Fake News Detection on social media: Survey

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Abstract

It is difficult to distinguish between fake and real information on social media networks due to the ease of access and information's exponential expansion. The rapid expansion of information fraud has been facilitated by the simple distribution of knowledge through sharing. Where the spread of false information is widespread, the credibility of social media networks is also at risk. Therefore, it has become a research problem to automatically identify information as accurate or false based on its source, substance, and publisher. Despite its limits, machine learning has been crucial in the classification of data. This research examines various machine learning techniques for the identification of fake news and the existing approaches and the new methods proposed by researchers have been summarized.

1. Introduction

Social media networks like Twitter, Instagram, and LinkedIn become very popular in the world. Social media is now a day a main source of news spreading. The number of users of social media increases and the consumers of news on social media also increases. Many time the news published by the users are misleading the news consumers. Usually, they are spreading Fake news in the form of text, videos, and pictures. As the number of users increases the spread of misleading and inaccurate news also increases. News posted by users on social media spread quickly and goes viral. Detecting fake news on social media is difficult as fake news is written to mislead the user. It makes it difficult to distinguish fake news from accurate news. Many methods have been proposed to detect Fake news on social media.

Fake news has become a significant problem on social media platforms, spreading misinformation and causing social unrest. The extensive broadcast of false information can harm people, businesses, and even entire communities. It is difficult to identify fake news on social media because it necessitates the analysis of vast amounts of unstructured data, such as text, photos, and videos. The problem of detecting fake news on social media, therefore, requires the development of effective algorithms and techniques that can accurately detect and differentiate fake news from legitimate news. These algorithms should be able to analyze and interpret different types of media, including text, images, and videos, and use advanced techniques, such as natural language processing and machine learning, to detect patterns and inconsistencies that indicate fake news.

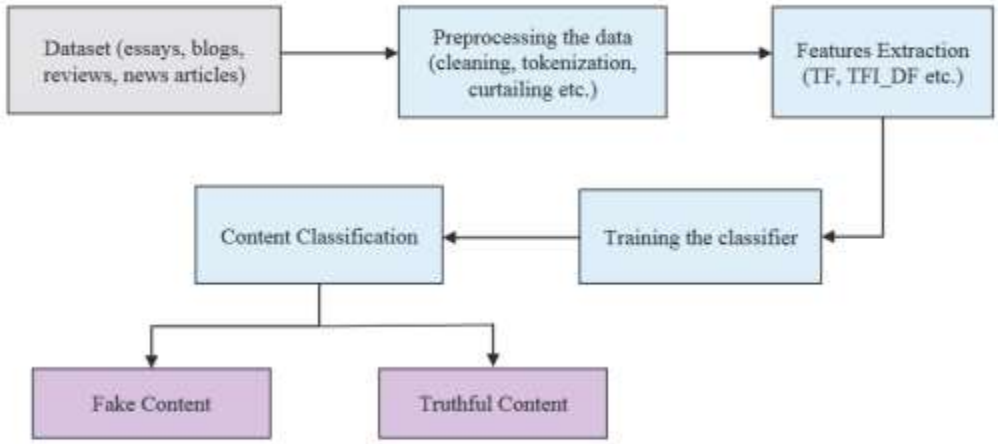

Figure 1 Fundamental Fake News Model [1]

[2] The survey highlights the effectiveness of deep learning models, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), in detecting fake news. However, the authors note that the interpretability of deep learning models remains a challenge in this field.[3] The review identified a variety of features that were used in the ML models, including lexical, semantic, syntactic, and metadata features. It was found that combining multiple types of features improved the accuracy of the models. Another important finding was that the use of neural networks, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), was effective for fake news detection.[4] The review also identified several features that have been used in these models, including lexical, semantic, and syntactic features. Additionally, the use of metadata features, such as the source of the news and the time of publication, has been shown to improve the accuracy of the models. [5] The review highlighted the importance of having large and diverse datasets for training deep learning models. the review also noted that the use of transfer learning, where a pre-trained model is fine-tuned for fake news detection, has been effective in improving model performance. In addition, the use of ensemble models, which combine multiple models, has been shown to improve the accuracy and robustness of the models.

Table 1 Summary of Survey of Fake News Detection

Year	The main focus of the survey	Major contribution	Enhancement
2019	Survey of Fake News Detection on social media	[2] review the various techniques used for fake news detection. The authors evaluate the strengths and weaknesses of each technique.	The survey provides a thorough critical examination and identifies any holes in all current strategies.

2019	Fake news detection using Machine Learning approaches	[3]review various machine learning-based approaches for fake news detection, including supervised, unsupervised, and deep learning methods. The authors provide a detailed analysis of the different techniques used in each approach, such as feature extraction, feature selection, and classification algorithms. The advantages and disadvantages are also described by the author.	The survey provides a thorough critical examination and identifies any holes in all current strategies.
2020	Recent State-of-the-art of Fake News Detection: A Review	[4] explores recent advancements in machine learning and natural language processing (NLP) techniques for fake news detection. Also, the importance of incorporating external features and data sources in fake news detection.	The survey provides a thorough critical examination and identifies any holes in all current strategies.
2020	Review of fake news detection using deep learning	[5]The author presented the challenges and limitations of deep learning-based approaches, including the lack of large-scale labeled datasets, the computational cost of deep learning models, and the difficulty in interpreting model results.	The survey provides a thorough critical examination and identifies any holes in all current strategies.

Table 1 shows the gaps in the previous survey which has been conducted. To contribute to the field and fill in the gaps in the current surveys, we have created this thorough literature review. Modern techniques and the most recent methodologies for false news identification are presented in this article.

Social media usage has been growing every day. Numerous studies that offer a thorough understanding of various Machine learning and Deep learning methodologies have been carried out. This SLR seeks to locate research holes in the area of fake news detection. The research articles from the previous four years were used to identify research gaps. All strings that had three synonyms were looked up. The articles were then eliminated using the title and abstraction criteria. Using predetermined goals as a guide, every technique was carefully examined. This publication offers a thorough critical review of the practices now in use. This SLR gives a thorough performance analysis of all Fake News Detection methods after a comprehensive examination of every methodology. This is followed by a section outlining the difficulties that were found. This SLR concludes that numerous researchers have offered various strategies based on various goals. Based on detection precision, performance, efficacy, and generalizability, several approaches are assessed. The paper's organization is shown in Figure 1.

