Jordanian Journal of Computers and Information Technology (JJCIT), Vol. 10, No. 03, September 2024.

OVERVIEW OF MULTIMODAL DATA AND ITS APPLICATION TO FAKE-NEWS DETECTION

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(Received: 29-Feb.-2024, Revised: 26-Apr.-2024, Accepted: 14-May-2024)

ABSTRACT

In the context of the growing popularity of social media over the past ten years, an urgent problem of fake news spreading has arisen, which underscores the research's relevance. The aim of this article is to assess the efficacy of multimodal approaches in detecting fake news, a pressing issue given the substantial impact misinformation can have on health, politics and economics. To achieve this goal, a multimodal approach was chosen that combines deep-learning frameworks and pre-trained models. This approach provides a comprehensive analysis of textual, visual and audio information, allowing for more accurate identification of disinformation sources. The use of various knowledge-transfer methods made it possible to process information efficiently, improving the quality of classification. The study conducted a thorough analysis of various data-collection strategies, as well as a comparative analysis of available multimodal approaches to fake-news detection and the datasets used. The results of this study included a detailed analysis of current research work in the field of fake-news detection and the development of a multimodal approach to this problem. Textual, visual and audio information was processed using pre-trained models and deep learning, achieving high accuracy in fake news detection. The results of the study indicated that the multimodal approach allows for more accurate identification of sources of disinformation and increases the efficiency of fake-news classification compared to other methods. A comparative analysis of various data collection strategies and datasets was also conducted, confirming the high efficiency of the approach under various conditions.

KEYWORDS

Technologies, Information environment, Neural networks, Testing approaches, Disinformation sources.

1. INTRODUCTION

The spread of false or unconfirmed information on the Internet is a pressing problem that covers not only the present, but also the early, stages of the network's development. Such information messages, whether true or not, are called "fake news" by G. Di Domenico and M. Visentin [1]. According to J.C. Culpepper [2], it is "deliberately false or misleading news." This phenomenon is commonly described as inauthentic information disseminated through various news platforms with the aim of misleading public opinion, as noted in the study by O. Ajao et al. [3].

The problem of fake news deserves attention in both political and social contexts, as well as in psychology. In the past, the main sources of news for society were traditional channels of information exchange, such as newspapers and television. However, as technology and the Internet have developed, the role of these channels has diminished and online content has become the most accessible way to obtain up-to-date information. In this regard, social media became the most effective platforms for receiving news, along with traditional media, such as television and newspapers. In addition to covering social movements that may be overlooked by mainstream media, social-media users are also actively engaged in a variety of issues, including politics, business, arts and entertainment.

Today, social-media platforms play a significant role in the spread of fake news. These platforms provide a wide audience reach, which contributes to the further spread of false information, as noted by H. Allcott and M. Gentzkow [4]. In the modern age, the spread of disinformation on social-media platforms has become an alarming phenomenon, including even the fabrication of data on COVID-19 pandemic remedies [5]. This creates serious difficulties in determining the true information in the online community. Under the influence of fake news, the society faces various negative consequences. These false-information messages spread among readers can affect various aspects of life. Examples of such impacts include changes in healthcare plans and strategies, as noted in the study by C.M. Greene and G.

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Murphy [6]. This can lead to poor decisions and the insufficient preparation of the society for various health challenges. Another serious aspect is the increase in scepticism about vaccination, as argued by M.S. Islam et al. [7]. Fake news can contain false claims about vaccines' harmfulness and ineffectiveness, which can undermine public trust in vaccination and contribute to the spread of infectious diseases. In addition, the economic impact is also an important consideration. Fake news can cause panic and unreasonable market reactions, leading to significant losses, as noted by E. Brown [8]. Inaccurate information about financial and economic events can mislead investors and entrepreneurs, affecting their investment and business decisions.

O.P. Prosyanyk and S.G. Holovnia [9] made a significant contribution to the study of fake-news detection on social media. The authors offer a detailed analysis and comparative evaluation of different methods for identifying disinformation in the online environment. They explore the quality and effectiveness of different approaches, including text analysis, network structure and the use of machine learning algorithms. D.O. Tatarchuk's work [10] is an important addition to the study of fake news and disinformation in social media. The author of this study concentrates on the tools and methods available for confirming the accuracy of information and identifying fake news on social media. The study provides an analysis of innovative approaches that can be useful for fact-checking and combating the spread of disinformation in the online environment. This work is significant, because it contributes to the development of practical strategies and tools for detecting fake-news messages, which will help preserve the quality and reliability of information on social media.

