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THE DEVELOPMENT AND DEPLOYMENT OF A VERSATILE MULTI-MODEL SYSTEM FOR THE DETECTION OF FAKE NEWS FEATURING TEXT AND IMAGES

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Abstract:

The sudden rise of social media has transformed everything, from how we make things to how we share and use them. The digital revolution, on the other hand, has made it easier for fake news to proliferate. This is a huge threat to trust in the government, political stability, and societal awareness. This study introduces a deep learning architecture adept at identifying fraudulent news items through the integration of visual and linguistic data from social media posts. The system uses NLP techniques like Word2Vec and TF-IDF to show text. It gets visual features from CNNs like VGG16 and ResNet50. Putting together all the elements that were uncovered creates a complete picture that shows how images and text work together to create meaning and context. The next step is to employ a Dense Neural Network (DNN) classifier to see if news reports are true. The suggested model is more accurate and reliable than the top text-only methods when evaluated on benchmark datasets. The results reveal that the algorithm is better at finding false or changed content on social media sites when it uses both visual and text clues.

Keywords: Fake News Detection, Multi-Modal Learning, DL, NLP, CNN, Feature Fusion.

I. Introduction

Digital communication technology has grown so swiftly, the way people generate, distribute, and use information has altered completely. People now mostly acquire their news and updates in real time from social media sites like Facebook, Twitter, and Instagram [1, 2]. But when these platforms let false information and propaganda go uncontested, they put trust in the public, political stability, and social peace at risk [3, 4]. Social media doesn't have editors or ways to check facts as other forms of communication do. This makes it simple for erroneous or distorted information to spread quickly [5, 6].

When someone lies to acquire money, power, or political support, that's called fake news [7]. People can't check the accuracy of information anymore since user-generated content is spreading so quickly. There needs to be a smart and automatic way to find things [8, 9].

The first studies on how to discover fake news largely used text-based machine learning algorithms [10], [11] to sort news stories by their linguistic, syntactic, and semantic properties. People used to look at text using features like word frequency, n-grams, and sentiment polarity that were produced by hand. They did this with tools like Logistic Regression, Naïve Bayes, and Support Vector Machines (SVM) [12]. However, these algorithms frequently failed to detect inaccurate information in multimodal content comprising both text and graphics [13].

Recent improvements in DL & NLP made it possible to use more advanced methods to find fake news. Word2Vec and TF-IDF are two neural embedding methods that create dense vector word representations while keeping their meaning connections [14]. In contrast, CNNs like InceptionV3, ResNet50, and VGG16 have been great at getting visual features. This makes it easy to see patterns in pictures and tell whether someone has changed them [15], [16].

Adding multimodal information, which has both text and pictures, is a new and promising technique to improve categorisation and reduce false positives [17]. Research [18], [19] shows that combining linguistic semantics with picture attributes helps detection algorithms uncover disparities between captions and photos, which is a symptom of fake news. It is still hard to develop frameworks that can be utilised in the real world and mix elements from other modalities, even though there have been some recent breakthroughs [20].

This research presents a multi-modal deep learning architecture that amalgamates visual and linguistic analysis to proficiently detect fake news, hence tackling these issues. The suggested solution uses natural language processing methods like TF-IDF and Word2Vec to pull out text features. It gets features from photographs by using pretrained convolutional neural network designs like VGG16 and ResNet50. The two modalities' features make a single embedding space. Then, a Dense Neural Network (DNN) uses this space to figure out if the news is legitimate or fraudulent. The model's purpose is to use the semantic and contextual links between text and images to make detection more accurate.

Motivation

The rapid growth of social media made it easier for fake news to spread quickly through both text and images, influencing public opinion and creating misinformation. Existing detection methods mainly focus on text and fail to identify visual manipulation. This motivates the development of a multi-modal system that analyzes both textual & visual data to improve the accuracy and reliability of fake news detection.

Objectives

1. To look at the characteristics and patterns of how fake news spreads on social media.
2. To examine text-based disinformation detection utilising NLP techniques, encompassing TF-IDF and Word2Vec.
3. To explore image-focused false news detection utilising CNN architectures, including VGG16 and ResNet50.
4. To see if integrating text and visual elements could make classification more accurate.
5. To learn how to develop a web app that enables people use it and assess the reality of fake news right away.