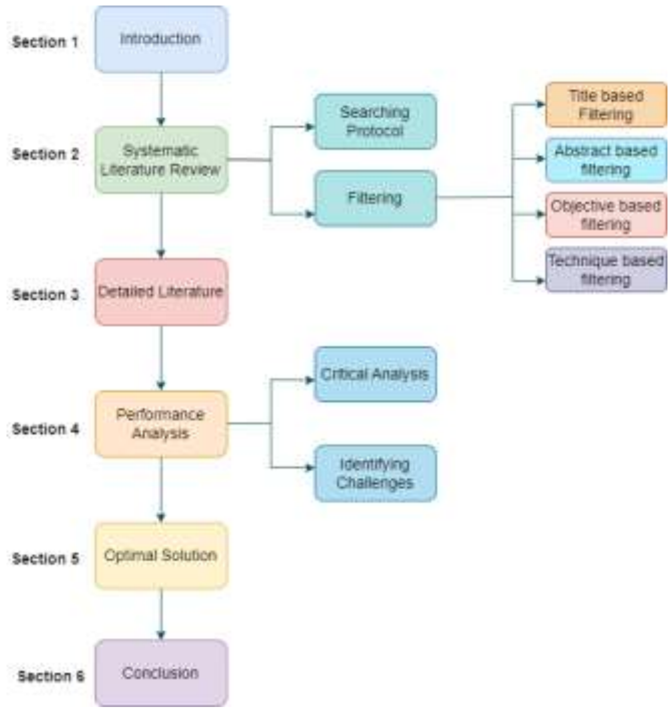

Figure 2 Paper Organization

The main contribution of work is

- To examine the issues with modern methods for detecting fake news, a thorough review is conducted.
- It provides a detailed review of Machine learning, Deep learning, and ensemble approaches.
- It provides a review of open research challenges and gaps in the scheme that were previously used for Fake news detection.

Figure 2 shows the organization of the paper i.e., organized in a way that Section 1 describes the introduction of the problem, and Section 2 is a literature review in which we describe the string development and searching strategy. in the searching strategy, we take 4 databases i.e. (ACM, IEEE, Arxiv, and Springer) and search with the year (2020,2021,2022,2023), the paper selected from this database and year are then applied Title-based filtering, abstract-based filtering, objective-based filtering, and technique-based filtering.in Section 3 we describe the detailed literature, Section 4 describes the Performance analysis and Section 5 the Optimal Solution, and Section 6 describes the Conclusion.

2. Systematic Literature Review

Data and findings from other authors are analyzed regarding one or more predetermined study subjects and are included in the systematic literature review. A comprehensive literature review is one of the research strategies that can be used to achieve this. Before the review is started, the criteria should be clearly outlined, and the systematic review should follow a well-defined method. A search methodology was first developed, and then systematic searches were conducted using it. These searchers followed strings that were generated following the chosen research subject. Following that, a search method was used to categorize each of the searches.

2.1 String Development

The string was developed by using three synonymous for each word. Following are the strings created using synonymous

Table 2 Synonymous strings

Word	Synonym 1	Synonym 2	Synonym 3	Synonym 4
Fake	False	Rumor	Bogus	Inauthentic
False news detection on social media				
Rumor news detection on social media				
Bogus detection on social media				
Inauthentic news detection on social media				

Table 3 Synonymous strings

Word	Synonym 1	Synonym 2	Synonym 3
Detection	Identification	Recognition	Observation
Identification of fake news on social media			
Recognition of fake news on social media			
Observation of fake news on social media			

2.2 Searching strategy

A search strategy is designed so that the research paper from the year (2020,2021,2022 and 2023) were selected for search. The four databases (IEEE, ACM, Arxiv, and Springer) were used for searching, and the string with 3 was synonymous with the original query. Figure 1 presents the search strategies. The strings were created using research questions and 55 paper was selected from the IEEE database, 24 papers were selected from ACM, 27 papers from Arxiv, and 21 papers from Springer.

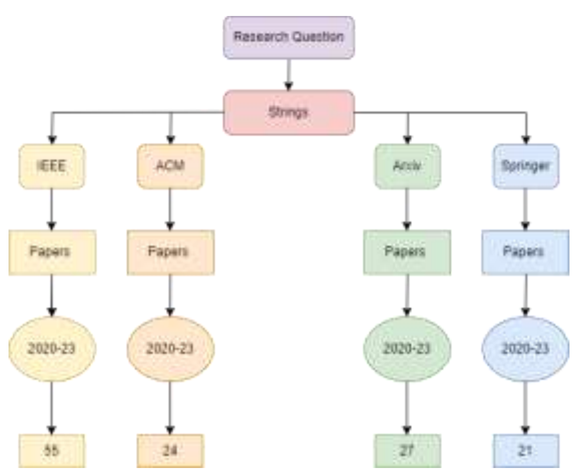

Figure 3 Searching strategy

2.2.1 Title-based Filtering

Title-based filtering is the initial step in the filtering process. All papers that did not address the problem at issue were excluded.

2.2.2 Abstract-Based Filtering

The second phase is Abstract Based Filtering, which involves excluding papers entirely on their abstracts. The papers that had no bearing on the issue were all excluded.

2.2.3 Objective-Based Filtering

The third step is objective-based filtering i.e., all the papers were filtered according to their objectives.

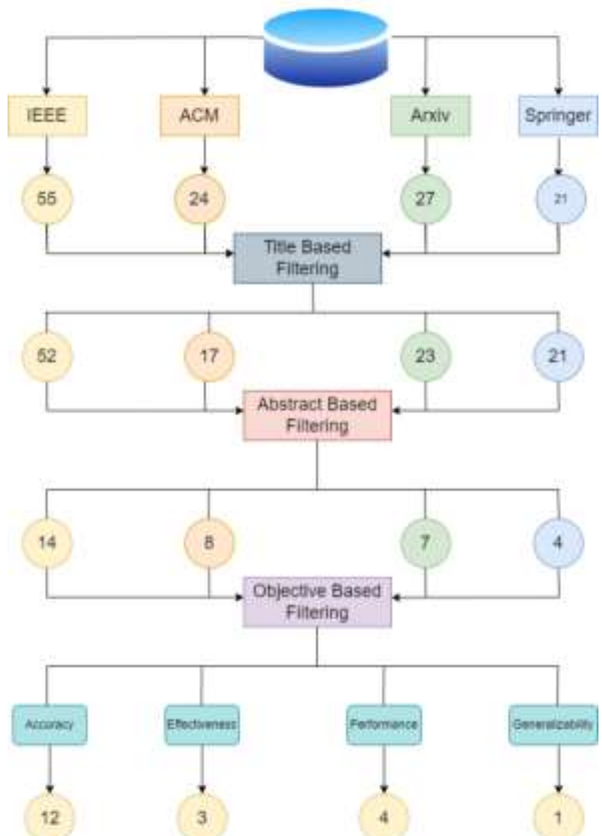

Figure 4 Objective-Based Filtering

A table was created showing papers organized by their objectives after all the papers were filtered according to their objectives. The Main objectives are 1 Accuracy 2 Effectiveness 3 Generalizability 4 Performance.