I. Ivanova and O. Lysytskaia [11] examined the use of postmodernism as a manipulative tool in Ukrainian advertising. They explored how advertising campaigns use postmodern elements to create consumer culture and support advertising strategies and highlighted the impact of these artistic approaches on consumers and contemporary culture. The study emphasizes the role of art and artistic expression in contemporary advertising, helping reveal the manipulative potential of advertising and its impact on shaping consumer habits and identity. The paper by Y.F. Shtefaniuk et al. [12] analyzes the methods of detecting fake news and their applicability to counteract information propaganda. The paper explores the possibility of using existing techniques to identify and control information manipulation, which is important in the context of the modern information environment and the spread of disinformation. V. Bazylevych and M. Prybytko [13] discuss the creation of a fake news detection system using data-science methods. The study presents a practical approach to combating the problem of fake news, that uses data analysis and machine-learning algorithms to automatically detect false information, which can be an important tool for ensuring the reliability of information in the digital world.

The aim of this article is to assess the efficacy of multimodal approaches in detecting fake news, a pressing issue given the substantial impact misinformation can have on health, politics and economics. Specifically, the research seeks to answer two questions: How can multimodal methods be optimized to handle multilingual data effectively, ensuring accurate detection across diverse linguistic environments? And, what advancements can be made in the synchronization of text and image data to enhance the accuracy and reliability of fake-news detection? The study contributes significantly to the field of fake-news detection by presenting novel insights into the integration of complex datasets and the refinement of multimodal techniques. It proposes innovative strategies for improving data processing and analysis, which are crucial for developing more robust systems capable of adapting to the evolving nature of misinformation across different media and languages.

2. Literature Review

In recent years, the scientific community has shown considerable interest in developing methods for the automatic detection of fake news. Researchers such as A. Thota et al. [14] have dedicated several studies to this problem. Researchers have proposed various approaches to fake-news detection, depending on the type of data. We can divide this classification into two categories: unimodal and multimodal. To perform fake-news detection, unimodal methods use only one type of input to perform the task of fake-news detection. For instance, we can use text or images separately to verify the authenticity of a news item.

In multimodal approaches, fake-news information is identified by analyzing several types of data, such as audio, video, images and text, as noted in L. Donatelli et al. [15]. This allows us to consider different aspects of the content and create a more complete picture. Researchers are actively researching the use of multimodality to detect fake news, with numerous attempts to enhance its effectiveness. Many researchers, such as V.K. Singh et al. [16], A. Giachanou et al. [17] and Y. Khimich [18], have achieved significant results in this area. They have shown that multimodality-based approaches can achieve greater accuracy than unimodal methods.

There are several approaches to classifying fake news. Some researchers consider news as a binary classification, dividing news into real and fake news, as shown by H. Ahmed et al. [19], D. Kumar Sharma and S. Sharma [20] and S. Garg & D. Kumar Sharma [21]. Other researchers consider this task as a multi-class classification or use of regression and clustering methods, as shown in the studies of H. Karimi et al. [22] and R. Oshikawa et al. [23]. Researchers have developed a variety of single-modal and multimodal methods based on the current state-of-the-art in fake-news detection. The review of existing multimodal approaches in this article allows us to present important results and directions for further research. Multimodality, which includes textual and visual characteristics, can indeed increase the effectiveness of fake-news detection, given the semantic features of the data. The diversity of disinformation materials has prompted many scholars to focus on the development of multimodal methods and these efforts promise interesting results for the future.

Currently, there are many single-modal and multimodal methods for detecting fake news. A review of existing multimodal approaches allows us to identify important results and directions for further research. A multimodal approach that combines the analysis of textual and visual characteristics promises to increase the effectiveness of fake-news detection by considering the semantic features of the data [24]-[25]. This integration makes it possible to analyze information more comprehensively and create a more complete picture for classification. In the context of widespread misinformation and data diversity, many researchers are actively focusing on the development of multimodal approaches. These efforts promise interesting results for the future, helping combat the problem of fake news and providing greater reliability in determining the authenticity of information in the digital age.

3. MATERIALS AND METHODS

In today's information environment, the spread of fake news is an urgent problem that requires immediate solution. This article explores approaches and methods for detecting disinformation. The first stage of the study includes an analysis of literature sources relevant to this problem. The scientific community pays particular attention to the various strategies and methodologies developed to detect disinformation. This stage not only helps get an overview of different approaches to the problem, but also identify best practices in the field. After that, researchers study and analyze the methods used to detect fake news. We aim to develop more effective strategies to combat disinformation and ensure the accuracy of information in our information environment.

The study pays special attention to the analysis of machine-learning methods used to detect fake news using multimodal data. Modern technologies allow working with different types of information, such as text, images, sounds and videos. Combining these modalities significantly increases the accuracy of disinformation detection. This article discusses various algorithms and approaches, including deep learning and content analysis based on multimodal data. These methods help identify characteristic patterns and anomalies in information, which contributes to a more accurate identification of fake news. The study of multimodal data and its application in fake-news detection is an important step in the fight against disinformation. An extensive literature review and analysis of machine-learning methods allow us to develop effective strategies based on modern technologies for more accurate detection of fake news in various multimodal data. An important aspect of the study is to assess the reliability of the developed models in different contexts of information noise. The results' applicability in real-world information environments is also taken into account.