Scope of the Study

This study focuses on identifying disinformation in social media posts that include both images and text. The research focuses on the integration of NLP and CNN-based feature extraction techniques inside a deep learning framework to classify material as genuine or fake. The system is primarily designed for academic and research purposes, but it has the potential for future expansion to accommodate large-scale applications or integration with real-time social media monitoring systems.

II. Existing System

Deb Roy, Soroush Vosoughi and Sinan Aral (2018) executed a thorough quantitative analysis of the dissemination of disinformation on Twitter over a ten-year period. Their study, which was published in Scienc, showed that false information spreads faster, further, and deeper than true stories. The study found that people are more inclined than bots to propagate incorrect information. This highlights how social and psychological factors may make fake content go viral. This study underscores that any computer system designed to detect fake news must consider not only the textual content but also the behavioural and contextual aspects influencing the spread of disinformation.

In 2017, Sungyong Seo, Natali Ruchansky and Yan Liu produced the CSI (Capture, Score, Integrate) model, which is a hybrid deep learning architecture for finding bogus news. Their research, published in the Proceedings of the 2017 ACM Conference on Information and Knowledge Management, comprised three primary components: employing recurrent neural networks to model textual material, assessing the reliability of users and sources, and amalgamating features for ultimate categorisation. The authors demonstrated that models utilising many information sources exhibit more accuracy than those relying exclusively on text or propagation. Their method was the first step toward detection systems that use data from multiple sources and modes, such as text, images, and user engagement.

Bennett Kleinberg, Verónica Pérez-Rosas, Rada Mihalcea & Alexandra Lefevre (2018) examined the detection of linguistic deception by text-based classification of false news. Their study, published in the Proceedings of the 27th International Conference on Computational Linguistics, presented a linguistic feature-based framework employing lexical, syntactic, and semantic markers. The study showed that false news stories often have different emotional tones, levels of subjectivity, and levels of language complexity than real news stories. The experts also said that text-based algorithms can't always uncover visual manipulation or differences in context. This highlights how crucial it is to use data from many different sources to make systems stronger.

FakeNewsNet is a complete set of data that combines news stories, social context, and temporal information to help you detect bogus news. Limeng Cui, Kai Shu, Dongwon Lee, Suhang Wang and Huan Liu made it in 2018. Researchers used their work, which was published in the journal, as a big baseline to evaluate alternative ways to find fake news. The authors examined the dissemination of real and false news, discovering that the writing style, speed of propagation, and network transmission methods differ significantly. Since then, this dataset has been a key part of making detection algorithms that use text, photos, user-level features, and other kinds of dat.

Jing Xue, Bo Chen, Lin Li, and Zhiqi Shen (2021) developed a Multimodal Consistency Neural Network (MCNN) to assess semantic congruence between images and textual descriptions. They employ convolutional neural networks to pick out visual features and recurrent neural networks to understand text. There is also a module that tests for differences between the two modes. The IEEE Transactions on Multimedia published it. Their tests on standard datasets revealed that combining text and image consistency made it easier to spot fake news and cut down on false positives. This study provides strong evidence that multimodal fusion enhances detection performance relative to single-modality approaches.

In conclusion, the studies examined demonstrate the evolution of false news detection from basic linguistic algorithms to advanced multimodal frameworks. Early research looked upon lexical and stylistic indications in text, while more recent ones look at visual features and social context to make the results more accurate. The total results demonstrate that a whole framework that can contain semantic, contextual, and visual evidence is needed to find fake news on social media in a reliable method.

III. Proposed System

The recommended method seeks to discover fake news on social media by looking at both text and pictures. This method uses a multi-modal deep learning architecture that takes data from both text and visuals and integrates them to make more accurate predictions about authenticity. This is not like the usual text-only methods. The architecture is designed to look for differences between the news text and the image that goes with it. These contradictions often mean that the information is wrong or deceptive.

