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Detecting Disinformation Using BERT-BiLSTM and ResNet-Based Deep Fusion Networks

Saranya N.[1]; Karmukilan B.[2]; Kishore P.[3]; Mohammed Safik M.[4]; Nithan Anto J.[5]

[1]Assistant Professor; Department of Computer Science and Engineering, Sri Eshwar College of Engineering,
[2]Department of Computer Science and Engineering, Sri Eshwar College of Engineering,
[3]Department of Computer Science and Engineering, Sri Eshwar College of Engineering,
[4]Department of Computer Science and Engineering, Sri Eshwar College of Engineering,
[5]Department of Computer Science and Engineering, Sri Eshwar College of Engineering,

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Abstract: Ever since the arrival of the digital world, misleading information through the use of manipulated pictures and poorly constructed text on news websites and social media has become a world wide issue. Detection of such manipulated or false information is required in order to protect the public opinion, state security, as well as trust to digital environments, so in order to detect misinformation using a single input, which is a visual information that also has hidden text (memes, posters, and screenshots), this work suggests a deep learning dual-stream fusion model. The system recognizes the text on the image using optical character recognition (OCR) and derives the semantic meaning with the help of a BERT-BiLSTM model. High-level features of the image are simultaneously extracted by feeding it through a ResNet convolutional neural network. After that, the two features (text and visual) are fused on a deep fusion layer and maintain context and multi-modal dependency and generate a more robust and accurate classification. Such an integrated solution provides the final classifier that can distinguish the authenticity of supplied image-text input and prevent the further propagation of the misinformation introduced by multimedia sources and can greatly enhance the correctness of fake news recognition based on either Natural Language Understanding or Visual Semantics.

Keywords: *Disinformation Detection, Sustainable Digital Infrastructure, Multimodal Deep Learning, BERT-BiLSTM.*

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I. INTRODUCTION

The spreading of information is faster than ever these days. A picture or a message can be delivered to millions of viewers worldwide at the press of few clicks. Although digital connectivity has made communication and gathering of information more revolutionary, the most harmful example of disinformation is multimodal content, which consists of misleading text and manipulated or falsified images, altered posters, and memes such forms of content tend to be emotive, easy to spread and difficult to fact check. They have the capacity to impact a mass opinion, propagate rumors, and even risk the stability of the country or society in general, and traditionally used methods of fake news detection work with either the text or the image. We would like to present a dual-stream deep learning model, which could perform the analysis of the picture and the text simultaneously to identify misinformation better. It works in the following way: To retrieve any text that may be embedded in the image, like a meme or a poster, the system at first applies optical character recognition, or OCR. The text extracted is then imported in a BERT-BiLSTM model. BERT is based on contextual understanding of the deeper meaning of the words, whereas BiLSTM takes the form of recognizing the information flow, which allows the system to see the text in the way a human sees it in the form of meaning, tone, and intention. Meanwhile, the actual picture is interpreted with the help of ResNet, which is a powerful model of image recognition. Its output with the findings of these two processes, including text analysis and visual inspection, is combined by a fusion layer. This layer ensures that the system does not only know each of the ones separately but the way that they relate with one another to potentially deceive the viewer by grabbing the connection between the text and the image. It identifies characteristics, trends, or edits that might point to a fake or manipulated image. This combined data is then used by a classification layer as to whether the content is authentic or a fraud. It allows much more accurate fake content identification as compared to systems processing a single form of data due to its multi-modal end-to-end design. The

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model serves as an efficient way to address a practical issue as it enables bridging the gap between the awareness of the language and the capability to see a picture and assist in avoiding the dispensation of harmful information and rediscover the faith we can have in what we browse and watch on the Internet.

