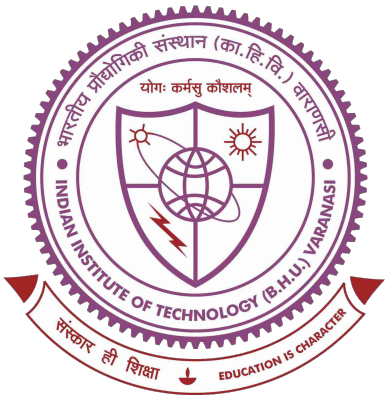
MULTIMODAL DEEP LEARNING FOR FAKE NEWS DETECTION



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in

Computer Science and Engineering

By: Y Yashwanth Raju, P Jaya Charan, T Bala Kotaiah

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY (BANARAS HINDU UNIVERSITY)
VARANASI – 221005

Submitted By:
23075097, 23075088, 23074023

Year of Submission:
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Supervisor
Prof. Dr. Lakshmanan Kailasam
Department of Computer Science and Engineering
Indian Institute of Technology (BHU) Varanasi
Varanasi – 221005

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Supervisor
Prof. Dr. Lakshmanan Kailasam
Department of **COMPUTER SCIENCE AND ENGINEERING**
Indian Institute of Technology
(Banaras Hindu University)
Varanasi – 221 005

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Preface

In the contemporary digital age, individuals are inundated with information from a wide array of sources, including websites, social media platforms, and news outlets. While this widespread accessibility to news facilitates rapid dissemination of information, it also introduces a significant challenge fake news. The spread of false or manipulated information can mislead individuals, create confusion, and potentially cause harm, particularly when such content is accepted without verification. Consequently, the detection of fake news has emerged as a pressing and complex issue, necessitating the application of advanced technological solutions.

Traditional fake news detection systems have predominantly focused on analyzing a single modality, such as the textual content of a news article or its associated imagery. While these approaches have shown some effectiveness, they often lack the robustness required to identify deceptive or subtly manipulated content. For instance, a news article may present itself as credible through well written text, while the accompanying image may be unrelated or misleading. In such cases, relying solely on textual or visual analysis is insufficient. This highlights the necessity for systems capable of processing and interpreting multiple data modalities concurrently—a capability made possible through multimodal deep learning.

This project represents a step forward in addressing this challenge. Specifically, we explore the integration of text and image data within a unified deep learning framework to enhance the accuracy and reliability of fake news detection. A comparative analysis of various deep learning models is conducted, including those trained solely on text, solely on images, and those utilizing both modalities. By evaluating these models on a curated dataset comprising both genuine and fabricated news samples, we aim to identify which approaches offer the most effective performance.

Through this project, we have gained valuable experience not only in developing deep learning models but also in data analysis, model evaluation, and addressing real-world challenges. It is our aspiration that the findings and methodologies presented herein will serve as a useful resource for students, researchers, and practitioners interested in the fields of fake news detection, artificial intelligence, and data science.

Contents

Chapter 1

Abstract

Fake news is a growing problem in the modern age of the internet and social media. Many people share news stories without checking if they are true, which can cause confusion and spread misinformation. Detecting fake news has become an important task for researchers and developers in the field of artificial intelligence. Traditional methods for fake news detection usually focus on analyzing only one part of the news, such as the text or the image. However, these single-method approaches may miss out on important clues. For example, the text of a news story might look real, but the image might give away that it is fake. To solve this issue, we explore multimodal deep learning techniques that analyze both the text and the image together.

In this project, we use a dataset called Mirage-News. This dataset contains thousands of news articles, each with a picture and a caption. Some of them are real, while others are generated using artificial intelligence tools like GPT and Midjourney. We use this dataset to train different models that can classify a news article as real or fake. First, we build and test models that use only text or only images. Then, we create combined models that use both text and images together.

For the text, we use models like CNNs, BiLSTM, and BERT to understand the content of the news. For the images, we use pre trained image classifiers like ResNet50 and VGG19. We then combine the features from both text and image models using various fusion methods. Some of these methods simply join the features, while others calculate similarity between text and image features. We train these models and evaluate them using standard metrics like accuracy, precision, recall, and F1-score.

Our results show that models that use both text and images perform better than those that use only one. This proves that multimodal deep learning is a powerful tool for detecting fake news. It helps the model understand the news more completely and make better decisions. In the future, we believe that these techniques can be improved further and used in real-world applications to stop the spread of misinformation.

Chapter 2

Introduction

The internet has changed how people receive and share news. Platforms like Twitter, Facebook, and Instagram allow news to travel faster than ever before. Although this has many benefits, it also creates problems, especially the spread of fake news. Fake news refers to false or misleading information presented as if it were real. It can be created for many reasons, such as to influence opinions, cause panic, or generate clicks for money. With the rise of AI-generated text and images, fake news is becoming harder to detect using traditional methods.

Many fake news detection systems in the past focused on just one type of data, such as the text in a news article. These systems try to understand the words, grammar, and meaning to find clues that something may be fake. Other systems look at images to see if they look real or suspicious. But in many cases, fake news uses a mix of real-looking text and misleading images. If a system checks only the text or only the image, it might miss important signs that the news is fake. That's why we need systems that can look at both text and images together.

This approach is known as multimodal learning. It means using more than one type of data to make a decision. In our case, we combine natural language processing (NLP) for the text and computer vision for the images. By doing this, we hope the model can understand both what the article says and what the image shows—and whether they match or not. For example, if the article talks about a recent event but the image looks old or unrelated, the model can use this mismatch as a clue that the article may be fake.