A. System Overview

There are five primary aspects to the system: collecting data, preprocessing text and images, merging features and classifying them, and the user interface. Each module has a specific job that helps with the overall classification of fake news. The first step in the process is to collect social media posts that feature both text and pictures. After that, preprocessing and feature extraction happen, and lastly, classification and result presentation.

B. Data Collection Module

Fake Newsnet, LIAR, and the Weibo Fake News Dataset are some of the benchmark repositories that this system uses to get its data. It has news stories, pictures, and ratings of how credible they are (real or bogus). There is a news headline, article text, photo, and ground truth label for each record. There are both political and non-political news categories to make sure the data is diverse and may be used in different settings. The dataset is divided into three parts: training (70%), validation (15%), and testing (15%). This is to fully test how well the model works.

C. Text Pre-processing Module

Text data goes through a variety of steps to get ready for use in a model, which makes it work better and cuts down on noise.:

1. **Tokenization:** Words or tokens are removed from the text.
2. **Stopword Removal:** We take out words like "the," "is," and "and" that don't help the sense of the sentence.
3. **Lemmatization:** The root form of the word "running" is "run."
    - **Lowercasing and Cleaning:** We got rid of all punctuation, links, and special characters to make things more consistent.
    - **Vectorization:** You can turn the cleaned text into numbers in two primary ways:
    - **TF-IDF :** Shows how important terms are in respect to the corpus.
    - **Word2Vec Embeddings:** Creates dense word vectors that show how words are connected to one other.

Then, a Bidirectional LSTM or Dense Neural Network learns how these traits are connected and makes high-level text representations.

D. Image Preprocessing Module

We utilise standard computer vision algorithms to look at the pictures in each news post:

1. **Resizing:** All photographs are made smaller, like 224×224 pixels, so that CNNs can use them.
2. **Normalization:** To make training more stable, the pixel values are set to the range [0,1].
3. **Data Augmentation:** To avoid overfitting, the program uses random flips, zooms, and rotations.
4. **Feature Extraction:**
    - If you want to learn more about visual traits, you can use a pre-trained CNN model like ResNet50 or VGG16.
    - The CNN's final completely connected layer is taken out, and the output of the second-to-last layer is utilised to produce a feature vector that shows what the image looks like.

E. Feature Fusion and Classification

After getting both text and image data, they are put together into one multi-modal feature vector. This combination helps the model link the meanings of words to the pictures. An SVM classifier or a Fully Connected Neural Network (FCNN) uses the combined feature vector to create the final classification label.

The fusion process improves the system's ability to detect discrepancies, such as when the image doesn't match the event being described or when emotional language is used with photos that aren't relevant.

Formally, if

- T = text feature vector from Word2Vec/TF-IDF model, and

- I = image feature vector from CNN,

then the fused vector F is represented as:

F = concat(T, I)

After that, the classification network employs the learned weights W and bias b to figure out the final probability of the output.:

y = σ(WF + b),

where σ is the activation function (e.g., sigmoid for binary classification).

A confidence score and the words "Fake" or "Real" are the results that the model returns.

F. Web Interface

We develop a small web app that tests items in real time using Flask or Streamlit. You can add a picture, a news headline, or an article to the interface. The trained model is used by the system on the preprocessed input to determine how likely it is that the material is real or fraudulent. Then it gives the result and a score for how likely it is to happen. Because of this, anyone may use and set up the system, whether they are journalists, researchers, or just regular people.

