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Fake News Detection Using Deep Learning: A Comprehensive Review

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Abstract– Organizations from various domains are working to find effective solutions for detecting online-based fake news, which is a major issue at the moment. It can be difficult to recognise fake information on the internet because it is frequently written to deceive individuals. Deep learning-based algorithms are more accurate at detecting fake news than many other machine learning techniques. Previous reviews focused on data mining and machine learning approaches, with little attention paid to deep learning techniques for detecting fake news. Emerging deep learning-based techniques like Attention, Generative Adversarial Networks, and Bidirectional Encoder Representations for Transformers, on the other hand, were not included in earlier surveys. This research looks into advanced and cutting-edge false news detection techniques in depth. We'll start with the negative consequences of fake news. Then we'll talk about the dataset that was used in earlier research and the NLP approaches that were used. To divide representative methods into several categories, a complete overview of deep learning-based techniques has been presented. The most often used evaluation measures in the detection of false news are also reviewed. Nonetheless, in future research paths, we propose additional recommendations to improve fake news detection techniques.

Keywords– Natural language processing, machine learning, deep learning, and fake news

I. INTRODUCTION

Because of its low cost, easy access, and rapid information transmission, the Internet has transformed the way individuals interact and communicate. As a result, many individuals prefer to seek for and read news on social media and internet portals rather than traditional newspapers. Despite its importance as a source of knowledge, social media causes harm to society through influencing key events. The subject of internet false news has grown in prominence, particularly since the 2016 presidential election in the United States [1], [2]. According to Zhang and Ghorbani [3], misleading political comments and claims can readily manipulate voters. Inspection reveals that false news or lies spread faster through humans than true information and have far-reaching consequences [4].

The terms "rumour" and "false news" are often used interchangeably. Fake news, often known as misinformation, is generated on intentionally. Rumors, on the other hand, are unsubstantiated and dubious information distributed without the intent to deceive [5]. Spreaders' motives on social media sites can be difficult to discern. As a result, any misleading or incorrect information on the Internet is often labelled as disinformation. It's difficult to tell the difference between true and false information. To overcome this problem, however, a variety of ways have been used. Several machine learning (ML) algorithms have been employed to detect erroneous information propagated online. Early studies focused on using textual data collected from the content of the article.

Deep learning (DL) is a relatively new technology in the research community that has shown to be more effective than classic machine learning (ML) methods in detecting fake news. DL has some distinct advantages over ML, including a) automatic feature extraction, b) reliance on data pre-processing to a lesser extent, c) ability to extract high-dimensional features, and d) higher accuracy. Furthermore, the widespread availability of data and programming frameworks has increased the use and reliability of DL-based techniques. As a result, numerous studies on false news detection have been published in the previous five years, the majority of them are based on DL methods. A concerted effort has been undertaken to study the present literature in order to compare the large number of DL-based false news detection research initiatives.

Existing research on deep learning-based architectures for detecting fake news does not provide a comprehensive overview, according to our findings. The present survey publications primarily focus on machine learning (ML) tactics for detecting fake news, with little attention paid to deep learning (DL) strategies [3]. We present a comprehensive list of NLP strategies, as well as descriptions of their advantages and disadvantages. We conducted an in-depth examination of current DL-based studies in the survey that follows. By performing a thorough survey on false news identification, the current study intends to solve the prior research's faults and merits. First, we divide existing research on fake news identification into two categories:(2) Deep Learning (DL) and (1) Natural Language Processing (NLP). We go over data pre-processing, data vectorizing, and feature extraction as examples of NLP approaches. Second, we look at how different DL architectures can be used to detect fake news. Finally, we go over the many evaluation measures that are employed in the detection of fake news. The broad taxonomy of fake news detecting approaches is depicted in Figure 1. We've also included a Table 1 with acronyms used throughout the survey to help researchers when they run into problems with acronyms.

The remainder of the paper is laid out as follows. The second section focuses on the effects of fake news. The datasets that were used are described in Section III. Section IV looks into the use of Natural Language Processing in the detection of fake news. Deep learning strategies are discussed in detail in Section V. The evaluation metrics used in prior investigations are presented in Section VI. Finally, Section VII brings the paper to a close.