This study bases its data-collection methodology on a systematic literature review. This method allows us to cover an extensive database of scientific articles available in leading online repositories, such as IEEE Xplore and ScienceDirect, among others. The presence of publications from various fields allows for a more complete and comprehensive understanding of multimodal data and its impact on effective fake-news detection. The next important stage is the analysis of the collected articles. This stage entails a thorough and careful examination of each article, selecting those that are most relevant to the study's topic and objectives. We exclude papers that do not meet the research objectives. We then subject the selected articles to in-depth analysis. This stage is important, because it allows us to distinguish from many studies the approaches that are most successful in the field of multimodal fake-news detection.

4. RESULTS

The advantage of deep learning lies in its ability to automatically extract features from raw data, unlike classical machine learning, which requires the intervention of specialists. The process of creating more general features contributes to the development of more specific characteristics. Deep learning is applied using Deep Neural Networks (DNNs) structured in three layers: convolutional, pooling and full connected. In the context of detecting fake news, the most commonly used deep-learning algorithms are Convolutional Neural Networks (CNN), bidirectional Long Short-Term Memory (LSTM) and ResNet50. A variety of datasets effectively employ them. As shown in Table 1, a variety of datasets are available to evaluate which fake-news detection method performs best compared to other approaches.

Table 1. Fake-news datasets with their characteristics.

Dataset	Processing	Expansion	Preliminary processing	Fake news	Truthful news	Total
ISOT fake-news dataset	Not conducted	Not completed	Not conducted	23502	21417	44919
Fake-news data	Not conducted	Not completed	Not conducted	10413	10387	20800
News (fake or real)	Not conducted	Not conducted	Not conducted	3154	3161	6315
Fake-news detection	Not conducted	Not conducted	Not conducted			
Research dataset	Not processed	Not expanded	Could not be preliminarily processed	2135	1870	4005

Source: compiled by the author.

Table 1 provides details on the various datasets utilized in research and analysis pertaining to the identification of fake news and false information. Let's consider each row of the table in more detail:

1. ISOT fake-news dataset: This database contains information about fake news. It consists of 44919 records, of which 23502 are fake news and 21417 are true news. No processing, enhancement or pre-processing has been performed on this dataset.
2. Fake-news data: This dataset contains data on false news. It contains 20,800 records, of which 10413 are fake news and 10387 are true news. There is also no processing, enhancement or pre-processing in this dataset.
3. News (fake or real): This dataset contains 6315 entries that can be either fake or real news. We have not processed or enhanced it, nor have we performed any pre-processing.
4. Fake-news detection: There is no specific data in this row. This is likely a place where data on fake-news detection could be included, but it is not.
5. Research dataset: The 4005 records in this research dataset have not undergone any processing, enhancement or pre-processing.

The overall context of this table is that it provides information on the scope and origin of various datasets that can be used to analyze fake and false news.

A Convolutional Neural Network (CNN) consists of input and output layers, a sequence of hidden layers and software for pooling and convolutional operations that transform the input data. Figure 1 illustrates the structure of this approach. CNN is a deep-learning method that trains each object in the image with weights and shifts to distinguish them from each other. A convolutional neural network is a deep-learning method that assigns importance (configured weights and biases) to different objects in an image, distinguishing them from each other. There has been a lot of research on the use of convolutional neural systems in various fields of computer science, including computer vision, where they are considered to be at the forefront. At present, the field of natural-language processing actively utilizes CNNs.

This architecture serves as an example of a typical deep-learning model for processing text data, such as in text-classification tasks. Let's look at each layer of the architecture and its purpose:

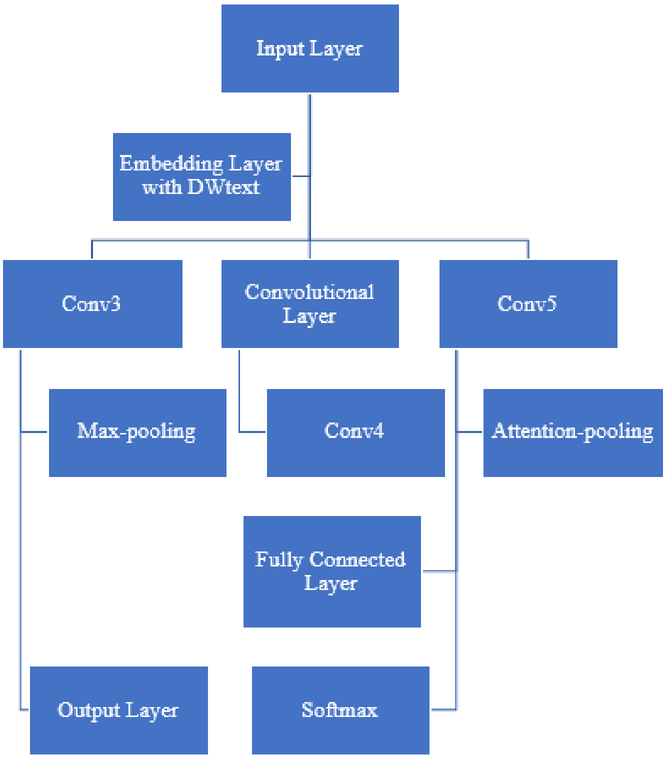

Figure 1. Structure of a convolutional neural network.