In this project, we use the Mirage-News dataset, which contains pairs of images and captions that are either real or fake. Some of the fake samples are generated using powerful tools like GPT and Midjourney, making them very convincing. We build several models for both text and image analysis. For text, we use models like CNN, BiLSTM, and BERT. For images, we use well-known networks like ResNet and VGG. We also explore how to best combine these features—whether by joining them, comparing them, or feeding them through more layers.

The purpose of this project is to understand how combining different types of data can improve fake news detection. We compare single-modality models (text-only or image-only) with our multimodal models to see which ones perform best. Our results suggest that models that look at both text and images together give more accurate and balanced predictions.

Chapter 3

Dataset Description

In this study, we use the MiRAGeNews dataset, a recently introduced benchmark designed for detecting AI-generated news using both textual and visual modalities. The dataset contains a total of 15,000 image-caption pairs, evenly divided between real and AI-generated content.

Each sample consists of a news-style image paired with a corresponding caption, along with a binary label indicating whether the pair is real (label 0) or synthetically generated (label 1). This binary classification task is intended to reflect realistic disinformation detection scenarios, where both the textual and visual elements of a news item may be manipulated.

The real samples are sourced from the *New York Times corpus* via the *TARA dataset*. These include authentic images and captions that offer rich contextual information such as specific dates, locations, and named entities.

In contrast, the synthetic samples are generated through a two-step process. First, GPT-4 is used to rewrite real captions, introducing fictional or misleading information while retaining key named entities. These captions are then used to generate photorealistic images using Midjourney version 5.2, a state-of-the-art text-to-image diffusion model. Prompts are carefully crafted to reflect the stylistic and compositional traits of real news photography.

For our experiments, we apply a custom data split to facilitate model training and evaluation. Specifically, 7,000 samples are allocated for training, 1,500 samples for validation, and 1,500 samples for testing.

The dataset is split using stratified random sampling to maintain the original 1:1 ratio between real and fake samples across each subset. This ensures consistency and unbiased evaluation throughout the pipeline, preserving a balanced distribution for model learning and testing.

Chapter 4

Unimodal Approaches

4.1 Text Preprocessing and Sequence Preparation

Before implementing the models for classifying fake news, the text data is carefully prepared through a series of preprocessing steps. First, common words that do not add much meaning (called stopwords) are removed using a standard list from the NLTK library. Then, each sentence is broken into individual words (tokens). These words are further cleaned using a process called lemmatization, which reduces each word to its most basic form. This is done in three steps—first treating each word as a noun, then as a verb, and finally as an adjective. This ensures that different forms of the same word are treated uniformly by the model. These steps are consistently applied to the training, validation, and test datasets.

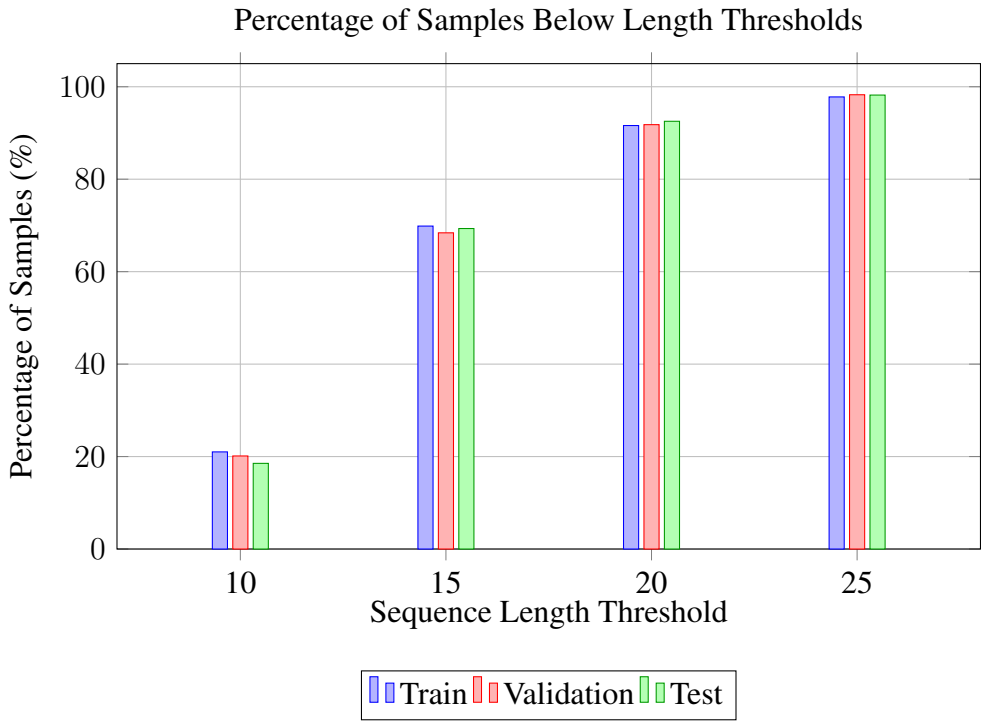

Figure 1: Percentage of samples with sequence lengths less than thresholds:
Train: (21.01, 69.86, 91.61, 97.8)%, Validation: (20.13, 68.4, 91.8, 98.27)%, Test: (18.53, 69.33, 92.53, 98.2)%

After cleaning, the text is converted into numerical form using Keras's Tokenizer, which assigns a unique integer to each word based on its frequency. The tokenizer is trained on all available data (training, validation, and test), resulting in a vocabulary of 128,022 unique words. Each sentence is then transformed into a sequence of these integers.

