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Original Article

A Multi Model Classifier for Fake News Detection Using Machine learning Technique

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Abstract: The proliferation of fake news poses an increasingly serious threat to information integrity in the digital age, undermining trust and distorting public discourse. As a consequence, our society becomes more vulnerable to the harmful effects of misinformation and disinformation spread across various platforms. Consequently, developing robust tools for the automatic detection of fake news is imperative to mitigate its detrimental impact. While many existing methods focus solely on textual information for detection and classification, our study introduces a novel architecture for fake news classification using a multimodal approach, integrating both text and image data. Specifically, we conducted experiments on the Fakeddit dataset, revealing that our multimodal approach, employing a Convolutional Neural Network (CNN) architecture, outperforms single-modal methods. Achieving an impressive accuracy of 90%, this approach demonstrates the efficacy of combining textual and visual cues in fake news detection. In comparison, single-modal approaches relying solely on text, such as Bidirectional Encoder Representations from Transformers (BERT), achieved an accuracy of 81%. These findings underscore the significant improvement in performance gained by leveraging both text and image data, highlighting the potential of multimodal approaches in enhancing fake news detection systems.

Keywords: BERT, deep learning, Multimodal Fake News Detection, Natural Language processing.

1. INTRODUCTION

In the digital age, combating the proliferation of fake news has become a pressing concern, posing significant threats to the credibility and authenticity of online content. The imperative to distinguish between genuine reporting and deceptive information has spurred the development of sophisticated methods for effective fake news detection. This study presents a pioneering solution to this challenge through the introduction of a multi-model classifier tailored for fake news detection, leveraging the capabilities of convolutional neural networks (CNNs). Fake news, characterized by deliberate dissemination of misinformation, disinformation, and propaganda, holds the potential to manipulate public perception, undermine trust in the media, and influence decision-making processes. Conventional approaches to fake news detection often rely on singular models, such as natural language processing or statistical methods, which may struggle to capture the nuanced and evolving nature of deceptive content. Acknowledging these shortcomings, our research adopts a multi-model approach to enhance the accuracy and resilience of fake news identification.

The incorporation of Convolutional Neural Networks marks a significant leap forward in the proposed model's capabilities. CNNs have demonstrated remarkable prowess in image recognition tasks, and their integration into text-based analysis introduces a fresh perspective for uncovering intricate patterns within textual data. By harnessing convolutional layers, the model autonomously learns hierarchical features from the input text, thereby facilitating a deeper understanding of language structures and context. The Multi-Model Classifier amalgamates the strengths of CNNs with other complementary models, creating a comprehensive system that considers various linguistic, semantic, and contextual aspects. This fusion aims to address the limitations inherent in single-model approaches, ensuring a more holistic analysis of information and consequently enhancing the classifier's proficiency in distinguishing authentic news from misinformation.

The study delves into the effectiveness of the newly proposed Multi-Model Classifier through exhaustive experimentation and evaluation. Through rigorous comparison with conventional single-model classifiers, the research aims to showcase the superior performance of the multi-model approach in bolstering accuracy in detecting fake news. These research findings offer potential contributions to the advancement of more robust tools for combating the rampant spread of misinformation in the digital realm, thus reinforcing trust and integrity in information dissemination. The study delves into the effectiveness of the newly proposed Multi-Model Classifier through exhaustive experimentation and evaluation. Through rigorous comparison with conventional single-model classifiers, the research aims to showcase the superior performance of the multi-model approach in bolstering accuracy in detecting fake news. These research findings offer potential contributions to the advancement of more robust tools for combating the rampant spread of misinformation in the digital realm, thus reinforcing trust and integrity in information dissemination.

Machine learning for fake news classification:
The field of machine learning in combating fake news entails deploying algorithms to automatically identify and categorize misleading or false information proliferating across digital platforms. By scrutinizing patterns, linguistic cues, and user interactions, machine learning models discern between credible and deceptive content. Supervised learning techniques rely on annotated datasets for training, while unsupervised methods uncover irregularities in data without explicit labeling. Advanced deep learning models, such as recurrent neural networks and transformer-based architectures, bolster detection accuracy by capturing intricate patterns within extensive datasets. Machine learning stands as a cornerstone in the battle against the dissemination of fake news, crucially contributing to upholding the authenticity and trustworthiness of information circulating online.

2. BACKGROUND AND RELATED WORK

Numerous researchers, authors, data scientists, and scholars have contributed extensively to the field of fake news detection through their publications. In this context, we delve into notable works that have significantly influenced the landscape in recent years.