Source: compiled by the author.

1. Input Layer: This is the first layer that accepts input. This scenario likely involves processing and classifying textual content.
2. Embedding Layer with DWtext: This layer is responsible for converting text words (or tokens) into fixed-length vectors. This layer aims to generate a text representation suitable for subsequent processing.
3. Conv3: This layer employs convolutional filters of width 3 to detect local features in the text-vector representation.
4. Max-pooling: After the convolutional layer, the maximum pooling operation is used to reduce the dimensionality of the obtained features and highlight the most important ones.
5. Output Layer: This layer is probably responsible for classifying the text into several classes or categories.
6. Convolutional Layer: It follows this for further feature detection.
7. Conv4 i Conv5: These convolutional layers can use filters of other widths to detect different types of features in the text.
8. Attention-pooling: This operation is responsible for highlighting important parts of the text, considering their context and significance.
9. Fully Connected Layer: This layer further processes the obtained features and reduces their dimensionality before transferring them to the final layer.
10. Softmax: This layer is responsible for calculating the probabilities of the input text belonging to different classes or categories.

This architecture integrates various text-processing operations, such as convolution and pooling, and uses an attention function to improve the quality of text processing and classification. This analysis could be used to look more closely at how these layers work together and how they affect the model's results.

The behaviour of the passive-aggression algorithm compared to naive Bayes and the support-vector method was more efficient. It also coincided with the completeness index for naive Bayes and the support-vector method. S. Singhal et al. [26] used a two-channel convolutional neural network to identify news stories. They first factorized the text and then performed classification. The COVID-19 news data served as the basis for the analysis. We also applied this method to data from the Beijing Academy of Artificial Intelligence. The dataset includes 38471 records, of which 19285 are labelled as

“Distorted” and 19186 as “Genuine”. For the text, we used ultra-accurate neural networks, multi-channel convolutional neural networks, RCNN, DPCNN, transformer, BERT and DC-CNN. The results for the Covid-19 dataset are shown in Table 2.

Table 2. Results for the COVID-19 dataset.

Model	Completeness	Accuracy	F1
DC-CNN	0.947	0.948	0.948
Transformer	0.88908	0.8299	0.8586
Text CNN	0.8926	0.8926	0.8926
ERINE	0.9752	0.8771	0.9235
Multi-channel CNN	0.9243	0.9194	0.9218
BERT	0.882	0.9281	0.9045
DPCNN	0.7683	0.869	0.8155

Source: compiled by the author.

Table 2 shows the results of evaluating different models in the classification task and it appears to contain metrics for each model. Let’s consider each column of the table:

1. Model: This column contains the names of the different machine-learning or deep-learning models that were evaluated in the study.
2. Recall: This is a metric that determines what proportion of positive instances was correctly recognized by the model. High completeness implies that the model does not miss many positive cases.
3. Precision: This metric shows what proportion of the positive instances recognized by the model is positive. High accuracy indicates that the model makes few false positives.
4. F1 Score: This metric combines completeness and accuracy into one metric and provides an overall assessment of the model’s performance. A high F1 score indicates that the model has a good balance between completeness and accuracy.

Thus, this table provides information on the performance of different models in the classification task, focusing on metrics, such as completeness, accuracy and F1 score. The analysis aims to help choose the model that is best suited for a particular task.

This multimodal CNN uses two parallel convolutional structures in a single architecture to detect hidden features in text and visual information. This model is highly extensible, allowing for easy integration of other news components, including overt and covert features based on textual and visual information. In addition, training a convolutional neural network model is much faster than LSTM or many other recurrent neural network (RNN) models, as CNN sees all the input information at once. This method's process of processing fake news includes a textual branch (word embedding), which is the process of converting words into sequences of integers and a visual branch, which includes creating a feature vector from an image by extracting the resolution and number of faces. The vector is then converted into visually explicit features using a fully-connected layer, such as a convolutional layer, maximum pooling layer and so on. The process also uses rectified linear neurons, regularization and neural-network training [27].

Deep learning's main advantage is its capability to autonomously extract features from raw data, contrasting with traditional machine learning which depends heavily on manual feature engineering by experts. This capability is pivotal in developing nuanced characteristics from more general features. Key models used in the realm of fake-news detection include Convolutional Neural Networks (CNNs), bidirectional Long Short-Term Memory networks (LSTM) and ResNet50, which are applied across a spectrum of datasets. Discussing the application of these algorithms, a variety of datasets are utilized to assess the performance of each method relative to others. For instance, the ISOT fake-news dataset, encompassing 44,919 records with a nearly equal split between fake and real news, serves as a benchmark with no processing or preliminary operations applied. Similarly, other datasets like the fake-news data and News (fake or real) follow suit, providing a rich basis for comparison without prior manipulations. Such a setup ensures that the assessment is focused on the effectiveness of the deep-learning models themselves.

