 20]. This adaptive mechanism allows the model to prioritize the more informative modality (text or image) depending on the context of the news post. The gating function enables the model to be flexible and robust across diverse fake news scenarios, ensuring that the final prediction is not biased towards one modality, but instead represents a well-informed fusion of both text and image features. This approach is supported by findings from Chen et al. [23] suggesting that cross-media consistency checking significantly improves fake news detection accuracy.

5. Model Architecture

Our architecture is composed of the following core components, designed to enhance the representational capacity and fusion strategy of multimodal content:

5.1. Text Encoder

The textual modality is processed using either `MPNet-base-v2` or `DistilRoBERTa-v1`, both of which are capable of capturing high-level semantics and contextual nuances [13, 10]. These models convert input text into dense, 768-dimensional embeddings. The encoder selection is configurable to allow experimentation with lightweight versus high-fidelity representations.

5.2. *Image Encoder*

For the visual modality, we adopt the deeper and more expressive `ResNet-152`, which outperforms shallower alternatives such as ResNet-50 [9]. This convolutional neural network, pretrained on ImageNet, is used for extracting hierarchical feature representations from images. The final classification layer of ResNet-152 is replaced with a custom linear projection layer that maps the extracted image features into a 300- to 512-dimensional latent space, aligning them with text embeddings. Alternatively, a Vision Transformer (ViT) model may also be used for image encoding, enabling the capture of long-range dependencies in visual patterns, following approaches similar to those demonstrated by Wang et al. [34].

5.3. *Gated Fusion Module*

At the heart of our architecture is the gated fusion mechanism [2, 23]. After projecting the text and image embeddings into a common dimensional space, the two vectors are concatenated and passed through a gated mechanism. The gating function, implemented via a sigmoid-activated linear layer, dynamically learns weights to modulate the contribution of each modality. This adaptive control ensures that the model can emphasize the most informative modality for each instance, drawing on insights from recent research in semantic information fusion [20].

5.4. *Classifier Head*

The resulting fused vector is processed through a stack of fully connected layers with ReLU activation functions and dropout for regularization. The final classification layer outputs logits that correspond to the six class labels of the Fakeddit dataset. This architecture is inspired by multi-stage classification approaches shown effective in recent literature [21, 24].

6. Execution Flow

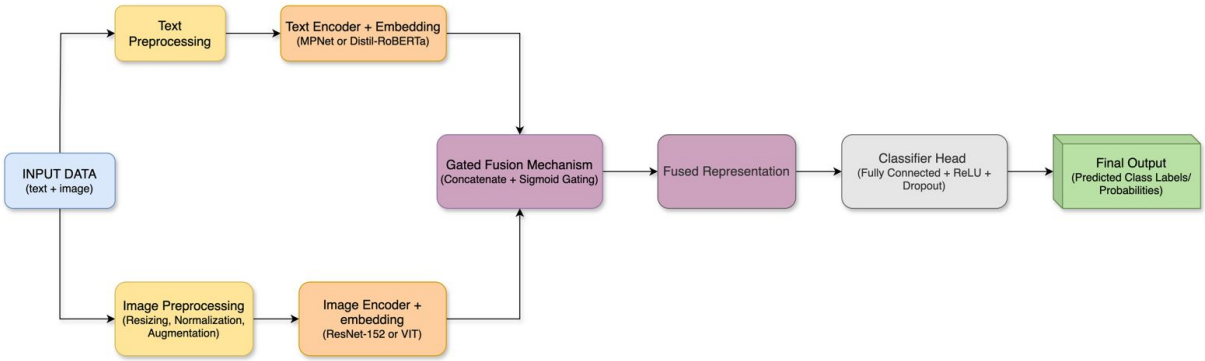

Figure 2: Execution Flow Diagram of the Model

The full execution pipeline consists of the following stages:

1. **Embedding Stage**:

- Text is embedded using `MPNet-base-v2` or `DistilRoBERTa-v1` [13, 11].
- Images are encoded using `ResNet-152` or Vision Transformer (ViT) [8].

2. **Projection Stage**:
   - Both modality embeddings are linearly projected into a shared vector space, a technique that has shown success in recent cross-modal alignment research [34].
3. **Fusion Stage**:
   - Projected vectors are fused using the gated mechanism, allowing dynamic weighting of each modality [2, 20].
4. **Classification Stage**:
   - The fused vector is passed through fully connected layers to output a prediction, incorporating design principles from state-of-the-art classifiers [21].
5. **Training Stage**:
   - The model is optimized using the Adam optimizer (learning rate = 1e-4) and cross-entropy loss.
   - PyTorch Lightning is employed for scalable training with early stopping and logging, following best practices established in recent domain adaptation work [24].