II. LITERATURE SURVEY

The growing threat of misinformation, in particular, the type of multimodal content both containing text and incorporating images has led to a large number of studies in the field of fake news detection. Various deep learning frameworks, based on Natural Language Processing (NLP) on textual data and Convolutional Neural Networks (CNNs) on visual data, have been investigated. A summary of ten latest and topical research papers (2022-2025) along with their methodology, fusion strategies and indispensable findings are summarized in the table below. This information creation and consumption has been brought about through the ruthless advancement in digital media. The contemporary disinformation is advanced and multi-modal, and, therefore, the existing text-based approach to comprehending false information is no longer adequate since the multimodal one, involving the use of both computer vision (CV) in visual representations and natural language processing (NLP) in text can be used to overcome these obstacles. Cross-modal transformer fusion approaches between early fusion, and spatially unified visual analysis coupled with sequential textual comprehension to place such complex data in context and extract semantic meaning is an emerging popular approach. Other than improving the quality in terms of identifying fake content, these systems are also designed to be cross platform i.e. Facebook, Twitter, news websites, and image sharing applications. The ten notable research articles that have been published during the time span between 2022 and 2025 have been scrutinized in the table below. It presents the main results of each of the studies and models, datasets, and cross- fusion mechanisms used, which enabled us to design our preferred model to identify multimodal fake news using BERT BiLSTM and ResNet based on the suggestions of this review. Another new direction uses pre-trained vision-language models like CLIP. For example, FND-CLIP uses ResNet-based and BERT-based encoders along with CLIP encoders for images and text. It combines their representations through similarity-weighted fusion. This method uses large-scale contrastive pretraining on pairs of images and texts to create strong initial representations, which are then fine-tuned to find fake news. Similar concepts are present in contemporary ensemble and residual fusion architectures for analogous tasks, including multimodal hate speech. Detecting harmful memes by combining pre-trained visual and textual backbones through residual fusion or decision-level averaging to make them more resistant to noise on social media. Traditional CNN– RNN or CNN–Transformer combinations remain robust baselines, particularly when integrated with enhanced fusion and optimization techniques. Some studies, for instance, suggest using hyperparameter- tuned BERT with ResNet-based visual encoders to find fake news in multiple ways on datasets like Fakeddit. These studies show that well-tuned BERT + ResNet pipelines work much better than unimodal baselines and simpler feature-engineering methods.Other research combines residual networks with attention mechanisms to better focus on important areas in both images and text. These models are more accurate and efficient than plain CNN models. These architectures are similar to our suggested BERT-BiLSTM + ResNet model, which shows that combining deep visual features with contextual text understanding works and that careful design of fusion layers is very important. Simultaneously, several survey and review articles released from 2022 to 2025 conduct a systematic analysis of multimodal fake news detection on social media. These works classify current methodologies into early, late, and hybrid fusion models; propagation-aware and user-behavior-aware models; as well as contemporary transformer and contrastive learning-based systems. They also draw attention to enduring issues like the lack of high- quality multimodal datasets with fine-grained annotations, robustness to adversarial or subtle manipulations, and domain generalization. These surveys highlight the fact that, although multimodal systems consistently outperform text-only models, their performance can deteriorate considerably when tested on different platforms or languages than those observed during training. This suggests that there is a continuous need for architectures that are more domain-generalizable. Alongside the development of models, the dataset landscape has also changed. Textual claims or posts with a single associated image and binary or multi-class veracity labels are paired in early datasets (such as Fakeddit, Weibo, and PHEME). Our method directly addresses the gaps in handling text-in-image misinformation and attempts to provide a more reliable and practically deployable solution for multimodal fake news detection by fusing cutting-edge contextual language modeling with high-level visual feature extraction.

Table 1 Natural Language Processing (NLP) on textual data and Convolutional Neural Networks (CNNs)

Year	Title &Authors	Technique s Used	Fusion Strategy	Key Findings
20 25	Zidan et al., *Multi modal Fake News Detection*	BERT for text, ResNet for image	Cross- modal fusion using attention	Challenges of consistency in multimodal learning
20 25	Ahmad et al., *BMM FN*	BERT, VGG-19	Domain- specific multimodal fusion	Improve d results on Twitter & Weibo datasets
20 24	Alam et al., *TM- FID*	BERTweet, Vision Transform er	Transfer- learned fusion model	Robust with limited labeled data
20 23	Song et al., *MMC N	BERT + ResNet	Cross- attention with multi- level fusion	High accuracy across benchmarks