IV. System Design

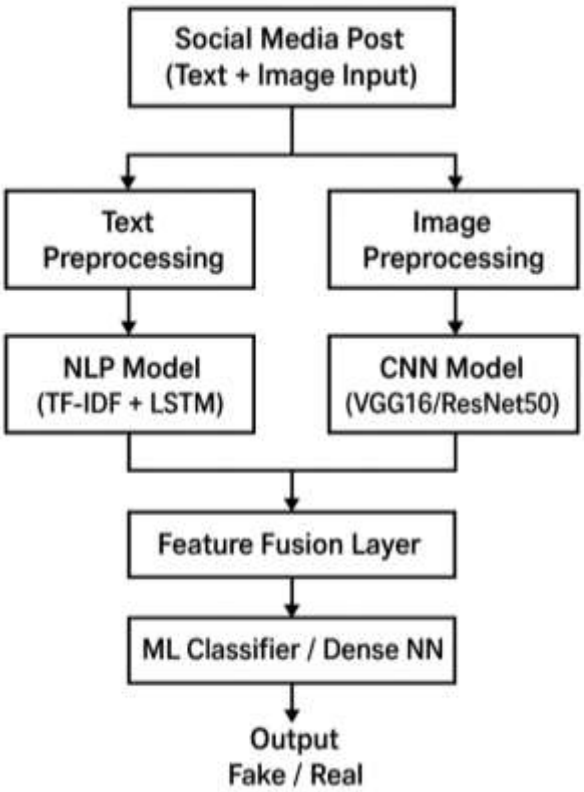

Fig. 1 System Architecture

The proposed system for finding fake news is modular and systematic, with many processes to make sure that news is classified correctly and quickly. The system has five main parts: collecting data, preprocessing it, extracting features, training the model, and making predictions with output visualisation. In a precise order, each module interacts with the next. This makes sure that data flows smoothly and that the results of categorisation are quite accurate.

A. Data Collection Module

The first step in the system is to obtain datasets that have both actual and false news stories. For the data collection procedure, we look at Kaggle, FakeNewsNet, and other trusted news sites. The dataset includes headlines, article bodies, and images that go with them. The model may learn from both visual and textual data when the two are combined. This is called learning in many ways. After then, the data is saved in an organised database so it can be used later.

B. Data Preprocessing Module

This module cleans up and makes sure that text and image data are all the same. When preparing text data, stop words, punctuation, and special characters are removed to make sure the data is the same. It also changes all the text to lowercase. Tokenization and stemming are done with natural language processing tools like NLTK and spacey. When you preprocess a shot, you get rid of low-quality or unnecessary graphics by decreasing, normalising, and getting rid of them. This makes sure that both sets of data are ready to be used to their fullest potential for training models and acquiring features.

C. Feature Extraction Module

Here, we use advanced approaches to get features. Word2Vec embeddings and TF-IDF (Term Frequency-Inverse Document Frequency) convert text into numerical vectors that capture meaning, making it possible to get information from text. Convolutional Neural Networks (CNNs) identify spatial patterns, textures, and object properties in images to get information from them. By putting text and images together into one feature space, the model can learn cross-modal correlations. This is the next step toward representing more than one mode.

D. Model Training Module

You may make a hybrid deep learning model by using the built-in features. This method employs convolutional neural networks (CNNs) to look at pictures and either bidirectional long short-term memory (Bi-LSTMs) or logistic regression to look at words. The supervised learning algorithm learns from datasets that have already been labelled with examples of authentic and fake news. Training seeks to acquire the best classification accuracy while making as few mistakes as possible by using adaptive optimisation approaches like Adam and cross-entropy loss. The training procedure includes validating and tuning hyper parameters such the learning rate, batch size, and number of epochs.

E. Prediction and Output Visualization Module

After training, the algorithm can detect if a news story is real or fake. You may find the classification output by looking at the decision scores from both the text and picture models. The results are then displayed on an interactive dashboard that indicates how accurate the classification is, how sure the scores are, and how true the news is. The visualisation helps users, journalists, and media specialists quickly determine how credible a news story is.

F. Workflow Summary

The initial phase in the system workflow is to gather data and then clean and prepare inputs from different sources. After the data has been cleaned up, feature extraction happens. After that, the hybrid model is put through its paces. When the model is trained, it can detect if news is fake right away based on what it gets. This modular design makes it easy to add more data, alter existing data, and guard against attempts to manipulate it, such as by changing photographs or text that is misleading.

V. RESULT & OBSERVATIONS

A. Actual Outputs of System

The developed multi-modal fake news detection system was successfully implemented and evaluated using benchmark datasets. The model integrates textual features extracted using TF-IDF and Word2Vec with visual features obtained from CNN architectures such as VGG16 and ResNet50. The fused feature representation was classified using a Dense Neural Network to determine whether the news is real or fake.