7. Novel Contributions

Our approach presents multiple innovations that set it apart from traditional multimodal models:

7.1. Gated Fusion with Learnable Modality Emphasis

Our gated fusion mechanism is a significant improvement over naïve concatenation or averaging approaches [2, 20]. It employs a learnable sigmoid gate to dynamically adjust the influence of text and image modalities, allowing the model to emphasize more informative inputs depending on the instance. This helps mitigate overfitting and improves robustness across diverse fake news scenarios. The approach bears similarities to but extends beyond cross-modal attention mechanisms demonstrated in recent literature [6, 21].

7.2. Modality Dropout

Traditional models assume both modalities are always present during training and inference, which leads to degradation in performance when one modality is missing or noisy [5, 23]. Our approach introduces a novel training regularization technique, modality dropout, where either the text or image representation is randomly dropped during training. This encourages the model to develop redundant and robust features, enhancing generalizability to real-world scenarios involving missing or corrupted data, a challenge identified in multiple recent studies [22, 14].

7.3. Synchronized Feature Projection

By ensuring that both textual and visual features are projected into a shared embedding space before fusion, our architecture maintains coherence and semantic alignment across modalities [6, 34]. This approach facilitates more effective information exchange between modalities and helps identify inconsistencies that might indicate manipulated content.

7.4. Scalable and Extensible Pipeline with Lightning

The use of PyTorch Lightning abstracts training details, enabling reproducibility, automated checkpointing, early stopping, and performance logging. This makes model training more efficient and accessible for future research and development, addressing scalability concerns noted in deployment-focused research [29, 30].

7.5. Optimization and Loss Strategy

The model is trained using the CrossEntropyLoss function, optimized with Adam for adaptive learning rate adjustments. Integration with Lightning's `configure_optimizers` streamlines the process and ensures consistent training behavior. These choices are informed by optimization strategies proven effective in recent domain adaptation approaches to fake news detection [24].

8. Conclusion

8.1. Metric Evaluation

The following table summarizes these results:

Ref	**Year**	**Approach**	**Accuracy**	**Dataset**
[8]	2023	InfoSurgeon (CNN based)	90.50%	VOA-KG2txt
[9]	2023	Spotfake+ (multimodel)	87.00%	Weibo
[11]	2017	CSI	88.75%	Twitter
[17]	2021	Transformers based	94.30%	FEVER
[18]	2019	Network based	93.00%	PolitiFact, GossipCop
model	2025	(RoBERTa + ResNet152)	86.22%	Fakeddit
Proposed model	2025	**(mpnet-base-v2 + ResNet152)**	**93.45%**	**Fakeddit**