II. EFFECTS OF FAKE NEWS

Since the beginning of civilisation, there has always been fake news. However, modern technologies and the transformation of the global media landscape have aided the propagation of fake news. Fake news could have huge ramifications for social, political, and economic situations. Fake news and fake information come in a variety of forms. Fake news has a significant impact on our worldview since information shapes it. On the basis of the information, we make vital decisions. We build an opinion about a situation or people based on the information we get. If we find fraudulent, false, twisted, or invented information on the Internet, we will be unable to make good decisions. The following are the key effects of fake news:

Consequences for Innocent People: Rumours can have a huge impact on the lives of those who are completely innocent. As a result of their usage of social media, these people may be harassed. They may also be subjected to threats and insults with real-world consequences. False information on social media should not be used to lead people astray or to pass judgement on others.

Health Effects: The number of people searching the Internet for health-related information is continually increasing. Due to pressure from doctors, lawmakers, and health advocates, social media firms have made changes to their policies to reduce or prevent the spread of health misinformation.

Financial Implications: Fake news is a huge problem in many industries and enterprises right now. Dishonest entrepreneurs produce phony news or reviews to boost their profits. False information might cause stock values to drop. It has the potential to ruin a company's image. Fake news has an impact on customer expectations. Fake news has the potential to promote a business mindset that is immoral.

Democratic impact: The media has devoted a lot of attention to fake news since it played such a big role in the last American presidential election. This is a critical issue for democracy. Because erroneous information has a genuine impact, we must cease sharing it.

Benchmark Dataset

The datasets utilised in various studies are discussed in this section. Benchmark datasets were used for both training and testing. The lack of a labelled benchmark dataset with reliable ground truth labels and a large dataset is one of the challenges in recognising false news. Researchers can derive practical features and create models based on this. Over the previous few years, large datasets have been gathered for a variety of uses in DL and ML. Because of the many study agendas, the datasets are drastically different from one another. For example, some datasets (like PolitiFact) are solely made up of political remarks, whereas others (like FNC-1) are exclusively made up of news stories or social media posts (Twitter). Datasets might vary in terms of modality, labels, and size. As a result, these datasets are categorised in table 2 based on these features. Fake articles are frequently obtained from deceptive websites that are aimed to spread misinformation. The creators of these fake news reports finally post them on social media channels. The dissemination of fake news on social media is aided by malicious individuals or bots, as well as inattentive users who do not examine the source of the storey before sharing it. The majority of datasets, on the other hand, contain simply news content. However, present language characteristics and writing style are insufficient for constructing an effective detection model.

The most popular publicly available datasets are fake news, Twitter15, and Liar. However, other studies used their own dataset to train their model. These datasets were classified as self-collected by us. We find it difficult to fully compare with other studies because they do not disclose enough information about their self-collected datasets. A comparison study using current state-of-the-art approaches for detecting false news can be constructed using the benchmark dataset. Using the Kaggle dataset, Kaliyar et al. [6] conducted a comparison analysis of their proposed model with existing approaches and reported an accuracy of 93.50 percent, which is the highest, for fake news detection.

NATURAL LANGUAGE PROCESSING

12 fonts, bold, centered, roman numbered in block capital letters, text after double, 10 font, text single spacing Natural Language Processing (NLP) is a branch of machine learning that involves a computer's ability to comprehend, interpret, alter, and possibly synthesise human language. Data pre-processing and word embedding are two techniques used in NLP.NLP has made huge strides in recent years because to the use of deep learning techniques. To offer machines a feeling of natural language, the natural language must be converted into a mathematical structure. NLP approaches are addressed in sections IV-A, IV-B, and IV-C.

A. DATA PRE-PROCESSING

To represent complicated structures with attributes, binarize attributes, alter discrete attributes, persist, and handle lost and obscure attributes, data pre-processing is used. Different visualisation approaches are useful during data pre-processing. Because social media data sources are scattered, unstructured, and noisy, ingesting the data into a neural network for fake news identification requires caution. It is common knowledge that data pre-processing reduces computing time and space during the learning step. Furthermore, text pre-processing reduces the influence of artefacts throughout the learning

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process by preventing all ingests of noisy data. After adequate text pre-processing, the data becomes a logical representation. The most representative descriptive terms were also included. The data pre-processing stages employed in diverse studies are data quality evaluation, dimensionality reduction, and dataset splitting. some of them like – Data Quality Assessment, Train Test split, Tokenization-stemming and lemmatization.