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	Model*			
2023	Qian et al., *HMCAN*	BERT + ResNet	Hierarchical contextual attention	Handles intra- and inter-modality well
2023	Chen et al., *CAFE*	BERT + CNN	Ambiguity- aware attention fusion	Detects misaligned multimodal content
2022	Yadav et al., *ETMA*	Transform er encoder + Visual attention	Joint attention across modalities	Improved multimodal alignment
2022	Zhou et al., *FND- CLIP*	CLIP (Text+Ima ge), BERT	Contrastive similarity fusion	Outperformed earlier Models on multiple datasets
2023	Akhtar et al., *Surve yon Fact Checki ng*	Multiple modality analysis	Task- based fusion strategies	Survey on automat ed fact-checking pipeline s
2022	Alam et al., *COLI NG 2022 Survey*	Text/Imag e/Video disinfo detection	Compa rative study of techniques	Identifie s gaps & future directions in fusion

III. PROPOSED METHODOLOGY

➢ *Overview*

We propose a dual-stream deep fusion model that takes a single multimodal input x=(I , S):an image I(meme/poster/screenshot) and its embedded textual content S(which may be obtained by OCR). The model produces a binary label y ∈ {0,1}(0 = genuine, 1 = misinformation) and optionally a localization mask for visual manipulations. The system has four main blocks:

- OCR + Text Encoding → text feature t
- Visual Encoding (ResNet) → visual feature v
- Multimodal Fusion (attention / gated / co-attention) → fused feature h
- Classifier & Losses→ prediction ŷ and training objectives

Below we give mathematical detail for each block.

Extract embedded text from images (such as screenshots or memes).

➢ *OCR and Text Representation*

Let the raw image I be processed by an OCR engine (Tesseract/Google OCR) that extracts a sequence of tokens:

$$S = \{w_1, w_2, \ldots w_n\}$$

Each token wi is embedded via a pretrained tokenizer + embedding (BERT).Let $ei \in Rde$ be the BERT token embedding for wi . We feed token embeddings into a BiLSTM to capture sequential context and reduce noise from OCR:

BiLSTM recurrence (forward / backward):

$$\overrightarrow{\mathbf{h}_i} = \overrightarrow{\mathrm{LSTM}}\left(\mathbf{e}_i, \overrightarrow{\mathbf{h}}_{i-1}\right), \overleftarrow{\mathbf{h}_i} = \overleftarrow{\mathrm{LSTM}}\left(\mathbf{e}_i, \overleftarrow{\mathbf{h}}_{i+1}\right)$$

Token-Level Contextual Vector:

$$\mathbf{h}_i^{\text{text}} = \left[\overrightarrow{\mathbf{h}_i}; \overleftarrow{\mathbf{h}_i}\right] \in \mathbb{R}^{2d_h}$$

Pool across tokens to get a fixed-length text feature t:

$$\mathbf{t} = \mathrm{Pool}\left(\left\{\mathbf{h}_i^{\text{text}}\right\}_{i=1}^{n}\right) (\text{e.g., max-pool or attention-pool})$$

If attention pooling is used, compute attention weights:

$$\alpha_i = \frac{\exp\left(\mathbf{u}^\top \tanh\left(\mathbf{W}_t \mathbf{h}_i^{\text{text}}\right)\right)}{\sum_j \exp\left(\mathbf{u}^\top \tanh\left(\mathbf{W}_t \mathbf{h}_j^{\text{text}}\right)\right)}, \mathbf{t} = \sum_i \alpha_i \mathbf{h}_i^{\text{text}}$$

Notes:

- Use BERT token embeddings (option: freeze or fine-tune BERT).
- OCR confidence scores c_i can be used to weight tokens (multiply α_i by c_i).

➢ *Visual Feature Extraction*

Pass the input image I through a pretrained ResNet (or ResNet50/101) feature extractor. Let the last convolutional feature map be $F \in \mathbb{R}H \times W \times C$. We obtain a global visual vector by global average pooling (GAP):

$$\mathbf{v}_g = \mathrm{GAP}(\mathbf{F}) \in \mathbb{R}^C$$

Optionally extract object-level features (for region-aware fusion) using a pretrained detector (Faster R- CNN). Let object proposals $\{r_k\}$ produce region features $v_k \in \mathbb{R}^G$ Then form.

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$$V = [v_1, \ldots, v_m]$$

For uniform notation we denote the final visual representation as).

➢ *Multimodal Fusion*

We propose two fusion variants — Gated Fusion (simple, effective) and Co-Attention Fusion (richer cross-modal interaction). Use one or both in your experiments.