Table 4 Objectives-Based Filtering

	Accuracy	Effectiveness	performance	Generalizability
[6]	✓	-	-	-
[7]	-	✓	-	-
[8]	✓	-	-	-
[9]	✓	✓	-	-

[10]	-	-	-	√
[11]	-	-	√	-
[12]	-	-	√	-
[13]	-	-	√	-
[14]	√	-	-	-
[15]	√	-	-	-
[16]	√	√	√	-
[17]	√	-	-	-
[18]	√	-	-	-
[19]	√	-	-	-
[20]	√	-	-	-
[21]	√	-	-	-
[22]	√	-	-	-

2.2.4 Technique-Based Filtering

In technique-based filtering, it involves using specific techniques or tools to filter, analyze, and interpret research data. It is a systematic and objective approach to analyzing research data, aimed at identifying relevant information and patterns.

Table 5 Technique Used for Fake News Detection

Ref	Datasets	Techniques
[6]	FakeNewsNet	Credibility Score-Based Model
[7]	Twitter and Weibo	MetaFEND model
[8]	Twitter and Weibo	Cross-modal Ambiguity Learning
[9]	Use their own dataset	Curriculum Contrastive model
[10]	Twitter	Post-User Interaction Network
[11]	Liar Dataset	GAME-ON: Graph Attention Network
[12]	Twitter and Weibo	Us-DeFake
[13]	Liar Dataset	Hypergraph Neural Networks
[14]	Liar Dataset	Meta Path-based Global Local Attention Network
[15]	Facebook News Dataset	K-Nearest Neighbor Classifier
[16]	Twitter and Weibo	SVM, CNN, LSTM, KNN, and Naïve Bayes
[17]	Fake News Challenges	A Hybrid Neural Network Architecture RNN LSTM
[18]	Twitter and Weibo	Cultural Algorithm
[19]	Twitter and Weibo	Logistic regression, Decision trees, and Naive Bayes classifiers
[20]	Dataset from Kaggle	LSTM

[21]	Dataset from Kaggle	Graph Neural Network Based Modal
[22]	FakeNewsNet	Self-learning Semi-supervised Deep Learning Network

3. Detailed Literature

[6] to assess the trustworthiness of both the sources (publishers) and the consumers (users) of news content. By considering both aspects, this approach aims to provide a more comprehensive and accurate evaluation of the credibility of news articles. In this technique, various factors are taken into account to estimate user credibility. These factors can include the user's past behavior, such as their engagement with reliable or unreliable sources, their social network connections, and their interaction patterns with news articles. By analyzing these factors, a credibility score can be assigned to the user, indicating their likelihood of spreading or consuming fake news. By jointly estimating user and publisher credibility, the fake news detection system can leverage the interplay between these two aspects. It helps in enhancing the accuracy of fake news detection systems by capturing the dynamics and interactions between the different actors in the news ecosystem. By considering user and publisher credibility, these systems can provide more reliable assessments of the trustworthiness of news articles and aid in combating the spread of misinformation.

[7] The approach which are neural network architectures that can adapt and learn from new tasks with limited labeled data. By utilizing meta-learning, the model can generalize knowledge learned from a large labeled dataset to new, unseen tasks with limited labeled data, such as detecting fake news. The method involves two key components: a base Neural Process Network (NPN) and a meta-learning component. The base NPN is responsible for processing and modeling the multimodal data, capturing the complex relationships between different modalities. It can effectively encode textual content, analyze image features, and consider user engagement patterns to understand the context and content of news articles. The meta-learning component enables the model to learn from a large labeled dataset of fake and genuine news articles. By meta-learning, the model acquires knowledge about how to adapt and learn from new tasks, even with limited labeled data. This enables the model to generalize its understanding of fake news detection to new, unseen articles.

[8] aims to detect fake news by analyzing multiple modalities, such as text, images, and videos, and learning how to handle cross-modal ambiguities. The proposed method uses a deep neural network that takes into account various features related to each modality, such as text content, image content, and video content. The network is trained on a dataset of real and fake news articles, using multiple modalities as input. The study introduces a new approach to handling cross-modal ambiguities by learning a mapping between the different modalities. This approach helps the network to overcome inconsistencies or contradictions that may arise when analyzing different modalities.

[9] detection aims to detect fake news by training a deep neural network to learn representations of news articles that can distinguish between real and fake news. The proposed method uses a contrastive learning approach, which trains the network to learn representations that are similar to real news articles and dissimilar to fake news articles. The training process uses a curriculum learning approach, where the network is gradually exposed to more difficult examples to improve its ability to distinguish between real and fake news. The study uses a large dataset of news articles and evaluates the performance of the

proposed method using various metrics. The results show that the curriculum contrastive learning approach can effectively detect fake news, outperforming existing state-of-the-art methods.

[10] the research paper proposes a new method for detecting fake news on social media. The method is based on a divide-and-conquer approach that splits the problem into two parts: identifying fake news posts and identifying fake news users. To identify fake news posts, the method uses a combination of textual and network analysis. The textual analysis involves examining the content of the post to identify any patterns that may indicate that it is fake. Network analysis involves examining the interactions between users who have shared the post to identify any suspicious patterns, such as a high number of interactions from users who have a history of sharing fake news. To identify fake news users, the method uses a user-level analysis approach that looks at the behavior of individual users rather than individual posts. This involves examining the network of interactions between users to identify any suspicious patterns, such as a high number of interactions with other users who have a history of sharing fake news.

[11] the research paper proposes a new method for detecting fake news using a multimodal approach. The method uses a graph attention network (GAT) to fuse information from different modalities, including textual, visual, and social network features, to improve the accuracy of fake news detection. The method first processes the textual and visual features of each news article using a convolutional neural network (CNN) and a long short-term memory (LSTM) network, respectively. These features are then fed into a GAT, which uses attention mechanisms to assign importance to different features based on their relevance to the task of fake news detection. In addition to the textual and visual features, the method also considers social network features, such as the number of likes, shares, and comments on the news article. These features are used to construct a graph of social interactions, which is also fed into the GAT for multimodal fusion

[12] the research paper proposes a new method for detecting fake news in large-scale online social networks. The method is based on mining user-aware multi-relations, which involves considering multiple types of relationships between users, such as friendship, follow, and mention, in addition to the content of the news article. The method uses a two-stage approach to detect fake news. In the first stage, the method constructs a user-aware multi-relation graph (UMRG) that captures the different types of relationships between users. The UMRG is then used to generate a set of user-aware features, including user centrality and user similarity, which are used to train a machine-learning model to predict the likelihood of a news article being fake. In the second stage, the method uses a reinforcement learning algorithm to iteratively update the UMRG based on the predictions of the machine learning model. The updated UMRG is then used to generate new user-aware features, which are fed back into the machine-learning model for further training. This process continues until the accuracy of the model reaches a satisfactory level.