TABLE 1: The table contains the acronyms used in this survey [17].

Acronym	Meaning	Acronym	Meaning
ML	Machine Learning	dEFEND	Explainable Fake News Detection
DL	Deep Learning	GCN	Graph Convolutional Network
NLP	Natural Language Processing	RvNN	Recursive Neural Networks
BoW	Bag of Words	PGNN	Propagation Graph Neural Network
TF-IDF	Term Frequency Inverse Document Frequency	SAGNN	Simplified Aggregation Graph Neural Network
SVM	Support Vector Machine	GANs	Generative Adversarial Networks
NB	Naive Bayes	SeqGAN	Sequence GAN
KNN	K-Nearest Neighbour	RL	Reinforcement Learning
GloVe	Global Vectors for Word Representation	EANN	Event Adversarial Neural Network
GI	Gini Coefficient	GCAN	Graph-aware Co-Attention Networks
IG	Information Gain	3HAN	Three-level Hierarchical Attention Network
1v1I	Mutual Information	att-RNN	attention on RNN
PCA	Principal Component Analysis	ACT	Automatic fake news Classification Through self-attention
CHI	Chi-Square Statistics	BERT	Bidirectional Encoder Representations for Transformers
TI-CNN	Text and Image information based convolutional neural network	BDANN	BERT-based Domain-Adaption Neural Network
DNNs	Deep Neural Networks	MLM	Mask Language Model
RF	Random Forest	NSP	Next Sentence Prediction
CNN	Convolutional Neural Network	exBAKE	BERT with extra unlabeled news corpora
RNN	Recurrent Neural Network	1d-CNN	One-dimensional Convolutional Neural Network
MLP	Multilayer Perceptron	A	Accuracy
MCNN	Multilevel CNN	P	Precision
TFW	Sensitive Word's Weight Calculating Method	R	Recall
LSTM	Long Short Term Memory Networks	F1	F1-score
GRU	Gated Recurrent Unit	ROC	Receiver Operating Characteristics
Bi-LSTM	Bidirectional LSTM	FPR	False Positive Rate
Bi-GRU	Bidirectional GRU	AUC	Area Under the ROC curve
CSI	Capture, Score, and Integrate	DBN	Deep Belief Network
FDML	Fake News Detection Multi Task Learning	GPT	Generative Pre-trained Transformer
AI	Artificial Intelligence	XAI	Explainable Artificial Intelligence