- *Gated Multimodal Fusion*

Compute a gating scalar/vector that adaptively weights visual vs text modalities:

$$z = \sigma(W_z[v;\ t] + b_z) \in \mathbb{R}^{dz}$$

Fused Representation:

$$\mathbf{h}_{\text{gated}} = \mathbf{z} \odot \phi(\mathbf{W}_v\mathbf{v}) + (1 - \mathbf{z}) \odot \phi(\mathbf{W}_t\mathbf{t})$$

Where σ is the sigmoid, ϕ an activation (ReLU), $\odot$ elementwise product. Optionally follow with a projection:

$$h = LayerNorm(W_h h_{gated} + b_h)$$

- *Co-Attention Fusion*

Compute cross-attention between text tokens and visual regions (or global image features). Let token vectors be $\{h_i^{text}\}$ and visual region $\{v_k\}$.

Compute attention scores $A \in \mathbb{R}^{n \times m}$

$$A_{ik} = \frac{\exp\left(\frac{\mathbf{h}_i^{\text{text}\top}\mathbf{W}_a\mathbf{v}_k}{\sqrt{d}}\right)}{\sum_{i',k'}\exp\left(\frac{\mathbf{h}_{i'}^{\text{text}\top}\mathbf{W}_a\mathbf{v}_{k'}}{\sqrt{d}}\right)}$$

Text-Attended Visual Feature:

$$\tilde{\mathbf{v}} = \sum_k \left(\sum_i A_{ik}\right)\mathbf{v}_k$$

Visual-Attended Text Feature:

$$\tilde{\mathbf{t}} = \sum_i \left(\sum_k A_{ik}\right)\mathbf{h}_i^{\text{text}}$$

Concatenate and Project:

$$\mathbf{h} = \phi\left(\mathbf{W}_c[\tilde{\mathbf{v}};\ \tilde{\mathbf{t}};\ \mathbf{v};\ \mathbf{t}]\right)$$

Multi-head attention variants follow the same pattern but with multiple projection heads.

➢ *Classifier & Output*

From fused **h** we compute logits and probabilities:

$$\mathbf{o} = \mathbf{W}_o\mathbf{h} + \mathbf{b}_o, \hat{\mathbf{p}} = \text{softmax}(\mathbf{o})$$

Where

The methodology involves several phases: Dataset Collection and Description:

The first step is to get access to the information provided by publicly available multimodal misinformation collections such as Fake edit Weibo, and MediaEval. These data will contain labelled instances of text and image-based posts of news which are genuine and those which are fake. We retain the following to each of our posts: The caption or headline text (fact, partially true, or misleading), the image accompanying that text (fact or altered), and the fact-checking labels that go under the fact remains as the ground-truth. Some of the misinformation cases that can be simulated in our system through this multimodal approach are memes with text encoded in disinformation, sharing of fake claims with manipulated images, or captions on genuine pictures.

➢ *Preprocessing Phase:*

- *Text Preprocessing*

The extracted text (sequences or obtained by OCR or direct input) is run through: Noise removal is the process of removing special characters, hashtags, URLs and user mentions. Conversion to word tokens that BERT uses the process of word removal through frequently used non-informative words Redundancy removal for deep learning, sequence padding/truncation Pad out the sequences to a fixed length BERT doesn't require near-terminals, and so it can be safely truncated.

- *Image Preprocessing*

The data is then augmented with random flips, rotations and crop (to make the data more robust), and with brightness and contrast modifications (to achieve the appearance of varying lighting conditions) after resizing the images to 224 x 224 pixels and normalizing them according to ImageNet statistics (mean and standard deviation).

- *OCR Integration*

The text that is embedded in an image (like memes or screenshots) is extracted using Tesseract OCR. This ensures that the text present on image and explicit captions are equally analyzed and thus, one analysis is performed.

✓ Feature Extraction:
✓ BERT-BiLSTM for Text:

BERT (Bidirectional Encoder Representations from Transformers) is used in order to produce context- aware word embeddings. Unlike the representations obtained by

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purely static embedding, BERT learns context-sensitive meanings (such as exaggeration and sarcasm), and semantic nuances that are often present in fake news.

The BiLSTM layer that takes the BERT embeddings into account captures forward and backward sequential dependencies. This enables the system to check on the usual features of disinformation of structures of the language pattern and plotlines, including dramatic introductions and vague supporting data.