[13] the research paper proposes a new approach to fake news detection. The paper argues that current approaches to fake news detection, which rely on analyzing individual news articles in isolation, are limited in their effectiveness because fake news often relies on complex relationships and dependencies between multiple articles and sources. To address this issue, the researcher proposes using hypergraph neural networks (HNNs) to model the relationships between news articles and sources. HNNs are a type of neural network that can handle complex, higher-order relationships between entities, making them well-suited for modeling the interdependent nature of fake news. The researcher tests their approach on two real-world datasets and shows that their HNN-based approach outperforms several existing state-of-the-art

fake news detection methods. They also demonstrate the interpretability of their model by analyzing the importance of different relationships between articles and sources in detecting fake news.

[14] the research paper proposes a novel approach to detect rumors on social media using meta paths. The researcher argues that rumors on social media can spread quickly and have significant consequences, so detecting them early is crucial. The approach presented in the paper involves constructing a heterogeneous information network (HIN) that captures the relationships between users, tweets, and hashtags on social media. The researcher then uses meta-path-based measures to capture the semantic and structural relationships between nodes in the network. Meta paths are predefined paths that connect nodes of different types, and the researcher uses them to extract meaningful features for rumor detection. The researcher tests their approach on a dataset of Twitter rumors and shows that their approach outperforms several existing state-of-the-art rumor detection methods. They also demonstrate the effectiveness of their approach in identifying the most influential users in spreading rumors.

[15] The K-Nearest Neighbor (KNN) classifier is suggested in the study report as a method for identifying false information on social media. According to the study, it is critical to identify fake news as soon as possible because it can spread swiftly and have serious repercussions on social media. The strategy described in the study involves applying natural language processing (NLP) methods like bag-of-words and TF-IDF to extract features from social media posts. The researcher then classifies social media posts as either phone or authentic based on their feature vectors using the KNN classifier. A machine-learning technique called the KNN classifier categorizes incoming data points according to how closely they are located to existing data points in a feature space.

[16] the research paper proposes an approach to detecting fake news using ensemble learning. The researcher argues that fake news on social media can be difficult to detect using a single classifier, as they can be highly variable in their content and presentation. The approach presented in the paper involves combining the output of multiple classifiers to improve the accuracy of fake news detection. The researcher uses several machine learning algorithms, including support vector machines (SVMs), decision trees, and Naive Bayes classifiers, to train individual models on a dataset of social media posts. The researcher then combines the output of these classifiers using an ensemble learning approach called stacking. Stacking involves training a meta-classifier on the output of individual classifiers to make the final prediction.

[17] the research paper proposes an approach to detecting the stance of news articles using a deep learning architecture that combines convolutional neural networks (CNNs) and long short-term memory (LSTM) networks. The researcher argues that detecting the stance of news articles (i.e., whether they support, oppose, or are neutral towards a particular topic or claim) can help identify potential instances of fake news. The approach presented in the paper involves representing news articles as word embedding and using a CNN-LSTM architecture to learn their stance. The CNN is used to extract features from the word embeddings, while the LSTM is used to capture the temporal dependencies between words in the article. The researcher tests their approach on a real-world dataset of news articles and shows that their CNN-LSTM architecture outperforms several existing stance detection methods. They also demonstrate the effectiveness of their approach in detecting potential instances of fake news.

[18] the research paper proposes an approach to detecting fake news using a Cultural Algorithm (CA) that incorporates both situational and normative knowledge. The authors argue that detecting fake news on social media requires an understanding of both the context in which the news is shared and the norms of

the society in which it is shared. The approach presented in the paper involves using a multimodal dataset of news articles and images, as the combination of text and images can provide a more complete representation of the news. The authors use natural language processing (NLP) techniques to extract features from the text and computer vision techniques to extract features from the images. The authors then use a CA to combine the output of multiple classifiers trained on the multimodal dataset. The CA is a metaheuristic algorithm that mimics the evolution of cultural traditions and can incorporate both situational and normative knowledge to guide the search for the best solution

[19] A tool for identifying fake news using machine learning approaches is presented in a research article. The authors contend that the proliferation of fake news on social media underscores the demand for technologies that can rapidly and effectively distinguish incorrect information. The program described in the research uses machine learning techniques to examine news article content and determine whether or not it is likely that it is a hoax. The authors train their models using a dataset of news stories classified as fake or not fake using a variety of machine learning algorithms, such as logistic regression, decision trees, and Naive Bayes classifiers. Additionally, the authors create a web tool that lets users enter a news article and get a prediction of whether or not it is likely to be fake. The programmer generates predictions using trained machine learning models and informs users of the features that went into making the prediction.

[20] the research paper proposes an approach to detecting fake news on social media in real-time using a memory-based system. The authors argue that traditional approaches to fake news detection, which rely on machine learning models trained on static datasets, are not suitable for detecting fake news in real-time. The approach presented in the paper involves using a memory-based system that stores previously encountered news articles and their corresponding labels. When a new article is encountered, the system compares it to previously encountered articles and their labels to determine if it is likely to be fake or not. The authors use several text-processing techniques, including tokenization and part-of-speech tagging, to represent news articles as feature vectors. They also use cosine similarity to compare the feature vector of a new article to those of previously encountered articles.

[21] The research paper investigates the effectiveness of graph neural networks (GNNs) in detecting fake news from social media feeds. The authors argue that traditional machine learning approaches to fake news detection may not be suitable for capturing the complex relationships between users, content, and propagation patterns on social media platforms. The approach presented in the paper involves representing social media feeds as graphs, with users and content as nodes and relationships between them as edges. The authors use a GNN to analyze the graph and predict whether a news item is likely to be fake or not. The authors test their approach on a real-world dataset of social media feeds and show that their GNN-based system achieves high accuracy in detecting fake news. They also demonstrate the effectiveness of their approach in capturing the complex relationships between users, content, and propagation patterns on social media platforms, improving the system's ability to detect false information. The authors also conduct several experiments to investigate the performance of different GNN architectures and parameters in detecting fake news. They show that a Graph Convolutional Network (GCN) architecture with multiple layers and high-dimensional node embeddings achieves the best performance.