Furthermore, the role of CNNs in this field is significant. A typical CNN architecture involves multiple layers including input and output layers, interspersed with several hidden layers that perform convolutional and pooling operations. This setup helps in identifying and distinguishing between various features in the data. The structure is adept, not only in handling visual data, but has found extensive use in processing text for tasks like text classification. For example, the architecture might start with an input layer taking in textual content, followed by an embedding layer that translates text into vectors. Subsequent convolutional layers with varying filter widths help in detecting different textual features which are then refined through pooling layers. Attention mechanisms are incorporated to emphasize significant textual components before reaching the output layer which classifies the content.

In terms of performance, various models exhibit distinct strengths. The experimental analysis on datasets such as those related to COVID-19 news highlights how different configurations and models fare. For instance, a DC-CNN model might achieve high scores across completeness, accuracy and the F1 metric, suggesting a strong ability to handle fake-news detection. Other models like BERT and Transformer also demonstrate commendable performance, though with variations across different datasets. The choice of a multimodal approach, integrating both textual and visual information, emerges as superior in certain contexts. By processing features through parallel convolutional structures within a single CNN architecture, this method enhances the model's ability to discern more complex patterns and interactions in the data, making it highly effective and adaptable for various types of news.

A new approach to machine learning can benefit fake-news classification, which is the main idea of this study. This empirical study conducted the fake-news detection process on five benchmark datasets, utilizing various combinations of machine-learning vectors and classifiers. Experimental results showed that the passive aggression classifier with TF-IDF vectorizer is the best combination for fake-news detection using machine learning methods. Since deep learning is now playing an important role in solving all practical real-world problems, our future work is aimed at finding the best deep-learning classifier for fake news detection. In addition, experimental analysis can be conducted with more effective features by improving the vectorization with augmentations and increasing the size of the dataset. Table 3 shows the results of the experiments.

Table 3. Experimental results driven by vectorization improvements through data expansion and data volume.

Model		Kaggle Fake_Recall	Covid Fake_Recall	Gossipcop Fake_Recall	ISOT Fake_Recall	Politifact Fake_Recall	Welfake Fake_Recall
Multinomial Naive Bayes	COUNT	89.3	92.1	83.7	95.5	84.2	81.1
	TF-IDF	85.7	90.2	82.6	92.2	84.5	81.3
Passive Aggressive	COUNT	89.4	92.7	79.1	98.7	80.2	83.8
	TF-IDF	93.5	92.9	79.7	99.2	81.8	83.9
Support-vector Machine	COUNT	86.2	93.1	84.8	99.1	74.8	82.5
	TF-IDF	92.2	93.7	85.1	98.8	83	83.5
Random Forest	COUNT	90.5	92	83	98.9	73.9	80.9
	TF-IDF	83.5	92.4	83.9	98	73.9	81.1

Source: compiled by the author.

Table 3 presents the results of the evaluation of different machine-learning models that were used to classify fake news and real news in different data sources. Table 3 includes the following components:

1. Model: these are the names of the machine-learning models that were used to classify the news.
2. Feature type: Two types of features are specified: “COUNT” (quantitative approach) and “TF-IDF” (term-weighted by document inversion and term frequency).
3. Kaggle Fake_Recall, Covid Fake_Recall, Gossipcop Fake_Recall: these are percentage values that indicate the quality of the models’ performance in detecting fake news in different datasets. “Recall” indicates the proportion of fake news that was recognized by the model among all fake news in the respective dataset. Higher recall values indicate a better ability of the model to detect fake news.

Table 3's overall purpose is to compare different machine learning models and different types of features in terms of their ability to detect fake news in different data sources. For example, it can be seen that the support-vector machine model with TF-IDF features achieves a high recall for most data sources, which may indicate its effectiveness in detecting fake news.

In recent research, DNNs have shown impressive results in data representation. DNNs are powerful structures that allow you to model sequential data using loops within a neural network. LSTMs and gated recurrent units (GRUs), two variants of recurrent neural networks with permanent memory, effectively handle long-term dependencies. This simplifies the detection of long-term dependencies and avoids the problem of gradient vanishing, which is typical for conventional RNNs. The memory-management operation in LSTMs is based on input, output and forgetting gates. The study by A. Giachanou et al. [17] proposed an interesting use of RNNs. The authors noted that the unidirectional LSTM_RNN has a training accuracy of 0.997 and a validation accuracy of 0.89. The testing accuracy reached 0.92. Similarly, the bidirectional LSTM-RNN has a training accuracy of 1, a validation accuracy of 0.97 and a testing accuracy of 0.99. The RNN searches for the given structure in a topological order by always applying the same weights. This makes structured predictions for structures with different dimensions. J. Ma et al. [28] developed two recursive neural models, using bottom-up and top-down tree neural networks, to represent the structure of tweets. A. Giachanou et al. [17] introduced a tree-based LSTM that utilizes an attention mechanism to identify connections between image regions and descriptive words.