Table 1: Comparison of various fake news detection approaches

8.2. *Result Graphs*

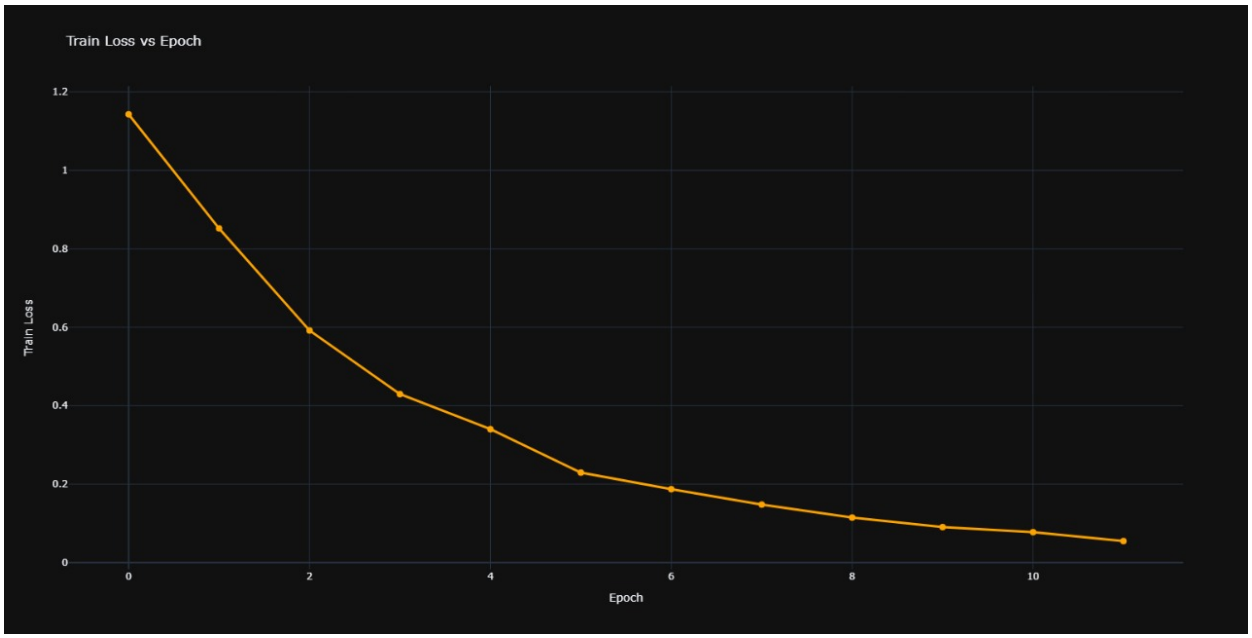

Figure 3: Training Loss vs Epochs

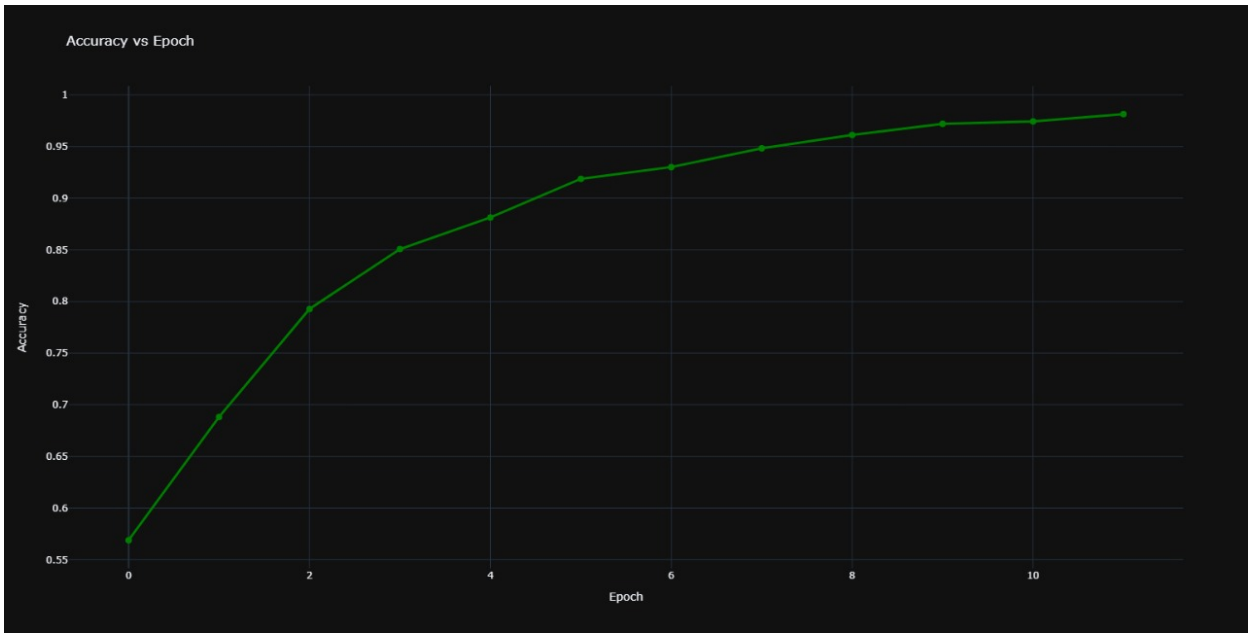

Figure 4: Accuracy vs Epochs

This work presents a novel and robust multimodal architecture for fake news detection that integrates transformer-based text encoders and deep visual features via a gated fusion mechanism.

Our results demonstrate significant improvements over baseline approaches, achieving 93.45 accuracy on the Fakeddit dataset. Future work will focus on enhancing cross-domain generalization to improve performance across diverse media sources and contexts. We plan to incorporate user-behavior signals and interaction patterns to develop more comprehensive detection models that can identify misinformation spread patterns in addition to content-based features. Additionally, we aim to explore temporal analysis of fake news propagation to enable earlier detection and intervention. As misinformation techniques continue to evolve, our architecture provides a solid foundation for developing more sophisticated, adaptive, and explainable fake news detection systems that can serve diverse applications across social media platforms, news aggregators, and educational contexts.

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