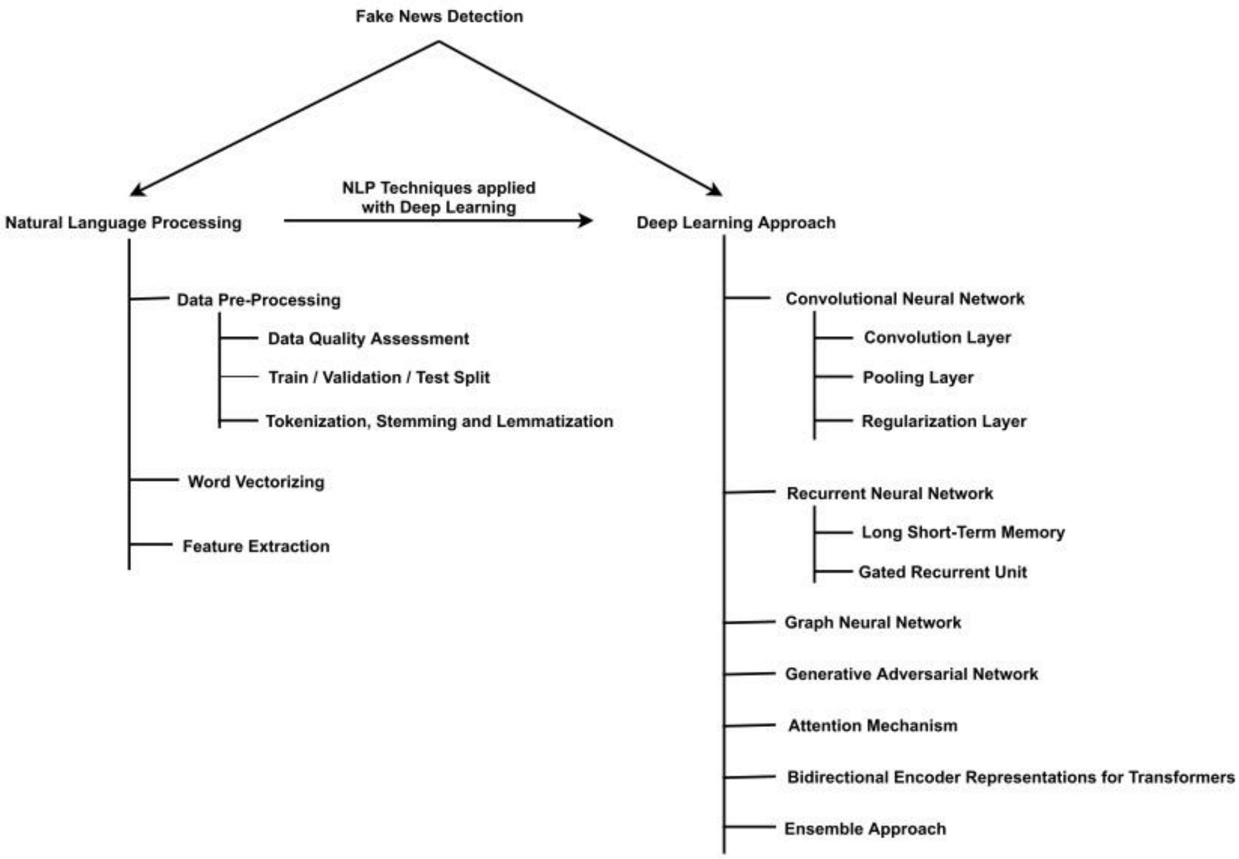

Fig-1. A taxonomy of deep learning-based fake news detection [17].

TABLE 2: The table provides details of publicly available datasets and corresponding URLs.

Dataset	Modality	Size	Labels	Type	URL
Fake news	Text	20,800	Unreliable, reliable	NEWS article	https://www.kaggle.com/c/fake-news/data
LIAR	Text	12.8k	Pants on fire, false, barely true, half true, mostly true and true	Political statements	https://paperswithcode.com/dataset/liar
PHEME	Text	5800 tweets	Rumour, non-rumour	Social media data	https://figshare.com/articles/dataset/PHEME_dataset_for_Rumour_Detection_and_Veracity_Classification/6392078
FNC-1	Text	75k	Agree, disagree, discusses, unrelated	News articles	https://paperswithcode.com/dataset/fnc-1
News aggregator	Text	422,937	Real	News articles	https://www.kaggle.com/uciml/news-aggregator-dataset

B. WORD VECTORIZING

Word vectorizing involves mapping the word/text to a list of vectors. TF-IDF and Bag of Words (BoW) vectorization techniques are commonly used in machine learning strategies to identify fake news [4]. In term frequency inverse document frequency (TF-IDF), the value rises proportionally to the number of times a word emerges in the document but is balanced by the frequency of the word in the body. Although this vectorization is successful, the semantic sense of the words is lost in its attempt to translate to numbers. The BoW technique considers every news article to be a document and computes the frequency count of each word within this document, which is then used to produce a numeric representation of the data. In addition to data loss, this approach also has limitations. The relative location of the words is overlooked, and contextual information is lost. However, this approach may suffer due to loss of information. Neural network-based models have accomplished victory on diverse language-related roles as opposed to traditional machine learning-based models such as logistic regression of support vector machine (SVM) by utilizing word embeddings in fake news detection. It maps words or text to a list of vectors. They are low-dimensional, and disseminated feature representations are appropriate for natural languages. The term ``word embedding" refers to a combination of language modeling and feature learning. Words or expressions from the lexicon are allocated to real-number vectors. Word representation was performed using dense vectors in word embedding. These vectors represent the word mapping onto a continuous, high-dimensional vector space. This is considered an improvement over the BoW model; wherein large sparse vectors of vocabulary size were used as word vectors. Recently, fake news detection researchers have used pre-trained word-embedding models such as global vectors for word representation (GloVe) and Word2vec. Unlike Word2Vec, GloVe supports parallel implementation, making it easier to train the model on huge datasets. Table 5 gives a summary of the NLP techniques and word vector models used in deep learning-based fake news detection papers