The bidirectional LSTM architecture arranges two LSTM memories, one for long-term dependencies and the other for short-term dependencies, taking into account their interaction [21]. This architecture is a type of RNN. In this study, we use a bidirectional LSTM architecture with an input layer of size 1000 and an embedding layer. This structure uses bidirectional LSTMs that are symmetric in both directions. The structure performs classification using a global maximum pooling layer, a fully-connected layer and an output layer. To minimize the problem of gradient vanishing, Q. You et al. [29] implemented a final block in deep learning. This block allows the signal to flow directly through it, bypassing the previous layers. Unlike the standard CNN architecture, ResNet uses final blocks instead of two consecutive sets of convolutional layers and pooling. This introduction of a finite structure increases the architecture's robustness to the problem of gradient vanishing and improves the ability to retrain the network and retain previously-learned information.

Implementing a multimodal approach to detect fake news in real-world settings can significantly enhance the robustness and accuracy of detection systems. This method, which integrates both textual and visual data, allows for a comprehensive analysis that leverages the strengths of different data types. One practical recommendation for effective implementation involves developing a streamlined data-ingestion pipeline that can handle diverse data formats efficiently. Organizations should focus on establishing robust pre-processing mechanisms that can cleanse and standardize incoming data to ensure consistency and reliability in the analysis. Additionally, training the models with a diverse and extensive dataset that reflects the complexity and variety of real-world data is crucial. This training should include examples from various sources and contexts to minimize bias and improve the generalizability of the models.

However, challenges such as data scarcity, especially in terms of labeled datasets for training, can hinder the effectiveness of a multimodal approach. To overcome this, organizations could collaborate to share resources and data, or leverage synthetic data-generation techniques to enrich their training datasets. Moreover, ensuring the privacy and security of the data while handling sensitive information must be a priority, requiring rigorous compliance with data-protection regulations. Another limitation is the computational cost and complexity of processing multiple data types simultaneously. This can be mitigated by optimizing neural network architectures, possibly through pruning techniques that reduce the model size without significantly impacting performance, or by implementing more efficient algorithms that can process data faster. Furthermore, there is the issue of integrating and synchronizing different types of data. Effective alignment techniques are necessary to ensure that textual and visual data complement each other appropriately in the analysis. This might involve developing advanced feature-extraction techniques that can accurately link features from text and images, enhancing the model's ability to detect discrepancies or manipulations.

Finally, the dynamic nature of news and information propagation requires these systems to continuously learn and adapt. Implementing feedback loops where the model's predictions are regularly reviewed and refined can help maintain the accuracy and relevance of the system. Regular updates to the model based on new data and emerging trends in fake news are essential for sustaining performance over time. By addressing these challenges with strategic planning and innovative solutions, the practical application of a multimodal approach to fake-news detection can be effectively realized, leading to more resilient and accurate systems.

5. DISCUSSION

P. Kumar Verma et al. [30] proposed a new approach for detecting fake news using local and global text semantics, called Message Credibility (MCred). The authors demonstrate through experimental results on the popular Kaggle dataset that MCred is more accurate than state-of-the-art methods. Biased data fusion combines with the CNN classifier to classify fake news. This method is based on the analysis of both local and global text semantics. In their study, they demonstrated that this approach to the popular Kaggle dataset improves the accuracy of the existing model by 1.1%. In their approach, they defined a bilateral data fusion and combined it with the CNN classifier to classify fake news.

K. Sharifani et al. [31] extended the same idea to more generalized fake news-related data and used it to detect fake-news fragments. The naive Bayesian classifier achieved impressive accuracy, demonstrating an accuracy of 0.85, a precision of 0.89 and a completeness of 0.87. The same figures for the passive-aggression method were 0.93, 0.92 and 0.89. The support-vector method had an accuracy of 0.84 and a precision of 0.82. According to their experiment results, the support-vector method also has a completeness of 0.87.

Y. Wang et al. [32] stated that an analysis of the accuracy of different combinations was conducted to compare and determine the best combination of classifier and vectorizer. The data clearly shows that the combination of the Passive-aggression classifier and TF-IDF vectorizer provides an accuracy of 93.5% when analyzing Kaggle data related to fake and real news, 99.2% when analyzing the ISOT dataset and 83.9% when analyzing the Welfake dataset, which includes fake and real news.