To standardize the input length, the distribution of sentence lengths was analyzed. In the training set, 18.34% of sequences are shorter than 10 words, 66.36% are shorter than 15 words, 90% are shorter than 20 words, and 97.09% are shorter than 25 words. In the validation set, 18.07% of sequences are shorter than 10 words, 64.2% are shorter than 15, 89.13% are shorter than 20, and 97.27% are shorter than 25. Similarly, in the test set, 15.93% of sequences are shorter than 10 words, 65.33% are shorter than 15, 90.33% are shorter than 20, and 98% are shorter than 25. Based on these statistics, the maximum sentence length was set to 25 words. Sentences shorter than this are padded with zeros, and longer ones are truncated to ensure uniform input size for the CNN model, which expects inputs of shape `(batch_size, 25)`.

4.2 CNN (Text-Only)

We now explain the CNN architecture for the text classification of fake news. The model starts with an embedding layer that converts input sequences of tokens into dense vector representations. We initialize the embedding matrix using both random initialization and the pre-trained GloVe word embeddings of dimension 300. We chose this size for the word embeddings over other options (50, 100, or 200) because word embeddings of a larger dimension have been proven to yield better results. Any words not found in the GloVe vocabulary are initialized randomly. The input to the model has a shape of (batch size, 25), where 25 is the maximum sequence length. After the embedding layer, the output shape becomes (batch size, 25, 300), providing a dense and continuous representation of the text that can be processed by convolutional layers.

After the embedding, the model applies four convolutional layers in parallel. Each convolution uses a different window size across the sequence: 2, 3, 4, and 5. The width of each filter always matches the embedding dimension of 300. Each convolution uses 50 filters, resulting in outputs of shapes (batch size, 24, 50), (batch size, 23, 50), (batch size, 22, 50), and (batch size, 21, 50) for the different filter sizes. These convolutions slide over the embedded text to detect important local patterns and features across different n-gram combinations. After convolution, a ReLU activation function is applied element-wise to introduce non-linearity without changing the output shapes.

The outputs from the convolutional layers are passed through a max-pooling layer. For each feature map, the maximum value across the sequence is selected, reducing each set of feature maps to 50 values. After max-pooling, the outputs from all four convolutional layers are concatenated, resulting in a feature vector of size 200 for each input. This vector contains the most important features extracted from the text across different n-gram lengths.

The concatenated feature vector is then passed through two fully connected layers. The first dense layer reduces the size from 200 to 128 and applies a ReLU activation to introduce non-linearity. The second dense layer maps the 128 features into 2 output units, corresponding to the two classes: fake news or real news. Finally, a log-softmax activation function is applied to the output, producing log-probabilities that are used for classification.

The model is trained using the Adam optimizer with a learning rate of 0.001. We use a batch size of 32 during training. Early stopping is applied to monitor the validation loss and halt training once performance no longer improves.

4.3 BiLSTM + CNN

We now present a hybrid model that uses a bidirectional LSTM followed by a CNN layer. First, texts are preprocessed as described above, and these inputs are passed through an embedding layer. The embedding matrix is initialized either randomly or with pre-trained GloVe embeddings of 300 dimensions. Words not present in the GloVe vocabulary are initialized randomly. Therefore, each input sequence of length 25 is transformed into a matrix of shape (batch size, 25, 300).

Then, the matrix with the word embeddings goes through a bidirectional LSTM layer with hidden states of length 70. The output of this layer is a matrix of size (batch size, 25, 140), where 140 corresponds to the concatenation of the forward and backward hidden states for each word embedding.

The output of the BiLSTM layer is then passed to a convolutional layer. Before applying the convolution, an additional channel dimension is added, and the tensor becomes of shape (batch size, 1, 25, 140). The convolutional layer applies 240 filters with a kernel size of (3, 140). After applying the convolution, the output shape is (batch size, 240, 23, 1), where 23 results from the convolution over a sequence of length 25 with a kernel size of 3. The last dimension is then removed, and the tensor becomes of shape (batch size, 240, 23).

Then, a ReLU activation function is applied element-wise without changing the output shape. After the ReLU activation, a max-pooling operation is applied across the sequence length dimension. For each feature map of size 23, the maximum value is selected, resulting in an output of shape (batch size, 240).

The output of the max-pooling layer is passed through two dense layers. First, the feature vector of size 240 is mapped to 64 units, and a ReLU activation is applied. Then, a dropout layer with a probability of 0.5 is applied. Finally, the 64-dimensional vector is mapped to the number of output classes by a second dense layer. The resulting vector goes through the log-softmax function, and the predicted class is obtained.

Early stopping is again used for selecting the optimal number of epochs. We use Adam as the optimization algorithm with a learning rate of 0.003 and the negative log-likelihood as the loss function.

4.4 BERT

We now explain the BERT-based architecture for the text classification of fake news. In this case, instead of using random initialization or pre-trained GloVe embeddings, we use the contextual embeddings provided by BERT to represent the input tokens. Unlike GloVe, which assigns the same vector to a word in all contexts, BERT generates different embeddings for a word depending on its surrounding words, which helps to capture more information from the sentence.

The texts are preprocessed using the BertTokenizer from the transformers library. This tokenizer maps each word to its corresponding token ID from the BERT vocabulary. Special tokens are added during tokenization: a [CLS] token is placed at the beginning and a [SEP] token is placed at the end. The maximum sequence length is set to 25 tokens. If a sequence is shorter than 25 tokens, it is padded with zeros. If it is longer, it is truncated to fit the maximum length.