[22] a research paper presents a new approach to detecting fake news on social media using a self-learning semi-supervised deep learning network. The authors argue that traditional supervised learning

approaches to fake news detection may be limited by the availability of labeled data and that self-learning and semi-supervised approaches can help overcome this limitation. The approach presented in the paper involves using a deep learning network to analyze the content of news articles and predict whether they are likely to be fake or not. The authors use a self-learning approach, where the network updates its parameters based on both labeled and unlabeled data, and a semi-supervised approach, where the network is trained on both labeled and unlabeled data. The authors also develop a web application that allows users to input a news article and receive a prediction of whether it is likely to be fake or not. The application uses the trained deep learning network to generate a prediction and provides users with an explanation of the features that contributed to the prediction. In our survey on fake news detection on social media, our research draws upon foundational insights presented in [59-73].

4. Performance Analysis

4.1 Critical Analysis

[6] it can improve the accuracy of fake news detection compared to models that only consider one aspect of credibility, such as user behavior or publisher reputation. The modal uses a deep neural network the main limitation of this is it requires large amounts of labeled data to achieve high levels of accuracy. This can be a major limitation in applications where labeled data is scarce or expensive to obtain [23].

[8] the method uses a deep neural network that takes into account various features related to each modality, such as text content, image content, and video content. The limitations of deep neural networks are DNNs are prone to overfitting, especially when the dataset is small or noisy. DNNs require a large number of computational resources, including memory and processing power, to train and deploy. DNNs require large amounts of labeled data to learn meaningful representations, which is time-consuming to obtain in some domains[24].

[9] uses a contrastive learning approach, which trains the network to learn representations that are similar to real news articles and dissimilar to fake news articles. The limitations of deep neural networks are DNNs are prone to overfitting, especially when the dataset is small or noisy. DNNs require a large number of computational resources, including memory and processing power, to train and deploy. DNNs require large amounts of labeled data to learn meaningful representations, which can be time-consuming to obtain in some domains[24].

[16] a dataset of social media posts is used to train individual models using machine learning methods. Machine learning's drawbacks include To discover useful patterns, machine learning algorithms need a lot of high-quality labeled data. As a result of the model becoming overly complex and fitting the training data too closely, machine learning algorithms can overfit the training data, which leads to a poor generalization of new data. Deep neural networks are one example of a machine learning algorithm that can be computationally expensive and resource-intensive, which restricts their scalability and accessibility.

[15] benefits of using the KNN classifier for fake news detection is that it is easy to implement and does not require extensive computational resources it may not be as accurate as more complex machine learning algorithms on large datasets with many features. The limitation of KNN is the Complexity of

computation Memory restrictions, being a slow-running, supervised learning system, and being easily duped by irrelevant characteristics [25].

[17] using the CNN-LSTM architecture for fake news stance detection is that it can capture both the local and global dependencies of the text, which can improve the accuracy of the classification. The Limitation of using LSTM is that it needs more training data to work properly, not suitable for online learning tasks where the incoming data is not a sequence, such as prediction or classification tasks training LSTMs on sizable datasets can be time-consuming[26]. LSTMs are sensitive to the quality and quantity of input data, particularly when the data is noisy or contains outliers[27].

[19] The fact that the independence premise among attributes may not always be met by real-world data is a significant drawback of using the Naive Bayes classifier. The Nave Bayes classifier's prediction accuracy may become highly sensitive to the correlated characteristics [28].

[11], [13], [21] the main limitation of GNNs is the over-smoothing problem, where the network assigns similar representations to nodes that are far apart in the graph. This can lead to loss of information and decreased accuracy. The computational complexity of GNNs increases with the number of nodes and edges in the graph, making it difficult to apply GNNs to very large graphs. GNNs often struggle with generalization to unseen graphs or tasks, particularly when the training data is limited or biased[29], [30].

[20] Although LSTMs are designed to address the vanishing gradient problem that affects traditional RNNs, they still struggle to capture long-term dependencies in sequences that extend beyond a few hundred-time steps[31]. LSTMs are sensitive to the quality and quantity of input data, particularly when the data is noisy or contains outliers. This can lead to decreased accuracy and increased overfitting, where the model performs well on the training data but poorly on the test data[27].

[18] CAs are complex algorithms that require several parameters and sub-components, such as belief space, population space, and assimilation and accommodation processes. CAs are highly sensitive to the choice of parameters, such as belief space size, learning rate, and assimilation and accommodation probabilities. CAs lack a solid theoretical foundation that explains their behavior and convergence properties[32].

[22] This modal is traditional supervised learning approaches to fake news detection may be limited by the availability of labeled data, and self-learning and semi-supervised approaches can help overcome this limitation. The main limitation of supervised deep learning models is the need for large amounts of labeled data, which can be expensive and time-consuming to obtain. On the other hand, unsupervised learning models can use large amounts of unlabeled data but often produce lower accuracy results than supervised learning models[33]–[35].

[7] MetaFEND is that it can incorporate a wide range of meta-features and content features, which can improve its accuracy in detecting fake news. However, one limitation of MetaFEND is that it relies on the accuracy of the pre-trained deep-learning model used to extract content features. If the pre-trained model is not accurate or does not generalize well to new data, this could negatively impact the performance of the MetaFEND model[36].

[12] the challenges of mining multi-relational data, including the need to deal with multiple types of objects and relationships, the curse of dimensionality, and the difficulty of modeling complex dependencies[37].

[14] Learns the representations of the nodes and edges in the social network using a graph convolutional network (GCN). The GCN learns the representations of nodes and edges and captures the intricate interactions between them using the features that were derived from the meta-paths. The main limitations of GCN are that the depth of the network and the nonlinearity of the activation functions play a crucial role in the performance of GCNs. However, increasing the depth of the network and using more nonlinear activation functions can lead to the vanishing or exploding gradient problem, which limits the training of the network. Furthermore, the distribution of node degrees affects the performance of GCNs, with GCNs performing better on graphs with a power-law degree distribution[38].

[10] The main limitations of GCN are that the depth of the network and the nonlinearity of the activation functions play a crucial role in the performance of GCNs. However, increasing the depth of the network and using more nonlinear activation functions can lead to the vanishing or exploding gradient problem, which limits the training of the network. Furthermore, the distribution of node degrees affects the performance of GCNs, with GCNs performing better on graphs with a power-law degree distribution[38]. Dividing a problem into sub problems and combining the solutions requires additional overhead that can reduce performance[39].