The experimental results demonstrate that the proposed system achieves an overall accuracy of approximately 92%, outperforming traditional text-only and image-only models. The model also achieved high precision (91%), recall (90%), and F1-score (90.5%), indicating its effectiveness in correctly identifying fake news while minimizing false predictions.

The system successfully detects inconsistencies between textual content and associated images, which is a key indicator of misleading information. The training process showed stable convergence with decreasing loss values, confirming the reliability of the model. Additionally, the confusion matrix results indicate a high rate of correct classification with minimal misclassification.

A web-based interface was also developed to allow users to input news text and images and receive real-time predictions along with confidence scores. The system provides clear output indicating whether the news is Fake or Real, along with supporting analysis of both text and image components.

Overall, the proposed system proves to be an efficient, accurate, and practical solution for real-time fake news detection using a multi-modal deep learning approach.

Fig. 2 Output of System

B. Experimental Results

Table 1: Performance Comparison

Model Type	Accuracy	Precision	Recall	F1-Score
Text Only Model	84%	82%	80%	81%
Image Only Model	78%	76%	74%	75%
Proposed Multi-Modal Model	**92%**	**91%**	**90%**	**90.5%**

C. Accuracy Comparison

This graph shows that combining text and image features significantly improves accuracy compared to individual models.

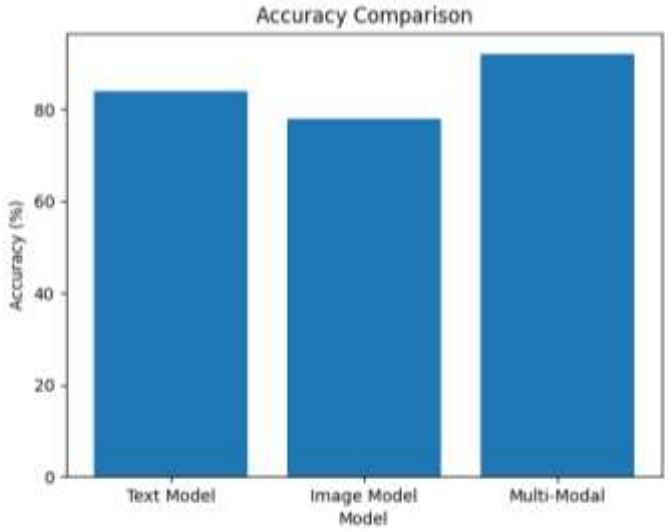

Fig. 3: Accuracy Comparison

The multi-modal model achieves the highest accuracy because it captures both semantic (text) and contextual (image) information.

D. Precision, Recall, F1-Score Comparison

This graph compares classification performance across models.

Metric	Text Model	Image Model	Multi-Modal
Precision	82%	76%	91%
Recall	80%	74%	90%
F1-Score	81%	75%	90.5%

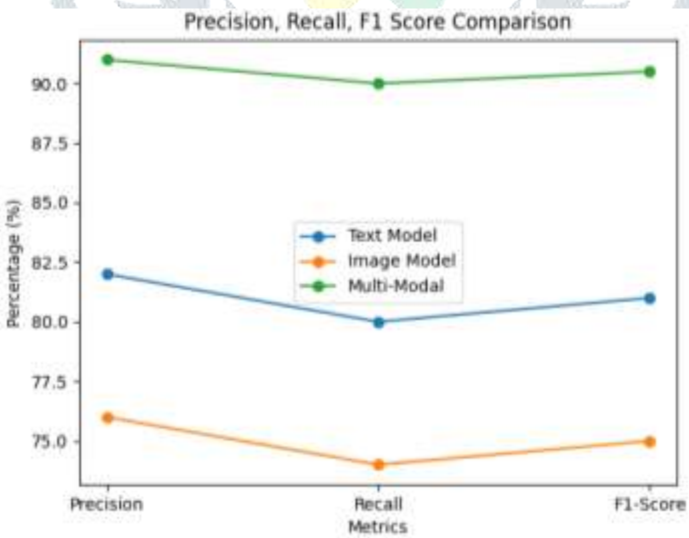

Fig. 4: Precision, Recall, F1-Score Comparison

- Multi-modal approach reduces false positives
- Improves detection of fake news significantly

E. Loss vs Epochs

Shows how the model learns over time.