An attention mask is also created for each sequence. The attention mask has 1s for real tokens and 0s for padding. It helps BERT focus only on the real input tokens during training. We use the bert-base-uncased model, which has 12 layers, 12 attention heads, and a hidden size of 768. The total number of parameters is about 110 million.

The processed input is passed through BERT, which outputs a hidden state for each token. We take the hidden state of the [CLS] token as the summary representation of the whole input sequence. This [CLS] vector, which is of size 768, is passed through a fully connected layer with ReLU activation. The output from this layer has a size of 512. Then, it is passed through a second fully connected layer which reduces the size to 2, corresponding to the two classes: fake news and real news. A log-softmax activation is applied at the end to produce the final class probabilities.

We fine-tune the entire model using the Adam optimizer with a learning rate of 2×10^{-5}. The model is trained for a maximum of 8 epochs. Early stopping is applied to monitor validation loss and stop training if the performance does not improve.

Chapter 5

Multimodal Architectures

We now describe the multimodal architecture designed for the classification of fake news by jointly using the associated text and image. In this setup, each input to the model consists of a text and its corresponding image, both referring to the same news sample. The model processes the two modalities separately before combining them to produce the final classification output.

5.1 CNN (Text + Image)

Preprocessing of text is done as mentioned in Section 4.1. Regarding preprocessing of images, each image is resized to a uniform size of 150×150 pixels with three color channels (RGB). No additional transformations, such as normalization or augmentation, are applied. The preprocessed images are then passed through a convolutional neural network specifically constructed for image feature extraction.

The first convolutional layer accepts the three input channels and produces six output channels using a 5×5 filter with a stride of 1 and no padding. After the convolution operation, a ReLU activation is applied, followed by a 2×2 max-pooling operation with a stride of 2. This sequence reduces the spatial dimensions from 150×150 to 73×73.

The resulting feature maps are then passed through a second convolutional layer with six input channels and three output channels, again using a 5×5 filter, a stride of 1, and no padding. This is followed by another ReLU activation and max-pooling layer, producing feature maps of size 35×35. Finally, the output feature maps are flattened into a single vector of size 3675, representing the visual features extracted from the image.

For the text input, we preprocess the news text by tokenizing it into words and limiting or padding the sequence to a maximum of 25 tokens. Each token is then mapped to a 300-dimensional vector using pre-trained GloVe embeddings. We use 300 dimensions because larger embedding sizes have been shown to capture richer word relationships and generally perform better. After embedding, the text input has the shape (25, 300). This embedded sequence is passed through a one-dimensional convolutional layer with 100 filters of size 5, followed by a ReLU activation. Then, max-pooling is applied across the sequence length to capture the most important features. The resulting output is flattened into a fixed-size vector that represents the text.

The final step is to combine the features extracted from both the image and the text. We concatenate the two vectors obtained from the image CNN and the text CNN. The combined vector is passed through a dense (fully connected) layer with ReLU activation, followed by another dense layer. At the end, a log-softmax activation function is applied to output the probabilities for each class. Since we are performing binary classification, the final output vector has two values corresponding to the probability of each class (real or fake news).

During training, we use the Adam optimizer to minimize the negative log-likelihood loss. Early stopping is applied to prevent overfitting by monitoring the validation loss. If the validation loss does not improve for a certain number of epochs, training is stopped early.

By processing both the text and the image together, the model can better capture the multimodal patterns that indicate whether a news sample is fake or real.

5.2 BERT and CNN Fusion (ResNet50, VGG16, VGG19)

First, we preprocess the text data as mentioned in Section 4.1, then we begin by extracting deep contextual features using the BERT model, specifically bert-base-uncased. Each text sample is first tokenized, with special tokens added at the beginning and end of the sequence. The tokenizer ensures each sequence has a fixed length of 128 tokens by padding or truncating as needed. This gives us a tensor input of shape (1, 128) per sample. When passed through BERT, the output is a hidden state tensor of shape (1, 128, 768), where each token has a 768-dimensional embedding. From this, we extract the embedding of the special [CLS] token at position zero, which is commonly used to represent the whole sentence. This gives us a 768-dimensional feature vector per text.

To enhance the semantic representation further, we also compute sentiment features for each text sample using the VADER sentiment analyzer. For each sentence, this tool outputs four scalar values: the compound score, and individual positive, negative, and neutral sentiment scores. These four values are appended to the 768-dimensional [CLS] vector, resulting in a final text embedding of size 772 dimensions per sample. Repeating this process for the entire training, validation, and test datasets gives us text feature matrices of shape (7000, 772) for training, (1500, 772) for validation, and (1500, 772) for testing.

In parallel, we extract features from the corresponding images. Each image is resized to 224 by 224 pixels and normalized to match the input format expected by pre-trained convolutional neural networks. The normalized image is passed through three well-known CNN architectures: ResNet50, VGG16, and VGG19. These models are pre-trained on the ImageNet dataset, and their final classification layers are removed, allowing us to use the feature vectors they produce as general-purpose image embeddings. From ResNet50, we extract a 2048-dimensional

vector. Both VGG16 and VGG19 produce 4096-dimensional vectors. Instead of concatenating these three vectors—which would result in a 10240-dimensional feature—we apply mean fusion. This means we average the representations from the three models into a single 1000-dimensional vector. This reduces the feature size, minimizes model-specific bias, and promotes more stable training. We obtain image feature matrices with shapes (7000, 1000) for training, (1500, 1000) for validation, and (1500, 1000) for testing.