Table 5 Summary of Critical Analysis of Fake News Detection on social media

Ref	Year	Technique	Short Coming
[6]	2020	Credibility Score-Based Model	It doesn't work on unlabeled datasets.[6]
[7]	2021	Multimodal emergent fake news detection	It relies on the accuracy of the pre-trained deep learning model used to extract content features.[7]
[8]	2022	Cross-modal Ambiguity Learning	Overfitting, Lack of interpretability, and High computational requirements[24]
[9]	2022	Curriculum Contrastive model	Overfitting, Lack of interpretability, and High computational requirements[24]
[10]	2022	Post-User Interaction Network	The distribution of node degrees affects the performance of GCNs[38]. Dividing a problem into subproblems and combining the solutions requires additional overhead that can reduce performance[39].
[11]	2022	GAME-ON: Graph Attention Network	GNNs are the over-smoothing problem, where the network assigns similar representations to nodes that are far apart in the graph.[38]
[12]	2022	Us-DeFake	It does not deal with multiple types of objects and relationships[12].
[13]	2022	Hypergraph Neural Networks	GNNs are the over-smoothing problem, where the network assigns similar representations to nodes that are far apart in the graph[38].

[14]	2022	Meta Path-based Global Local Attention Network	Limited scalability, Difficulty with unstructured data, and Difficulty with hierarchical relationships[40]
[15]	2020	K-Nearest Neighbor Classifier	It does not work on high-dimension data[25].
[16]	2020	SVM, CNN, LSTM, KNN, and NB	Data quality and quantity, Overfitting, and Computational complexity[41]
[17]	2020	A Hybrid Neural Network Architecture CNN LSTM	The main limitation is the availability and quality of labeled data. LSTMs are sensitive to the quality and quantity of input data and have limited memory capacity.[27]
[18]	2020	Cultural Algorithm	It requires several parameters and sub-components, such as belief space, population space, and assimilation and accommodation processes[32].
[19]	2022	Logistic regression, Decision trees, and Naive Bayes classifiers	Assumption of independence Limited training data Limited expressiveness[41]
[20]	2022	LSTM	Computational Complexity Difficulty in Training Limited Memory Capacity[31]
[21]	2023	Graph Neural Network Based Modal	GNNs are the over-smoothing problem, where the network assigns similar representations to nodes that are far apart in the graph.[40]
[22]	2022	Self-learning Semi-supervised Deep Learning Network	Need for large amounts of labeled data[40].

4.2 Identified Challenges:

This section outlines the problems and difficulties with each of the Table 7-listed techniques for identifying Fake news. It briefly describes all of the schemes' limitations. These are the unexplored areas for research that can be explored in the future to resolve the problems and difficulties that are addressed.

Table 6 Identified Challenges and their solutions

References	Challenges	Solutions
[6],	Lack of labeled data	Transfer Learning[42], Semi-supervised Learning[40], Active Learning[43] and data augmentation [44]
[8], [9], [16]	Overfitting	Increase Training Data[45], Cross-Validation[46], Regularization[47] and Dropout[48]
[17]	High dimension data	Dimensionality Reduction[49], Feature Selection and Feature

		Extraction[50],Manifold Learning [51] and Sparse Representation[49]
[21], [16]	Computational Complexity	Algorithmic Optimization[52], Sampling Techniques[53], Approximation Algorithms [54]and Parallel Computing[55]
[8], [9], [16]	Limited Feature Extraction	Deep Learning and Neural Networks[24], Transfer Learning[56], Feature Engineering[57] and Unsupervised Learning[58]

Conclusion:

Fake news is a growing research topic since it has so many adverse effects on society. New frameworks and systems for the detection of fake news have been proposed by numerous researchers. Despite the fact that fake news and posts can clearly be detected using a variety of machine learning techniques. Fake news is difficult to categories because to its ever-changing traits and features in social media networks. However, computing hierarchical features is the primary distinguishing trait of deep learning. Numerous research projects will use deep learning techniques as a result of the rapid adoption of deep learning research and applications.

References

[1] H. Ahmed, I. Traore, and S. Saad, “Detecting opinion spams and fake news using text classification,” Secur. Priv., vol. 1, no. 1, p. e9, 2018.

[2] M. K. Elhadad, K. F. Li, and F. Gebali, “Fake news detection on social media: a systematic survey,” in 2019 IEEE Pacific Rim conference on communications, computers and signal processing (PACRIM), IEEE, 2019, pp. 1–8.

[3] S. I. Manzoor and J. Singla, “Fake news detection using machine learning approaches: A systematic review,” in 2019 3rd international conference on trends in electronics and informatics (ICOEI), IEEE, 2019, pp. 230–234.

[4] D. K. Vishwakarma and C. Jain, “Recent state-of-the-art of fake news detection: A review,” in 2020 International Conference for Emerging Technology (INCET), IEEE, 2020, pp. 1–6.

[5] R. Katarya and M. Massoudi, “Recognizing fake news in social media with deep learning: a systematic review,” in 2020 4th International Conference on Computer, Communication and Signal Processing (ICCCSP), IEEE, 2020, pp. 1–4.

[6] R. Chowdhury, S. Srinivasan, and L. Getoor, “Joint estimation of user and publisher credibility for fake news detection,” in Proceedings of the 29th ACM International Conference on Information & Knowledge Management, 2020, pp. 1993–1996.

[7] Y. Wang, F. Ma, H. Wang, K. Jha, and J. Gao, “Multimodal emergent fake news detection via meta neural process networks,” in Proceedings of the 27th ACM SIGKDD conference on knowledge discovery & data mining, 2021, pp. 3708–3716.

[8] Y. Chen et al., “Cross-modal ambiguity learning for multimodal fake news detection,” in Proceedings of the ACM Web Conference 2022, 2022, pp. 2897–2905.

[9] J. Ma, Y. Liu, M. Liu, and M. Han, “Curriculum Contrastive Learning for Fake News Detection,” in Proceedings of the 31st ACM International Conference on Information & Knowledge Management, 2022, pp. 4309–4313.

[10] E. Min et al., “Divide-and-conquer: Post-user interaction network for fake news detection on social media,” in Proceedings of the ACM Web Conference 2022, 2022, pp. 1148–1158.

[11] M. Dhawan, S. Sharma, A. Kadam, R. Sharma, and P. Kumaraguru, “Game-on: Graph attention network based multimodal fusion for fake news detection,” ArXiv Prepr. ArXiv220212478, 2022.