In their study, Author [11] employed a web crawler along with comprehensive data preprocessing techniques, utilizing tools such as Jieba for text segmentation and Natural Language Processing (NLP) methodologies to train a computer system. Through multiple iterations of training and refinement, leveraging a substantial volume of training data, the experimental findings revealed an impressive accuracy rate of 97.43% in news classification.

The research highlighted in this paper [12] shows promise as it achieves a notable level of effectiveness in classifying large fake news documents using only one extraction feature. Moreover, ongoing efforts in further research and development are underway to identify and construct additional fake news classification frameworks. These endeavors aim to enhance the sophistication of classification schemes for both fake news and direct quotes, ultimately refining the accuracy and reliability of the classification process.

In our recent study [13], we delved into the nuanced mechanisms of natural language processing (NLP) and devised strategies for detecting fake news. Our research team meticulously examined past breakthroughs in fake news detection, conducting thorough analyses to understand the evolving landscape of dynamic fake news dissemination. We provided comprehensive explanations of the essential terminology related to diverse machine learning models, underscoring their crucial role in uncovering and combating fake news.

The objective of this research [14] is to create a robust and precise model employing machine learning (ML) algorithms and natural language processing (NLP) techniques to discern between authentic and false news articles, thereby ensuring only genuine news is disseminated to the public.

The study proposed by [15] leverages machine learning and natural language processing techniques to detect false news, particularly those originating from unreliable sources. The ISOT dataset, comprising both real and fake news gathered from diverse sources, serves as the foundation for this research. Employing web scraping methods, the text is extracted from news websites to enrich the dataset with up-to-date information. Subsequently, the data undergoes preprocessing and feature extraction procedures. Dimensionality reduction techniques are then applied, followed by classification utilizing various models including Rocchio classification, Bagging classifier, Gradient Boosting classifier, and Passive Aggressive classifier. To ascertain the most effective model in accurately predicting fake news, a comparative analysis of several algorithms is conducted. Through this comprehensive approach, the study aims to enhance the identification and mitigation of false information in the digital sphere.

3. PROPOSED MULTIMODEL APPROACH

3.1 Dataset:

In our research endeavors, we conduct extensive experiments utilizing the Fakeddit dataset [21], a comprehensive repository of posts sourced from Reddit users. This dataset encompasses a rich variety of content, including textual posts, images, comments, and accompanying metadata. The textual content comprises the titles of user-submitted posts, while the comments represent responses from other users within specific threads. With over 1 million instances, this dataset offers a substantial corpus for analysis. Notably, a significant advantage of the Fakeddit dataset lies in its capacity to support nuanced classification beyond the conventional binary categorization of news authenticity. While traditional approaches merely distinguish between true and fake news, the Fakeddit dataset introduces a novel perspective by categorizing instances into five distinct types of fake news, in addition to the category of authentic news. In the following sections, we provide a concise overview of each category:

- True: News falling into this category is verified to be accurate and factual.
- Manipulated Content: This classification applies when the content has been altered through various means, such as photo editing or manipulation.
- False Connection: Instances categorized under this label involve discrepancies between the text and accompanying images.
- Satire/Parody: News categorized here involves content where the original meaning is intentionally twisted or misrepresented in a satirical or humorous manner.
- Misleading Content: News classified as misleading contains deliberately manipulated or altered information aimed at deceiving the public.
- Imposter Content: This category encompasses news generated by bots or other automated systems, presenting fabricated or misleading information.

The Fakeddit dataset is segmented into training, validation, and test partitions. Additionally, it offers two distinct versions: the unimodal dataset, comprised solely of text instances, and the multimodal dataset, which includes both textual and visual elements. This diversification allows for comprehensive analysis and comparison across different modalities, enhancing the dataset's utility for various research and application purposes.

The complete dataset comprises a total of 682,661 news articles accompanied by images. Additionally, there are nearly 290,000 text-only articles present. Consequently, approximately 70% of the instances feature both textual content and accompanying images, while the remaining 30% consist solely of textual content. Notably, all textual content from the multimodal dataset is also included in the unimodal dataset. The distribution of classes within the unimodal dataset is detailed in Table 1, while Table 2 presents the same information for the multimodal dataset. It is evident from these tables that the distribution of classes remains consistent across both versions of the dataset, encompassing training, validation, and test splits. However, it's worth noting that both the unimodal and multimodal datasets exhibit clear class imbalances. Specifically, classes such as "true," "manipulated content," and "false connection" contain significantly more instances compared to "satire," "misleading content," and "imposter content," which are notably underrepresented. This class imbalance may pose challenges in the classification task, particularly for the less represented classes.