To make the text and image features directly comparable for the next step, we pad the text features with zeros to match the 1000-dimensional shape of the image features. Specifically, 228 zeros are added to each 772-dimensional text vector. This results in padded text features of shape (7000, 1000), (1500, 1000), and (1500, 1000) for the training, validation, and test sets, respectively. Now that the text and image features have the same dimension, we compute the cosine similarity between them for each sample. This similarity is a single scalar value that quantifies how semantically aligned the text and image are. This gives us cosine similarity vectors of shape (7000, 1), (1500, 1), and (1500, 1) for the respective splits.

We then create the final feature vector for each sample by combining three components: the original unpadded text features of 772 dimensions, the 1000-dimensional image features, and the single cosine similarity score. These are concatenated to form a final multimodal feature vector of 2001 dimensions per sample. The full dataset is now represented as (7000, 2001) for training, (1500, 2001) for validation, and (1500, 2001) for testing.

These 2001-dimensional vectors are passed through a fully connected feed-forward neural network that performs the classification task. The first layer is a dense layer that reduces the input from 2001 to 512 units and uses the ReLU activation function. This is followed by a batch normalization layer that helps stabilize the learning process and a dropout layer with a rate of 0.4 to reduce overfitting. The next dense layer takes the 512 units and reduces them to 256, again followed by batch normalization and a dropout rate of 0.3. The third dense layer reduces the 256 units to 128 and includes another round of batch normalization and dropout, this time with a rate of 0.2. Finally, a dense output layer with a single neuron and a sigmoid activation function is used to produce a prediction score between 0 and 1, which represents the probability of the sample being real or fake.

The use of mean fusion in combining the outputs of ResNet50, VGG16, and VGG19 is an important design choice. Instead of simply concatenating the outputs, which would produce a very high-dimensional vector of size 10240 and potentially cause overfitting or training instability, mean fusion allows us to combine the strengths of all three models in a compact, efficient way. It reduces the feature size significantly, leading to faster and more stable training. This fusion strategy also avoids giving too much weight to any single model's biases, resulting in more general and balanced representations. Furthermore, by averaging the representations, we

introduce a natural form of regularization that improves the robustness of the model to noisy or ambiguous visual data.

This architecture effectively integrates the semantic meaning of text, the visual content of images, and the relationship between them through cosine similarity.

Chapter 6

Results

In this section, we present the results obtained for each model. We report the precision, recall, and F1 scores for each class, as well as the overall accuracy computed across all classes. The accuracy reflects how well the model classifies both true and manipulated content. Additionally, to compare the performance more comprehensively, we calculate the macro and micro averages of the recall, precision, and F1 scores. Macro averaging computes these metrics for each class and then calculates the average, while micro averaging sums all true positives and false positives across all classes and then computes the metrics. The micro-average F1 score and overall accuracy are used to evaluate and compare the model's performance.

6.1 CNN(Text Only) Results

In our experiments, we evaluated four configurations: using random embeddings with trainable embeddings, GloVe embeddings with trainable embeddings, random embeddings without training, and GloVe embeddings without training. We report precision, recall, F1-score, support, as well as macro and weighted averages to analyze each model's performance.

1. Random Embeddings + Trainable Embeddings

This model achieves an overall accuracy of 73%, with a micro F1-score, macro F1-score, and weighted F1-score all at 0.73. The precision and recall for class 0 are 0.74 and 0.71 respectively, while class 1 scores 0.72 and 0.76. These balanced metrics suggest the model performs consistently across both classes. However, the confusion matrix shows a tendency to slightly overpredict the positive class, indicated by a higher number of false positives than false negatives.

Table 1: Classification Report for CNN with Random + Trainable Embeddings

Class	Precision	Recall	F1-Score	Support
0	0.74	0.71	0.72	750
1	0.72	0.76	0.74	750
Accuracy: 0.73 (Total: 1500)				
Macro avg	0.73	0.73	0.73	1500
Weighted avg	0.73	0.73	0.73	1500

2. GloVe Embeddings + Trainable Embeddings

When initialized with pre-trained GloVe vectors and allowed to fine-tune during training, the model performs best overall with 76% accuracy. It achieves a micro F1, macro F1, and weighted F1-score of 0.76. Precision and recall for class 0 are 0.76 and 0.75; for class 1, they are 0.75 and 0.77. The model maintains a near-perfect class balance, and errors are evenly distributed between false positives and false negatives.

Table 2: Classification Report for CNN with GloVe + Trainable Embeddings

Class	Precision	Recall	F1-Score	Support
0	0.76	0.75	0.75	750
1	0.75	0.77	0.76	750
Accuracy: 0.76 (Total: 1500)				
Macro avg	0.76	0.76	0.76	1500
Weighted avg	0.76	0.76	0.76	1500

3. Random Embeddings + Non-Trainable Embeddings

Without training the embedding layer, the model's performance declines to 68% accuracy, with precision, recall, and F1-scores all at 0.68 for both macro and weighted metrics. While class 0 has a recall of 0.75, class 1's recall drops to 0.61, indicating a difficulty in correctly identifying positive samples. The number of false negatives is notably higher than false positives, suggesting a bias toward negative predictions.

Table 3: Classification Report for CNN with Random + Non-Trainable Embeddings

Class	Precision	Recall	F1-Score	Support
0	0.66	0.75	0.70	750
1	0.71	0.61	0.66	750
Accuracy: 0.68 (Total: 1500)				
Macro avg	0.68	0.68	0.68	1500
Weighted avg	0.68	0.68	0.68	1500

4. GloVe Embeddings + Non-Trainable Embeddings

This configuration yields 74% accuracy, with macro and weighted averages of 0.74 across precision, recall, and F1-score. The performance is balanced between classes, with precision and recall values hovering around 0.74–0.75. Although the model doesn't outperform the dynamic GloVe setup, it still significantly surpasses the random non-trainable baseline. Misclassifications are split almost evenly between false positives and false negatives, indicating stable performance.