[12] X. Su, J. Yang, J. Wu, and Y. Zhang, “Mining User-aware Multi-Relations for Fake News Detection in Large Scale Online Social Networks,” ArXiv Prepr. ArXiv221210778, 2022.

[13] U. Jeong, K. Ding, L. Cheng, R. Guo, K. Shu, and H. Liu, “Nothing Stands Alone: Relational Fake News Detection with Hypergraph Neural Networks,” ArXiv Prepr. ArXiv221212621, 2022.

[14] B. Azarijoo, M. Salehi, and S. Najari, “A Meta Path-based Approach for Rumor Detection on Social Media,” ArXiv Prepr. ArXiv230104341, 2023.

[15] A. Kesarwani, S. S. Chauhan, and A. R. Nair, “Fake news detection on social media using k-nearest neighbor classifier,” in 2020 international conference on advances in computing and communication engineering (ICACCE), IEEE, 2020, pp. 1–4.

[16] A. Agarwal and A. Dixit, “Fake news detection: an ensemble learning approach,” in 2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS), IEEE, 2020, pp. 1178–1183.

[17] M. Umer, Z. Imtiaz, S. Ullah, A. Mehmood, G. S. Choi, and B.-W. On, “Fake news stance detection using deep learning architecture (CNN-LSTM),” IEEE Access, vol. 8, pp. 156695–156706, 2020.

[18] P. Shah and Z. Kobti, “Multimodal fake news detection using a Cultural Algorithm with situational and normative knowledge,” in 2020 IEEE congress on evolutionary computation (CEC), IEEE, 2020, pp. 1–7.

[19] K. R. Asish, A. Gupta, A. Kumar, A. Mason, M. K. Enduri, and S. Anamalamudi, “A tool for fake news detection using machine learning techniques,” in 2022 2nd International Conference on Intelligent Technologies (CONIT), IEEE, 2022, pp. 1–6.

[20] A. Azees and G. Titus, “Memory Based Online Fake News Detection System,” in 2022 International Conference on Computing, Communication, Security and Intelligent Systems (IC3SIS), IEEE, 2022, pp. 1–4.

[21] I. I. Shovon and S. Shin, “The Performance of Graph Neural Network in Detecting Fake News from Social Media Feeds,” in 2023 International Conference on Information Networking (ICOIN), IEEE, 2023, pp. 560–564.

[22] X. Li, P. Lu, L. Hu, X. Wang, and L. Lu, “A novel self-learning semi-supervised deep learning network to detect fake news on social media,” Multimed. Tools Appl., vol. 81, no. 14, pp. 19341–19349, 2022.

[23] S. Tsimenidis, “Limitations of Deep Neural Networks: a discussion of G. Marcus’ critical appraisal of deep learning,” ArXiv Prepr. ArXiv201215754, 2020.

[24] I. Goodfellow, Y. Bengio, and A. Courville, Deep learning. MIT press, 2016.

[25] N. Bhatia, “Survey of nearest neighbor techniques,” ArXiv Prepr. ArXiv10070085, 2010.

[26] “A Guide to Long Short Term Memory (LSTM) Networks.” https://www.knowledgehut.com/blog/web-development/long-short-term-memory (accessed Apr. 02, 2023).

[27] Y. Kim and A. M. Rush, “Sequence-level knowledge distillation,” ArXiv Prepr. ArXiv160607947, 2016.

[28] L. Fan and K. L. Poh, “Improving the naïve Bayes classifier,” in Encyclopedia of artificial intelligence, IGI Global, 2009, pp. 879–883.

[29] Z. Wu, S. Pan, F. Chen, G. Long, C. Zhang, and S. Y. Philip, “A comprehensive survey on graph neural networks,” IEEE Trans. Neural Netw. Learn. Syst., vol. 32, no. 1, pp. 4–24, 2020.

[30] R. Ying, R. He, K. Chen, P. Eksombatchai, W. L. Hamilton, and J. Leskovec, “Graph convolutional neural networks for web-scale recommender systems,” in Proceedings of the 24th ACM SIGKDD international conference on knowledge discovery & data mining, 2018, pp. 974–983.

[31] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” Neural Comput., vol. 9, no. 8, pp. 1735–1780, 1997.
[32] A. Maheri, S. Jalili, Y. Hosseinzadeh, R. Khani, and M. Miryahyavi, “A comprehensive survey on cultural algorithms,” Swarm Evol. Comput., vol. 62, p. 100846, 2021.
[33] C. Liu, J. Wen, X. Luo, and Y. Xu, “Incomplete Multi-View Multi-Label Learning via Label-Guided Masked View-and Category-Aware Transformers,” ArXiv Prepr. ArXiv230307180, 2023.
[34] Y. Yao et al., “Jo-src: A contrastive approach for combating noisy labels,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2021, pp. 5192–5201.
[35] D.-H. Lee, “Pseudo-label: The simple and efficient semi-supervised learning method for deep neural networks,” in Workshop on challenges in representation learning, ICML, 2013, p. 896.
[36] A. Bondielli and F. Marcelloni, “A survey on fake news and rumour detection techniques,” Inf. Sci., vol. 497, pp. 38–55, 2019.
[37] D. Meena and H. Gupta, “A Review: Data Mining over Multi-Relations,” Int. J. Comput. Appl., vol. 62, no. 8, 2013.
[38] A. Magner, M. Baranwal, and A. O. Hero III, “Fundamental limits of deep graph convolutional networks,” ArXiv Prepr. ArXiv191012954, 2019.
[39] “Introduction to Algorithms,” MIT Press. https://mitpress.mit.edu/9780262046305/introduction-to-algorithms/ (accessed Apr. 02, 2023).
[40] T. N. Kipf and M. Welling, “Semi-supervised classification with graph convolutional networks,” ArXiv Prepr. ArXiv160902907, 2016.
[41] M. I. Jordan and T. M. Mitchell, “Machine learning: Trends, perspectives, and prospects,” Science, vol. 349, no. 6245, pp. 255–260, Jul. 2015, doi: 10.1126/science.aaa8415.
[42] “Deep learning | Nature.” https://www.nature.com/articles/nature14539 (accessed May 23, 2023).
[43] B. Settles, “Active learning: Synthesis lectures on artificial intelligence and machine learning,” Long Isl. NY Morgan Clay Pool, vol. 10, p. S00429ED1V01Y201207AIM018, 2012.
[44] “A survey on Image Data Augmentation for Deep Learning | Journal of Big Data | Full Text.” https://journalofbigdata.springeropen.com/articles/10.1186/s40537-019-0197-0 (accessed May 23, 2023).
[45] J. H. Friedman, “Greedy function approximation: a gradient boosting machine,” Ann. Stat., pp. 1189–1232, 2001.
[46] R. Kohavi, “A study of cross-validation and bootstrap for accuracy estimation and model selection,” in Ijcai, Montreal, Canada, 1995, pp. 1137–1145.
[47] T. Hastie, R. Tibshirani, J. H. Friedman, and J. H. Friedman, The elements of statistical learning: data mining, inference, and prediction, vol. 2. Springer, 2009.
[48] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, “Dropout: A Simple Way to Prevent Neural Networks from Overfitting”.
[49] I. T. Jolliffe and J. Cadima, “Principal component analysis: a review and recent developments,” Philos. Trans. R. Soc. Math. Phys. Eng. Sci., vol. 374, no. 2065, p. 20150202, 2016.
[50] L. Yu and H. Liu, “Feature selection for high-dimensional data: A fast correlation-based filter solution,” in Proceedings of the 20th international conference on machine learning (ICML-03), 2003, pp. 856–863.
[51] J. B. Tenenbaum, V. de Silva, and J. C. Langford, “A global geometric framework for nonlinear dimensionality reduction,” science, vol. 290, no. 5500, pp. 2319–2323, 2000.
[52] J. Kleinberg and E. Tardos, Algorithm design. Pearson Education India, 2006.
[53] L. A. Stefanski and D. D. Boos, “The calculus of M-estimation,” Am. Stat., vol. 56, no. 1, pp. 29–38, 2002.
[54] D. P. Williamson and D. B. Shmoys, The design of approximation algorithms. Cambridge university press, 2011.