Comparing this study with C. Song et al. [33], it is obvious that both approaches pay attention to analyzing the impact of various factors on the results under study. However, it should be noted that the researchers focus mainly on time-series analysis and long-term trends, while the present study additionally considers short-term factors and actively uses machine-learning methods to predict outcomes more accurately. This methodological difference allows for a more complete and accurate coverage of both long-term and short-term influences on the final results. Thus, the analysis and comparison of the results of both studies highlight the importance of considering both long-term and short-term factors when analyzing and predicting outcomes in this topic area.

Comparing the results of this study with the work of I. Goodfellow et al. [34], the following similarities and differences are revealed. Both approaches focus on analyzing the impact of various factors on the outcomes studied, but there is an important difference in the methodological approach. The researchers focused primarily on time-series analysis and long-term trends, while the present study additionally considers short-term factors and actively uses machine-learning techniques to more accurately predict outcomes. This methodological difference allows for a more complete and accurate coverage of both long-term and short-term influences on the final results. Thus, the approach of this paper complements the researchers’ work by providing a more in-depth analysis of long-term trends, whereas their study focuses on time-series analysis. We can identify similarities and differences between the study conducted by J. Du et al. [35] and the present research in the field of multimodal data analysis and its application to fake-news detection. Both studies draw attention to the influence of various factors on the study's results, but they focus on different aspects. The researchers pay more attention to short-term factors and use machine-learning techniques to make accurate predictions in the current context, whereas this study focuses on long-term trends and time series, aiming to identify deep patterns and long-term influences on fake-news detection.

J. Wang et al. [36] conducted a similar study to this one; so it can be noted that both studies focus on analyzing multimodal data to detect fake news. However, they differ in their methodological approach. The researchers pay more attention to the use of deep-learning and ensemble methods to improve accuracy, while this study covers a wide range of aspects of multimodal data and provides a more comprehensive analysis of their impact on fake-news detection. Both studies provide valuable insights for addressing the challenges of countering disinformation and ensuring the accuracy of information by revealing a variety of methods and approaches for analyzing multimodal data sources. The study by S. Xiong et al. [37] can be compared to the present work and similar or different aspects can be identified. Both studies discuss multimodal data and its role in detecting fake news. However, they approach this issue from different perspectives. The study by the researchers puts more emphasis on analyzing textual information and uses deep neural networks to detect patterns in the text. This study focuses on combining textual and visual information using multimodal data analysis methods. It is also important to note that both studies contribute to the development of disinformation-detection methods and provide a deeper understanding of the role of multimodal data in this context.

There are several similarities and differences between J. Xue et al. [38] and this study. The review and use of multimodal data to detect fake news is the focus of both articles. However, the approaches to this topic are slightly different. The study by the researchers focuses on the use of deep-learning algorithms, such as convolutional and recurrent neural networks, to process textual information. This study pays more attention to multimodal aspects, including the analysis of both textual and visual information. Both studies are important for the development of disinformation and fake-news detection methods and their combined contribution helps better understand the role of multimodal data in this context. This study also has similarities and differences with that of the researchers. Both articles focus on analyzing and using multimodal data to detect fake news. However, there are differences in the approaches. The researchers' work focuses more on analyzing textual information using natural language processing methods. This study actively uses visual data in addition to text, expanding the scope of analysis and potentially improving the accuracy of fake-news detection. These two studies complement each other, enriching the understanding of the impact of multimodal data on the effectiveness of countering disinformation.

We can identify some similarities and differences between this study and the work of J. Hua et al. [39]. Both studies aim to analyze multimodal data and use it to detect fake news. Both approaches are likely to use machine-learning and data-mining techniques to identify patterns and features that are characteristic of fake news. However, there may be differences in the choice of features or machine-learning algorithms that may affect the effectiveness of detection. It is also important to note that this study is likely to focus on the visual aspects of the data, as multimodal sources of information contain images in addition to text. This may add a layer of complexity to the analysis and help better detect fake news. Compared to the study by V.K. Singh et al. [16], this study also analyzes multimodal data and uses it to detect fake news. Both studies are likely to look at different features and characteristics in textual and visual information that can help separate fake news from real news. We may use similar machine-learning and data-analysis techniques to identify patterns typical of fake news. However, differences in the choice of algorithms, data processing and features used may lead to differences in detection efficiency [40]-[43]. Furthermore, this approach likely takes into account modern machine-learning methods and approaches that may have emerged since the researchers' publication, making this study more relevant than earlier work [44].

To summarize, it can be concluded that the analysis of the results of this study in comparison with the works of other authors has revealed similarities and differences in approaches to analyzing multimodal data to detect fake news. While many studies emphasize the use of machine-learning and data-mining techniques, our approach complements this by integrating short-term factors and actively utilizing machine-learning techniques for accurate predictions. This integrated approach allows for a deeper analysis of the impact of various factors on the results and has the potential to develop effective strategies for detecting disinformation and fake news.