Table 4: Classification Report for CNN with GloVe + Non-Trainable Embeddings

Class	Precision	Recall	F1-Score	Support
0	0.75	0.74	0.74	750
1	0.74	0.75	0.74	750
Accuracy: 0.74 (Total: 1500)				
Macro avg	0.74	0.74	0.74	1500
Weighted avg	0.74	0.74	0.74	1500

In conclusion, the best-performing model is the one using GloVe embeddings with training embeddings, which shows an overall improvement in accuracy and a more balanced detection of both classes. Training the embeddings seems to provide a notable boost to performance, particularly when using pre-trained GloVe vectors, which capture semantic relationships between words more effectively than random embeddings.

6.2 BiLSTM+CNN Results

As a second deep learning approach, we evaluate a hybrid BiLSTM + CNN architecture. This model is tested under four different configurations: random embeddings with and without training, and GloVe embeddings with and without training. The evaluation metrics considered include precision, recall, F1-score, support, macro average, weighted average, and a summarized confusion matrix.

1. Random Embeddings with Training: In this setup, the model was initialized with random word embeddings, which were updated during training. The model achieved an accuracy of 70%. For class 0 (real), precision was 0.69, recall 0.73, and F1-score 0.71. For class 1 (fake), precision reached 0.72, recall 0.68, and F1-score 0.70. The macro and weighted averages for precision, recall, and F1-score were all 0.70. The confusion matrix ([548, 202], [242, 508]) shows that the model had 202 false positives and 242 false negatives, indicating some difficulty distinguishing between the two classes.

Table 5: Classification Report for BiLSTM+CNN with Random + Trainable Embeddings

Class	**Precision**	**Recall**	**F1-Score**	**Support**
0	0.69	0.73	0.71	750
1	0.72	0.68	0.70	750
Accuracy: 0.70 (Total: 1500)				
Macro avg	0.70	0.70	0.70	1500
Weighted avg	0.70	0.70	0.70	1500

2. GloVe Embeddings with Training: Using pre-trained GloVe embeddings with further training improved the model's accuracy to 72%. Class 0 had a precision of 0.72, recall 0.71, and F1-score 0.72. Class 1 had identical metrics (0.72 for all three). Both macro and weighted averages stood at 0.72. The confusion matrix ([535, 215], [207, 543]) showed improved class balance, with reduced false positives and negatives compared to the random-initialized case, suggesting better generalization through semantic pre-training.

Table 6: Classification Report for BiLSTM+CNN with GloVe + Trainable Embeddings

Class	**Precision**	**Recall**	**F1-Score**	**Support**
0	0.72	0.71	0.72	750
1	0.72	0.72	0.72	750
Accuracy: 0.72 (Total: 1500)				
Macro avg	0.72	0.72	0.72	1500
Weighted avg	0.72	0.72	0.72	1500

3. Random Embeddings without Training: When the random embeddings were kept static during training, the model achieved a slightly better accuracy of 71%. Class 0 recorded precision 0.75, recall 0.64, and F1-score 0.69, while class 1 achieved precision 0.68, recall 0.78, and F1-score 0.73. The macro average was 0.72 and the weighted average 0.71. From the confusion matrix ([480, 270], [163, 587]), we observe a higher false positive rate for class 0,

but improved recall for class 1, indicating the model is more confident in identifying fake news under this setting.

Table 7: Classification Report for BiLSTM+CNN with Random + Fixed Embeddings

Class	**Precision**	**Recall**	**F1-Score**	**Support**
0	0.75	0.64	0.69	750
1	0.68	0.78	0.73	750
Accuracy: 0.71 (Total: 1500)				
Macro avg	0.72	0.71	0.71	1500
Weighted avg	0.72	0.71	0.71	1500

4. GloVe Embeddings without Training: This configuration yielded the best performance, with the model achieving an accuracy of 78%. For class 0, precision was 0.76, recall 0.81, and F1-score 0.78. Class 1 recorded precision 0.79, recall 0.75, and F1-score 0.77. Both macro and weighted averages were 0.78. The confusion matrix ([604, 146], [187, 563]) highlights a better separation between the classes, with fewer misclassifications overall. This suggests that keeping GloVe embeddings fixed helps preserve semantic consistency during training.

Table 8: Classification Report for BiLSTM+CNN with GloVe + Fixed Embeddings

Class	**Precision**	**Recall**	**F1-Score**	**Support**
0	0.76	0.81	0.78	750
1	0.79	0.75	0.77	750
Accuracy: 0.78 (Total: 1500)				
Macro avg	0.78	0.78	0.78	1500
Weighted avg	0.78	0.78	0.78	1500

Among all embedding configurations, the use of pre-trained GloVe embeddings without training produced the highest accuracy and best balance in precision, recall, and F1-score. This indicates that fixed semantic-rich embeddings enhance the model's ability to generalize and discriminate between real and fake content more effectively. The results validate the hybrid model's potential in fake news detection, especially when combined with static, high-quality word vectors.

6.3 BERT Results

The BERT model demonstrates strong performance in binary classification, achieving an overall accuracy of 87%. This means the model correctly classifies 87% of all instances across both classes. Precision and recall for both classes are also 0.87, suggesting that the model is consistent in its ability to correctly identify both true and manipulated content. The F1-scores for both classes are equal at 0.87, reflecting a good balance between precision and recall. This indicates that the model does not favor one class over the other and performs well in identifying instances of both classes without significant bias toward either.