C. FEATURE EXTRACTION

A huge amount of computational power and memory is required to analyze a large number of variables. Classification algorithms may overfit the training samples and induce poorly to new samples. Feature extraction is a process of building combinations of variables to overcome these difficulties while still representing the data with adequate precision.

In contrast, social context information can also be aggregated for detecting fake news in social media. It is pivotal to choose the correct determination algorithm for decreasing features because feature reduction contains an incredible effect on the text classification results. Some common feature reduction algorithms include Gini Coefficient (GI), Term Frequency-Inverse Document Frequency (TF-IDF), Information Gain (IG), Mutual Information (1v1I), Principal Component Analysis (PCA), and Chi-Square Statistics (CHI). Neural networks are considered very powerful machine learning tools due to their ability of complex feature extraction. Instead of relying on manual feature selection and other existing techniques, researchers are currently focusing on neural networks for feature extraction.

III. DEEP LEARNING APPROACH FOR FAKE NEWS DETECTION

Deep learning systems have advantages over traditional machine learning methods. Deep learning is a subfield of machine learning strategies, which displays high precision and exactness in fake news detection. Generally, ML methods are based on hand-crafted features. Biased features may appear because feature extraction assignments are challenging and slow. ML approaches failed to achieve prominent results in fake news detection. Because ML approaches produce high-dimensional representations of linguistic information, resulting in the curse of dimensionality. In contrast, DL systems can acquire hidden representations from less complex inputs. The hidden features can be extracted from both the news content and context varieties. However, DNNs use more memory. Convolutional neural network (CNN) and recurrent neural network (RNN) are two broadly utilized ideal models for deep learning in cutting-edge artificial neural networks. After inspecting previous studies, we found a general framework for deep learning-based fake news detection. The first step was to collect a dataset or create one. Most studies have used news articles collected from publicly available datasets. The pre-processing technique was applied after collecting the dataset to feed the data in a neural network. The name of some famous DL architecture is given as follows:

A. CONVOLUTIONAL NEURAL NETWORK (CNN)

B. RECURRENT NEURAL NETWORK (RNN)

C. GRAPH NEURAL NETWORK (GNN)

D. D.GENERATIVE ADVERSARIAL NETWORK (GAN)

E. ATTENTION MECHANISM BASED

F. BIDIRECTIONAL ENCODER REPRESENTATIONS FOR TRANSFORMERS (BERT)

G. ENSEMBLE APPROACH

TABLE 3: The table contains the strength and limitation of popular existing studies with reference and used classifier.

Reference	Dataset	DL classifier	Merits	Demerits
Kaliyar [6]	Fake news	Deep CNN	The model is less prone to overfitting	The training process takes a longer time
Liao [15]	LIAR	Bidirectional LSTM	Tackles fake news detection task and news topic classification task together in a unified approach through multi-tasking learning	The performance of the model depends on author information
Ruchansky[13]	Weibo& Twitter	RNN	Extracting meaningful latent representations	Expensive computational cost
Asghar [14]	Pheme	Bi-LSTM+CNN	The model preserves the sequence information in both direction	The suggested approach is computationally expensive
Umer [7]	FNC-1	CNN+LSTM	When compare to pre-trained BERT, the combined CNN+LSTM with PCA and Chi-square performed better	Because PCA text messages may not have linear connection, some information may be lost, and so the underlying model is dependent on feature extraction
Wang [8]	Twitter and Weibo	EANN	The model is capable of learning transferrable feature for unseen events	Trained on a imbalanced dataset
Huang [16]	Twitter15 and Twitter16	GNN	Adequately extract user information	User behavior information bring some interference to the detection of non-rumor
Jwa [12]	FNC-1	BERT (exBAKE)	Incorporating extra knowledge from large news corpora	Absence of data pre-processing