Table 1. Class distribution for the unimodal scenario

Class	Training	Validation	Test
TRUE	400274	42121	42326
Satire/Parody	42310	4450	4446
Misleading Content	141965	14964	14928
Imposter Content	23812	2514	2471
False Connection	167857	17810	17472
Manipulated Content	26571	2677	2838
Total	**802789**	**84536**	**8438**

Table 2. Class distribution for the multimodel scenario

Class	Training	Validation	Test
TRUE	222081	23320	23507
Satire/Parody	33481	3521	3514
Misleading Content	107221	11277	11297
Imposter Content	11784	1238	1224
False Connection	167857	17810	17472
Manipulated Content	21576	2176	2305
Total	**56400**	**59342**	**59319**

3.2 Methodology

Our approach to detecting fake news involves several methods tailored to handle the task effectively. Initially, we employ text-only unimodal techniques, utilizing two distinct models: CNN and BiLSTM, which solely rely on textual data for classification. Subsequently, we introduce our multimodal strategy, integrating both textual and visual information to enhance detection accuracy. To prepare the textual data for analysis, we undertake several preprocessing steps. This includes the removal of stop words, punctuation, digits, and excessive whitespace. Following this, we tokenize each text and apply lemmatization to standardize word forms. The lemmatized texts are then encoded into sequences of numerical values, representing each word within a predefined vocabulary. These sequences are subsequently padded or truncated to ensure uniform length, a requirement for input into deep learning models. Each text is further represented as a sequence of word embeddings, with dimensions standardized to a matrix format of 15 rows and 300 columns, where 300 signifies the dimensionality of the word embeddings utilized. This structured approach enables efficient representation and processing of textual data, facilitating robust classification performance in our fake news detection system.

3.2.1 CNN

Let's delve into the architecture of the Convolutional Neural Network (CNN) tailored for text classification, particularly in discerning fake news. As previously mentioned, the initial layer comprises an embedding layer. Here, we initialize the embedding matrix using both random initialization and pre-trained GloVe word embeddings, each boasting a dimensionality of 300. Opting for this larger dimensionality over alternatives like 50, 100, or 200 has been substantiated to yield superior results [22].

Following the embedding layer, we proceed with a convolutional layer housing four distinct filters. Conceptually, a convolutional operation involves multiplying the embedding matrix with a filter to distill the most salient features from the matrix. Each filter traverses the (15, 300) matrix, representing the embeddings of the input sequence, yielding 50 output channels. The filter sizes are delineated as (2, 300), (3, 300), (4, 300), and (5, 300) correspondingly, aligning with the standard filter sizes utilized in CNNs tailored for text classification [22].

Consequently, the outputs of the preceding filters take on shapes of (14, 1), (13, 1), (12, 1), and (11, 1) respectively. Subsequently, the next stride involves channeling the outputs garnered from the prior layer through the Rectified Linear Unit (ReLU) activation function.

3.3 Multimodal Approach

Our innovative multimodal approach utilizes a Convolutional Neural Network (CNN) designed to process both textual and visual inputs associated with a given news article. The resulting class assignment is derived from a vector of six integers generated by the model. Subsequent to discussing the preprocessing techniques employed before feeding he data into the network, we elaborate on the network's architecture, as illustrated in Figure 3.1.

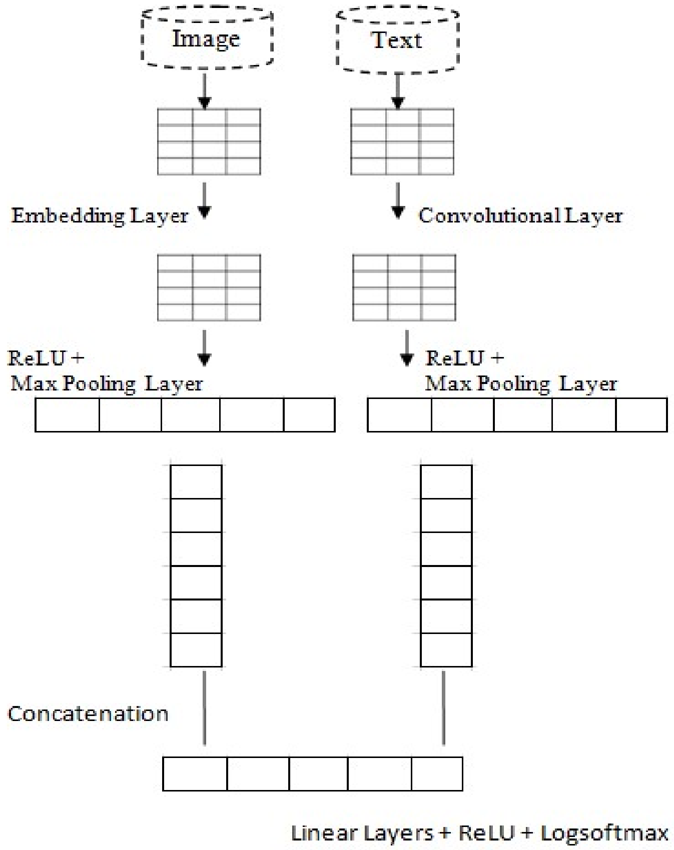

Figure 3.1 Architecture of the multimodal approach for fake news detection.