The model correctly identifies 652 instances of class 0 and 655 instances of class 1. There are 98 false positives and 95 false negatives, meaning the model occasionally misclassifies some instances, but these errors are relatively balanced across both classes. This further reinforces the model's strong ability to correctly classify the majority of the instances while maintaining a low error rate.

These results showcase the effectiveness of BERT's pre-trained contextualized embeddings, which capture rich, context-dependent information about the text. This is in contrast to simpler, static word representations like GloVe, or random initializations typically used in neural networks, which tend to underperform in tasks requiring deep semantic understanding. By using BERT, which leverages the power of contextual information, the model achieves superior classification performance compared to traditional deep learning models. Furthermore, the model's robust classification abilities across both classes, without showing significant bias or weakness toward either, highlight the advantages of using BERT in such tasks.

Table 9: Classification Report for BERT

Class	**Precision**	**Recall**	**F1-Score**	**Support**
0	0.87	0.87	0.87	750
1	0.87	0.87	0.87	750
Accuracy: 0.87 (Total: 1500)				
Macro avg	0.87	0.87	0.87	1500
Weighted avg	0.87	0.87	0.87	1500

6.4 CNN (Text + Image) Results

The model achieves an overall accuracy of 80.8%, which reflects its ability to correctly classify 80.8% of the instances across both classes. For precision, the model achieves 0.7924 for Class 0 (True) and 0.8254 for Class 1 (Manipulated Content), indicating that it is fairly good at identifying the correct class when making predictions. For recall, the model performs better on Class 0 with a recall of 0.8347, compared to Class 1, which has a recall of 0.7813. This means the model is slightly better at identifying true content, but still performs well on detecting manipulated content.

The F1-scores for both classes are also quite balanced, with Class 0 achieving an F1 of 0.8130 and Class 1 achieving 0.8027. The macro average for precision, recall, and F1-score is calculated by averaging the values across both classes. The macro-average precision is 0.8089, recall is 0.8080, and F1-score is 0.8079. These macro-average metrics show the model's balanced performance across both classes, with no significant bias towards either class. The macro average is useful for understanding the model's overall performance without being affected by class imbalances.

The weighted average also takes into account the class distribution, which can help assess the model's performance when classes are imbalanced. For this model, the weighted average precision is 0.8089, recall is 0.8080, and F1-score is 0.8079, identical to the macro averages in this case, which suggests that the class distribution in the dataset is relatively balanced between the two classes.

The confusion matrix shows 626 true positives and 586 true negatives, with 124 false positives and 164 false negatives. This further highlights that the model performs better in detecting true content (Class 0) but still performs reasonably well for manipulated content (Class 1), with an F1-score close to 0.80 for the manipulated content class.

Overall, these results suggest that the model is performing well in terms of both classification accuracy and the balance between precision, recall, and F1 scores for both classes.

Table 10: Classification Report for CNN (Text + Image)

Class	**Precision**	**Recall**	**F1-Score**	**Support**
0	0.7924	0.8347	0.8130	750
1	0.8254	0.7813	0.8027	750
Accuracy: 0.8080 (Total: 1500)				
Macro avg	0.8089	0.8080	0.8079	1500
Weighted avg	0.8089	0.8080	0.8079	1500

6.5 BERT and CNN Fusion (ResNet50, VGG16, VGG19) Results

The model achieves an overall accuracy of 88.53%, indicating its capability to correctly classify approximately 88.5% of instances across both classes. In terms of precision, Class 0 (True) achieves a precision of 0.88, and Class 1 (Manipulated Content) achieves 0.89, suggesting that the model is highly reliable when identifying both true and manipulated content. The recall is similarly strong, with Class 0 having a recall of 0.89, and Class 1 achieving 0.88, meaning the model does well at detecting both types of content.

The F1-scores for both classes are also well-balanced: Class 0 achieves an F1-score of 0.89, while Class 1 has an F1-score of 0.88, showing the model's balanced performance between precision and recall. The macro average for precision, recall, and F1-score are all approximately 0.89, which indicates that the model performs similarly across both classes. These macro averages provide a clear indication of the model's general effectiveness in handling both classes without favoring one.

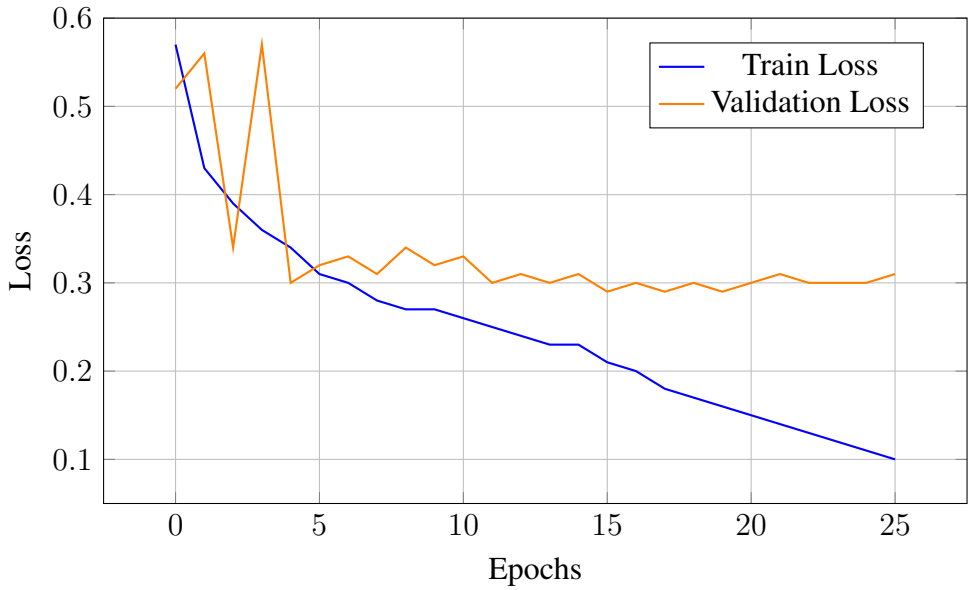

Figure 2: Training and Validation Loss across Epochs

The weighted average precision, recall, and F1-score are also 0.89, identical to the macro averages, which suggests that the dataset is fairly balanced between the two classes and that the model's performance is not skewed by class imbalances.