[55] P. Pacheco, "Parallel Programming with MPI. Morgan Kau man, San Francisco," CA Oct., 1996.

[56] S. J. Pan and Q. Yang, "A survey on transfer learning," IEEE Trans. Knowl. Data Eng., vol. 22, no. 10, pp. 1345–1359, 2010.

[57] M. A. Hearst, S. T. Dumais, E. Osuna, J. Platt, and B. Scholkopf, "Support vector machines," IEEE Intell. Syst. Their Appl., vol. 13, no. 4, pp. 18–28, 1998.

[58] C. M. Bishop and N. M. Nasrabadi, Pattern recognition and machine learning, vol. 4, no. 4. Springer, 2006.

[59] Sennan, S., Somula, R., Luhach, A. K., Deverajan, G. G., Alnumay, W., Jhanjhi, N. Z., ... & Sharma, P. (2021). Energy efficient optimal parent selection based routing protocol for Internet of Things using firefly optimization algorithm. Transactions on Emerging Telecommunications Technologies, 32(8), e4171.

[60] Hussain, K., Hussain, S. J., Jhanjhi, N. Z., & Humayun, M. (2019, April). SYN flood attack detection based on bayes estimator (SFADBE) for MANET. In 2019 International Conference on Computer and Information Sciences (ICCIS) (pp. 1-4). IEEE.

[61] Adeyemo Victor Elijah, Azween Abdullah, NZ JhanJhi, Mahadevan Supramaniam and Balogun Abdullateef O, "Ensemble and Deep-Learning Methods for Two-Class and Multi-Attack Anomaly Intrusion Detection: An Empirical Study" International Journal of Advanced Computer Science and Applications(IJACSA), 10(9), 2019. http://dx.doi.org/10.14569/IJACSA.2019.0100969

[62] Lim, M., Abdullah, A., & Jhanjhi, N. Z. (2021). Performance optimization of criminal network hidden link prediction model with deep reinforcement learning. Journal of King Saud University-Computer and Information Sciences, 33(10), 1202-1210.

[63] Gaur, L., Singh, G., Solanki, A., Jhanjhi, N. Z., Bhatia, U., Sharma, S., ... & Kim, W. (2021). Disposition of youth in predicting sustainable development goals using the neuro-fuzzy and random forest algorithms. Human-Centric Computing and Information Sciences, 11, NA.

[64] Kumar, T., Pandey, B., Mussavi, S. H. A., & Zaman, N. (2015). CTHS based energy efficient thermal aware image ALU design on FPGA. Wireless Personal Communications, 85, 671-696.

[65] Nanglia, S., Ahmad, M., Khan, F. A., & Jhanjhi, N. Z. (2022). An enhanced Predictive heterogeneous ensemble model for breast cancer prediction. Biomedical Signal Processing and Control, 72, 103279.

[66] Gaur, L., Afaq, A., Solanki, A., Singh, G., Sharma, S., Jhanjhi, N. Z., ... & Le, D. N. (2021). Capitalizing on big data and revolutionary 5G technology: Extracting and visualizing ratings and reviews of global chain hotels. Computers and Electrical Engineering, 95, 107374.

[67] Diwaker, C., Tomar, P., Solanki, A., Nayyar, A., Jhanjhi, N. Z., Abdullah, A., & Supramaniam, M. (2019). A new model for predicting component-based software reliability using soft computing. IEEE Access, 7, 147191-147203.

[68] Hussain, S. J., Ahmed, U., Liaquat, H., Mir, S., Jhanjhi, N. Z., & Humayun, M. (2019, April). IMIAD: intelligent malware identification for android platform. In 2019 International Conference on Computer and Information Sciences (ICCIS) (pp. 1-6). IEEE.

[69] Humayun, M., Alsaqer, M. S., & Jhanjhi, N. (2022). Energy optimization for smart cities using iot. Applied Artificial Intelligence, 36(1), 2037255.

[70] Ghosh, G., Verma, S., Jhanjhi, N. Z., & Talib, M. N. (2020, December). Secure surveillance system using chaotic image encryption technique. In IOP conference series: materials science and engineering (Vol. 993, No. 1, p. 012062). IOP Publishing.

[71] Almusaylim, Z. A., Zaman, N., & Jung, L. T. (2018, August). Proposing a data privacy aware protocol for roadside accident video reporting service using 5G in Vehicular Cloud Networks Environment. In 2018 4th International conference on computer and information sciences (ICCOINS) (pp. 1-5). IEEE.

[72] Wassan, S., Chen, X., Shen, T., Waqar, M., & Jhanjhi, N. Z. (2021). Amazon product sentiment analysis using machine learning techniques. Revista Argentina de Clínica Psicológica, 30(1), 695.

[73] Shahid, H., Ashraf, H., Javed, H., Humayun, M., Jhanjhi, N. Z., & AlZain, M. A. (2021). Energy optimised security against wormhole attack in iot-based wireless sensor networks. Comput. Mater. Contin, 68(2), 1967-81.