IV. EVALUATION METRICS

A key step in a predictive modeling pipeline is to evaluate the output of a machine-learning model. Although a model may have a higher classification result once constructed, it must be determined whether it can address the specific problem in different circumstances. Classification accuracy alone is usually insufficient to make this judgment. Other assessment metrics are necessary for proper evaluation. Since a promising method is required to pass the assessment metric's evaluation, it is easy to create a model, but it is more challenging to create a promising strategy. Diverse evaluation metrics are used to evaluate the model's efficiency. The evaluation matrix is an essential device for arranging and organizing an evaluation. The confusion matrix shows an overview of model performance on the testing dataset from the known true values. It provides a review of the model's success and useful results of true positive, true negative, false positive, and false negative. To test their models, researchers considered distinctive sorts of metrics such as accuracy (A), precision (P), and recall(R) [6]. The selection of metrics relies entirely on the model form and its implementation strategy. Result analysis of DL-based studies is presented in Table 4. We provide some evaluation metrics that were widely used in previous studies:

A. ACCURACY

The accuracy score, also known as the classification accuracy rating, is determined as the percentage of accurate predictions in proportion to the total predictions made by the model. The accuracy (A) can be depicted by the given formula in equation (1).

$$A = (TruePositive + TrueNegative) / TotalNumberofPredictions \quad (1)$$

B. PRECISION

Precision (P) is defined as the number of actual positive findings divided by the total number of positive results, including incorrectly recognized ones. The precision can be computed using Equation (2).

$$P = TruePositive / (Positive + FalsePositive) \quad (2)$$

C. RECALL

When the total number of samples that should have been identified as positive is used to divide, the number of true positive results is referred to as recall (R). The recall can be computed using Equation (3).

$$R = TruePositive / (TruePositive + FalseNegative) \quad (3)$$

D. F1-SCORE

The model's accuracy for each class is defined by the F1-score (F1). If the dataset is not balanced, the F1-score metric is typically used. The F1-score is often used as an assessment matrix in fake news detection [41], [157], [158]. F1-score computation can be performed using Equation (4).

$$F1 = 2 \text{x} (precision \text{ x } recall) / (precision + recall) \quad (4)$$

E. ROC CURVE AND AUC

The Receiver Operating Characteristics (ROC) curve shows the success of a classification model across several classification thresholds. True Positive Rate (Recall) and False Positive Rate (FPR) are used in this curve. AUC is an abbreviation for ``Area Under the ROC curve." In other words, AUC tests the whole two-dimensional field under the entire ROC curve. The FPR can be defined as in Equation (5).

$$FPR = FalsePositive / (FalsePositive + TrueNegative) \quad (5)$$

TABLE 4: The table contains the result in accuracy of DL-based studies along with used method and NLP techniques for Fake NEWS dataset (Kaggle).

Method	NLP Techniques	Accuracy	Reference
CNN	TF-IDF	98.3%	Kaliyar [11]
Deep CNN	GloVe	98.36%	Kaliyar [6]
Bi-directional LSTM-RNN	GloVe	98.75%	Bahad [10]
Passive aggressive	TF-IDF	83.8%	Mandical [9]

V. CONCLUSION

Fake news is escalating as social media is growing. Researchers are also trying their best to find solutions to keep society safe from fake news. This survey covers the overall analysis of fake news classification by discussing major studies. A thorough understanding of recent approaches in fake news detection is essential because advanced frameworks are the front-runners in this domain. Thus, we analyzed fake news identification methods based on NLP and advanced DL strategies. We presented a taxonomy of fake news detection approaches. We explored different NLP techniques and DL architectures and provided their strength and shortcomings. We have explored diverse assessment measurements. We have given a short description of the experimental findings of previous studies. In this field, we briefly outlined possible directions for future research. Fake news identification will remain an active research field for some time with the emergence of novel deep learning network architectures. There are fewer chances of inaccurate results using deep learning-based models. We strongly believe that this review will assist researchers in fake news detection to gain a better, concise perspective of existing problems, solutions, and future directions.

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