Regarding the preprocessing of the images, we simply reshaped them to ensure they all have the same dimensions (560 x 560). Once the preprocessed data is fed into the network, various operations are performed on both the texts and images. We utilize the same CNN structure employed in the unimodal scenario, with the exception that we omit the final dense layers with ReLU activation in between. Let's delve into the CNN architecture designed for image classification. The data initially passes through a convolutional layer. Given that each image consists of 3 channels, the input channels for this layer are also set to 3. Furthermore, it comprises six output channels. We utilize filters of size (5 x 5) with a stride equal to 1 and no padding. Consequently, the output for each input image comprises a set of 6 matrices with a shape of (556 x 556). Subsequently, the output of the convolutional layer undergoes a non-linear activation function (ReLU), followed by max-pooling with a filter size of (2 x 2) and a stride of 2. This process results in a set of six matrices with a shape of (278 x 278). The output from the max-pooling layer is then passed through another convolutional layer, featuring 6 input channels and 3 output channels. The filter size, stride length, and padding remain consistent with those employed in the previous convolutional layer. Once again, the ReLU non-linear activation function and max-pooling layer are applied to the feature maps generated by the convolutional layer. Consequently, for each input (image), we obtain a set of 3 feature maps with a shape of (137 x 137). Finally, these feature maps are flattened into a vector with a length of 56,307.

The text data undergoes processing using the CNN model designed for textual analysis, as previously detailed. However, instead of directly passing the output of the dense layer to the softmax layer within the CNN architecture, the output vector representing the textual content is concatenated with the vector obtained from the CNN model for images. Subsequently, this combined vector traverses through dense layers with ReLU non-linear activation functions interspersed. Finally, the logsoftmax function is applied to compute the logarithm of the probabilities, which determines the expected class of the input under consideration.

4. RESULT AND DISCUSSION

This model achieves an accuracy of 73%, with a micro F1 score of 58% and a macro F1 score of 48% (refer to Table 3.1). Notably, the classes "True" and

"Manipulated content" exhibit the highest F1 score at 81%.

Table 4.1 Results of unimodal CNN

Class	P	R	F1
TRUE	0.72	0.88	0.79
Manipulated content	0.76	0.85	0.79
False connection	0.73	0.48	0.57
Satire	0.63	0.26	0.37
Misleading content	0.73	0.55	0.61
Imposter content	0.72	0.07	0.14
micro-average	0.73	0.62	0.59
macro-average	0.71	0.45	0.49

Table 4.2. Multimodal approach results.

Class	P	R	F1
TRUE	0.87	0.89	0.88
Manipulated content	1	1	1
False connection	0.78	0.77	0.78
Satire	0.83	0.73	0.78
Misleading content	0.76	0.81	0.78
Imposter content	0.47	0.27	0.33
micro-average	0.89	0.87	0.88
macro-average	0.77	0.72	0.73

5. CONCLUSION

Advancements in the realm of fake news detection have seen the development of a multi-model classifier, utilizing machine learning techniques, marking a significant stride in the ongoing battle against misinformation. This approach integrates diverse models, leveraging various algorithms and data sources, resulting in a robust strategy that enhances the accuracy and reliability of fake news detection systems. In an era where navigating the complex landscape of digital information is increasingly challenging, sophisticated tools that can effectively differentiate between authentic and deceptive content are imperative. The effectiveness of the multi-model classifier lies not only in its capability to identify textual patterns but also in its ability to analyze diverse features such as image content, user behavior, and temporal patterns. This holistic approach is crucial in addressing the evolving tactics employed by purveyors of fake news, rendering the system more adaptive and resilient to emerging threats. Moreover, the ongoing refinement of machine learning models ensures that the classifier remains at the forefront of the dynamic fake news landscape, continuously adapting to new challenges and maintaining its efficacy in combating misinformation.

As we progress into the future, the utilization of these advanced classifiers will become increasingly vital in upholding the integrity of information ecosystems. Collaborative endeavors among researchers, technologists, and policymakers will be indispensable in continuously improving the accuracy, scalability, and ethical frameworks surrounding these systems. This collaborative approach aims to cultivate a digital landscape where trustworthy information thrives, ensuring the resilience and reliability of our digital infrastructure.

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