The confusion matrix shows 668 true positives, 660 true negatives, 82 false positives, and 90 false negatives. This demonstrates that the model has a strong capability to correctly identify

both true content (Class 0) and manipulated content (Class 1), though there are still some false positives and false negatives, especially with manipulated content.

The model demonstrates high accuracy, balanced precision, recall, and F1-scores for both classes, and it performs reliably in both detecting true and manipulated content. These results highlight the model's solid performance and ability to classify content accurately and efficiently across the two categories.

Table 11: Classification Report for BERT and CNN Fusion (ResNet50, VGG16, VGG19)

Class	**Precision**	**Recall**	**F1-Score**	**Support**
0	0.88	0.89	0.89	750
1	0.89	0.88	0.88	750
Accuracy: 0.89 (Total: 1500)				
Macro avg	0.89	0.89	0.89	1500
Weighted avg	0.89	0.89	0.89	1500

Chapter 7

Comparisons with Related Work

The performance of the proposed models on the Mirage-News dataset is compared with prior approaches from recent literature on multimodal fake news detection. The paper Multimodal Fake News Detection by Segura-Bedmar et al. presents a comprehensive evaluation of unimodal and multimodal deep learning models using the Fakeddit dataset. Their experiments demonstrate that while BERT achieves the best performance among text-only models with an accuracy of 78% and a micro F1 score of 74%, the CNN-based multimodal model combining text and image inputs further improves accuracy to 87% and micro F1 to 87%. The study highlights that image features significantly enhance classification, especially for fine-grained fake news categories such as Satire, False Connection, and Manipulated Content.

On the Mirage-News dataset, the text only models CNN, BiLSTM+CNN, and BERT showed similar trends, with BERT outperforming others in the unimodal setting. When multimodal features were introduced, a CNN based text+image model already exhibited noticeable improvements. The final fusion based model, which integrates BERT embeddings, sentiment scores, LBP descriptors, and deep image features from ResNet50, VGG16, and VGG19, achieved the highest performance, with an F1-score of approximately 90.7% and an AUC of 0.94. In comparison to the multimodal CNN in Segura-Bedmar et al., which primarily relied on early fusion of basic CNN features, the proposed fusion model benefits from richer feature integration, including affective and texture-based representations, and a more complex fusion strategy that incorporates multiple visual perspectives.

These results suggest that incorporating diverse and complementary features across modalities, particularly combining contextual and emotional textual information with deep and handcrafted visual descriptors, leads to more effective fake news detection. The enhanced performance on the Mirage-News dataset, which contains more realistic and visually deceptive content than Fakeddit, demonstrates the robustness and adaptability of the proposed model compared to earlier multimodal systems.

Chapter 8

Conclusion

In this project, we conducted a comprehensive evaluation of both unimodal and multimodal approaches for fake news detection using the Mirage-News dataset. Our experiments systematically examined models that utilize only text features, such as CNN, BiLSTM+CNN, and BERT, as well as multimodal architectures that combine textual and visual information through various fusion strategies.

The results provide strong and consistent evidence that multimodal architectures significantly outperform unimodal models across all evaluation metrics, including accuracy, precision, recall, F1-score, and AUC. While unimodal models particularly BERT demonstrated competitive performance within their respective domains, they were ultimately limited by their inability to capture the interplay between textual and visual signals. In contrast, multimodal models especially the fusion-based architecture integrating BERT, sentiment features, and deep image representations from ResNet50, VGG16, and VGG19 achieved the highest performance, with an accuracy of 88.5% and an F1-score approaching 0.89.

This performance gap highlights a critical insight: fake news often exhibits subtle inconsistencies or correlations between text and images that cannot be fully captured by single-modality systems. By jointly modeling both modalities, multimodal networks are able to learn richer, more discriminative representations that enhance the model's ability to identify manipulated or misleading content. Furthermore, the use of advanced fusion techniques, such as mean pooling of image embeddings and cosine similarity between modalities, further improves the model's semantic understanding and robustness.

Based on the evidence presented in this work, we strongly conclude that multimodal learning is not just beneficial but essential for high-accuracy fake news detection in realistic scenarios. The incorporation of diverse and complementary signals leads to models that are not only more accurate but also more resilient to subtle forms of misinformation that exploit either visual or textual ambiguity.

Future research could build on these findings by extending the current framework to larger and more diverse datasets, integrating additional modalities such as metadata or user behavior, and exploring advanced attention-based fusion mechanisms. Additionally, fine-tuning or co-training visual and textual encoders in a unified framework may further improve performance

and generalization.

In conclusion, this work reinforces the growing consensus in the field: multimodal approaches are fundamentally more effective than unimodal ones for complex tasks like fake news detection, where understanding the relationship between different types of content is critical to accurate classification.

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