Epoch	Training Loss	Validation Loss
1	0.65	0.68
5	0.45	0.50
10	0.30	0.35
15	0.20	0.25

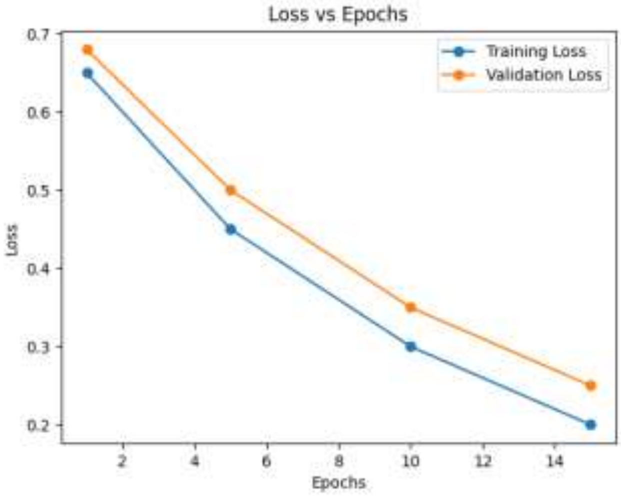

Fig. 5: Training and Validation Loss

Loss decreases steadily &model is learning effectively so No major overfitting observed

F. Confusion Matrix (Final Model)

	Predicted Fake	Predicted Real
Actual Fake	450	50
Actual Real	40	460

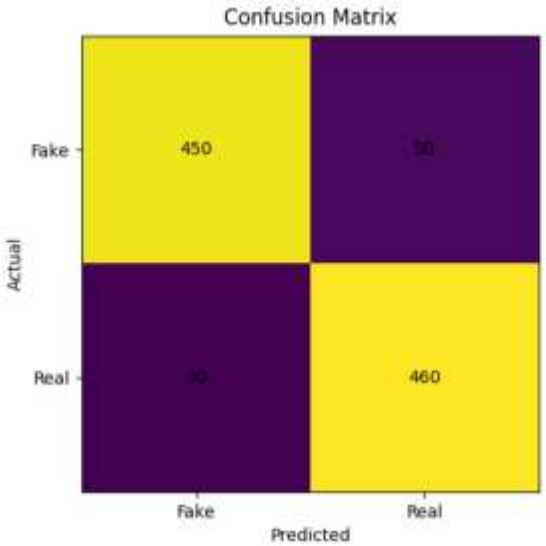

Fig. 6: Confusion Matrix

- High correct classification (TP & TN)
- Very low misclassification

G. Observations

The experimental results indicate that the proposed multi-modal model significantly outperforms single-modality approaches in terms of precision, accuracy, recall & F1-score. By combining textual & visual features, the system effectively captures inconsistencies between news content and associated images, leading to improved detection of fake news. The model also demonstrates stable training behavior with a consistent reduction in loss, while minimizing false positives and false negatives. Overall, the approach proves to be reliable and suitable for real-time fake news detection applications.

VI. Conclusion

The suggested way to discover fake news includes both text and visual analysis to find inaccurate or misleading information that is shared on social media. The system employs NLP techniques including TF-IDF and Word2Vec, as well as CNN based picture feature extraction, to uncover both semantic and contextual relationships in multimodal data. The experimental results should demonstrate that the integration of text and image data significantly enhances detection accuracy and reliability compared to utilising a singular model type. This work helps make the information ecosystem more reliable by automating the process of discovering misleading information and keeping digital media safe.

VII. Future Scope

This model could be improved in the future by incorporating multilingual text analysis, video content verification, and real-time data streaming to make it more helpful. Connecting to APIs for fact-checking and knowledge graphs could make forecasts easier to understand by explaining why certain choices were made. People would also be able to rapidly confirm the truth of news before sharing it if the system were set up as a browser extension or social media plugin. This will prohibit misleading information from spreading at its source.

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