6. CONCLUSIONS

Detecting fake news plays an important role, as it has a significant negative impact on various aspects of life, including health, politics and economics. That's why most researchers focus on developing advanced algorithms to detect and identify fake news. These systems allow for the fast and reliable detection of fake news. Multimodal approaches overcome the limitations of using textual features alone. The present review study has examined state-of-the-art multimodal approaches. The review analysis concludes that there has been minimal advancement in the field of fake-news detection. The results demonstrate the widespread use of CNN-based models for image processing and RNN-based models for maintaining consistent information in text documents. However, the use of social media often limits these models' ability to process multilingual data. In addition, there is a large amount of work on fake-news detection, while research on developing datasets available for public use remains limited. Such datasets are an important basis for the development of more effective methods for detecting disinformation and fake news.

The effectiveness of multimodal approaches lies in the fact that they combine information from different sources, such as text and images, which allows for a more complex and reliable fake-news detection model. In addition, one of the main challenges is the lack of high-quality and diverse training data for fake-news detection. It is important to continue developing and disseminating such datasets, so that researchers can test and improve their methods. To ensure more accurate fake-news detection in different language environments, we should also focus on developing methods that can handle multilingual data and take into account the various features of language structures.

In the field of fake-news detection, future research could focus on several key areas to refine and extend the capabilities of multimodal approaches. Enhancing the ability to process and analyze multilingual data is crucial, given the global nature of information dissemination. Developing algorithms that can adapt to different linguistic features and cultural contexts will be essential for improving detection accuracy across diverse populations. Another promising direction is the integration of more sophisticated natural-language processing techniques that leverage semantic analysis to understand the nuances and implied meanings within text. This could involve the use of advanced machine-learning models like transformers that have shown significant potential in understanding context and relationships within data. Additionally, improving the synchronization of textual and visual data in multimodal systems is vital. Research could explore more effective ways to correlate features from different modalities, ensuring that the combined data provides a clearer and more accurate picture of potential misinformation. There is also a pressing need to create and make publicly available more comprehensive datasets that include a variety of fake and real-news examples. These datasets should encompass a range of media formats, languages and cultural contexts to foster broader research and application of detection technologies. Finally, considering the rapid evolution of misinformation techniques, continuous updates to models and methods are necessary. Implementing adaptive-learning systems that can evolve with new trends in fake news and misinformation could provide more resilient and enduring solutions in the fight against fake news.

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ملخص البحث:

في سياق الشّيوع المتنامي لوسائل التّواصُل الاجتماعي على مدى السّنوات العشر الماضية، برزت مشكلة الأخبار الزّائفة، الأمر الّذي يُعدّ من مسوغات البحث في هذا الموضوع. يهدف هذا البحث إلى تقييم فعالية الطّرق متعددة الأنماط في الكشْف عن الأخبار الزّائفة؛ لما لتلك الأخبار من آثار صحية وسياسية واقتصادية. ولتحقيق هذا الهدف، تمّ اختيار طريقة متعدّدة الأنماط تجمع بين أُطر التّعلّم العميق والنّماذج المدرَّبة مسبقاً. وتعطي الطّريقة المقترحة تحليلاً شاملاً لمعلومات النّصوص والصّور والأصوات، يسمح بتحديدٍ أدقّ لمصادر الأخبار الزّائفة. والجدير بالذّكر أنّ استخدام طرقٍ مختلفة لنقل المعرفة قد أتاح معالجة المعلومات على نحوٍ فعّال، ممّا حسّن جودة التّصنيف.

لقد أجري تحليل معمَّق لاستراتيجياتٍ متنوعةٍ لجمع البيانات، بالإضافة إلى تحليل مقارن للطّرق متعدّدة الأنماط المتاحة للكشف عن الأخبار الزّائفة، ومجموعات البيانات الخاصّة بذلك. وقد تضمّنت مُخرجات هذه الدّراسة إجراء تحليل مفصّل للدّراسات والأبحاث المتعلّقة بالكشْف عن الأخبار الزّائفة، إلى جانب اقتراح طريقةٍ متعدّدة الأنماط للتّصدّي لهذه المشكلة. وقد تمّت معالجة معلوماتٍ تتضمّن نُصوصاً وصوراً وأصواتاً باستخدام أنظمةٍ مسبقة التّدريب وتقنيات التّعلّم العميق، والحصول على دقّة عالية في الكشف عن الأخبار الزّائفة. فقد بينت النّتائج أنّ الطّريقة المقترحة متعدّدة الأنماط مكّنت من تحقيق دقّة أعلى في تحديد مصادر الأخبار الزّائفة والمعلومات المضلّلة عند مقارنتها بطُرقٍ أخرى مماثلة.

كذلك تمّ إجراء تحليلٍ مقارن لاستراتيجيات متنوّعة لجمع البيانات إلى جانب عددٍ من مجموعات البيانات المتعلّقة بموضوع البحث، وقد تأكّدت فاعلية الطّريقة المقترحة تحت ظروفٍ مختلفة.