✓ *ResNet50 for Image:*

ResNet50 is applied in analyzing images since it employes skip connections to learn residual in which case deep networks can be trained on the residual conveniently without vanishing gradient issues. ResNet50 extracts hierarchical image features: Top layers determine objects, contextual clues and indications of image editing, bottom layers capture edges and textures. Fine-tuning the final layers of ResNet50 allows the network to adhere to patterns of misinformation such as image reuse, manipulation of logos, and image-text mismatch.

- *Deep Fusion Layer*

In order to produce multimodal relationship models simultaneously, the textual and visual feature vectors have been extracted and the two vectors are in a fusion layer concatenated. To optimize this process, we use: Mechanisms of Attention: Promote features that are informative and regularize dropouts on those that are irrelevant. Cross-modal focus: Identify differences between visual evidence (e.g. out of date photos or fatuous captions) and textual assertions. Full connections Unite dense layers with dropouts to deter overfitting.

In our experiments, the dataset is split into: 80 % training data: balanced between fake news and real news.10 percent validation data: used to do hyperparameter tuning.10 percent testing data: used to do performance evaluation.

To evaluate model performance, several quantitative metrics are employed:

✓ Accuracy: Measures the proportion of correctly predicted instances.
✓ Precision and Recall: Assess the correctness and completeness of fake news detection.
✓ F1-Score: Provides a harmonic mean between precision and recall, balancing both metrics.

ROC-AUC (Receiver Operating Characteristic –

- *Area Under Curve):*

Comprehensively assesses the model's ability to distinguish between authentic and fraudulent news at various thresholds. Additionally, confusion matrices, attention, and OCR output visualizations are produced to help interpret model predictions. One way to characterize the entire workflow is as follows: Include a picture and some text. OCR information extraction from text, Get the textual and visual data ready. BERT BiLSTM and ResNet50 are used to extract text and image features. Combine traits with a fusion layer, which is essentially founded on deep attention. Mark the information as true or false after determining the degree of confidence in it. The suggested system enables more accurate and context-sensitive fake news detection by offering an end-to-end pipeline for identifying multimodal disinformation in real- world social media and news conditions.

IV. CONCLUSION

In this paper, BERT BiLSTM has been applied to analyze the text data, and ResNet50 has been employed to obtain image features, and a deep fusion network has been proposed to apply a novel font of fake news detection, social network, and image detection. Converting the fake news to text: Harnessing the synergetic power of computer vision and the natural language processing (NLP) to face the increasingly multi-modal nature of fake news. Using OCR-based text extraction and advanced contextual language modeling and image analysis, the system is able to distinguish between textual and visual cues that are two crucial indicators of misleading information; compared to unimodal text- only models and image only models, our multimodal fusion technique shows a significant improvement in accuracy and robustness of fake news detection. In order to overcome those, the model is improved by focusing on the salient features of both modalities with integrating attention in the fusion layer resulting in a reduction of false positives and false negatives. It overcomes empirical challenges of automated detection of disinformation by ensuring better misinformation detection on various samples of misinformation, including doctored images, fake online social posts, and misleading news titles. It can also be further advanced by future researchers by incorporating explainability components, exploring more advanced fusion methods (e.g. transformer based multimodal architecture) and incorporating larger amounts of multimodal data to give end users confidence in interpreting results. At last, the proposed system, will contribute to raising public awareness and information integrity by helping journalists, social media companies and fact- checking organizations to prevent dissemination of misleading information. This work's contributions go beyond model performance. Future researchers can build upon the framework's scalable and adaptable foundation. Explainable AI (XAI) modules to improve model transparency, transformer-based multimodal architectures for better semantic alignment, and training on larger, more varied multimodal datasets to improve cross-platform applicability are some potential future developments. Adversarial robustness techniques, temporal propagation patterns, and user-behavior signals offer significant prospects for future growth. In the end, the suggested system helps to preserve information integrity and raise public awareness. It contributes to the larger social objective of lessening the dissemination of damaging false information by helping journalists, fact-checking groups, and social media platforms recognize deceptive content more successfully. Multimodal deep learning techniques like ours will be essential to protecting honest communication and boosting trust in online information ecosystems as the digital landscape develops.

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