A Survey on Machine Learning Approach for Fake News Detection on Facebook

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Abstract:- The digital era has access to a plethora of data in the Fourth Industrial Revolution (4IR, also known as Industry 4.0) period, including Internet of Things (IoT) data, cybersecurity data, mobile data, business data, social media data, health data, etc. Machine learning (ML), a subset of artificial intelligence (AI), is crucial for improving the corresponding smart and automated applications and for conducting intelligent analyses of these data. The prevalence of social networking sites (SNS) and their ease of use have steadily altered how knowledge is produced and disseminated in the modern world. Cheap access to the news does not, however, guarantee that more people will be aware of it. Social networks, in contrast to traditional media outlets, also hasten and widen the spread of material that has been purposefully misrepresented (fake news). Spreading fake news like wildfire has a negative impact on people's attitudes, behaviors, and beliefs, which in turn can gravely undermine democratic processes. The key problem facing researchers today is minimizing the detrimental effects of fake news through early detection and control of extensive diffusion. In this review article, we in-depth examine a wide range of several approaches for the early identification of fake news in the body of existing literature. We specifically look at Machine Learning (ML) models for the detection of fake news on Facebook, including their classification and identification. We conclude by outlining some unsolved research problems.

Keywords:- *Component; Deep Learning, Fake News, Machine Learning, Social Network Sites.*

I. INTRODUCTION

A real-time platform called microblogging enables users to post brief digital materials like text, links, photographs, or videos. Microblogs are referred to as social media. According to [1], users of social media sites including Twitter, Facebook, YouTube, Instagram, WhatsApp, Snapchat, and LinkedIn generated a lot of metadata that might be used for data mining and simulation modeling. Despite the fact that microblogging is a more recent form of communication than traditional media, it has gained more attention from users, organizations, and academics in a variety of sectors [2]. Microblogging is appealing because it allows for real-time communication with few or no content limitations and has special message features like portability, instant messaging, and user-friendliness [3].

One of the most important social developments of the last ten years has been the emergence of social network sites (SNS) like Facebook, Twitter, Instagram, and others. Facebook was first available to the public in 2006, but as of the end of 2012, reports indicate that it was already serving one billion active users per month [4]. Facebook is a global platform because 80% of these users are located outside of the US and services are offered in 70 different languages. One should acknowledge that the size of this SNS is at least sizable, and the increase rate is significant, despite concerns about the accuracy and reliability of these numbers (the number of frequently used accounts may differ from the actual number of users using the platform, and neutral information is not available). Scientists from a variety of different sectors have been interested in this growth rate. Facebook as a term on the ISI Web of Knowledge returned at least 3068 results in February 2013. Facebook's influence on modern life is undeniable. It was just introduced 15 years ago, yet as of this writing, it has 1.2 billion daily users and reaches over two billion people each month. In other words, Facebook is currently the most visited website on the internet in terms of both time spent and pages viewed. Facebook has come under fire for having the potential to be used to quickly and widely disseminate harmful content. During crucial democratic times, the platform has been used to encourage violent terrorism, skew presidential election outcomes, shape perceptions, and sway public opinion. Even though it was false, the rumor that Pope Francis had endorsed Mr. Trump for president was circulated about a million times [5]. Twitter is the most popular social media platform, with more than 320 million users and 500 million tweets sent every day [6]. In 2019, there were 68 million active monthly Twitter users in the US. Twitter comments are limited to 280 characters and are generally viewable by the general public. Users of Twitter are able to engage in social media activities such tweeting and retweeting previously published messages [7]. The aggregate group of Twitter Application Programming Interfaces (APIs) is a mechanism for gathering user information. According to [7], the primary social media data source for researchers and policymakers right now is Twitter API data. Today, the majority of social network users get their news from online sources. The use of the Internet, however, has evolved into a prime platform for communication and the dissemination of false information as a result of OSNs' rising popularity. The dissemination of false information in the form of satires, false reviews, false rumors, ads, and misleading content. False news currently spreads more quickly on social media than in traditional media [8]. information that has been manipulated by several propagandists to spread political and other influential messages through the internet. As an illustration, several users created fake accounts to propagate false information on Twitter and Facebook during the 2019 Indian [9]lot of false and unbelievable material is produced by several individuals and displayed on social network platforms [10]. Some information causes social network users to get perplexed. The process of spotting and identifying bogus news on a social platform is difficult [11]. People employ a variety of manual techniques for fact-checking websites like FaceChek.org and PolitiFact.com. These websites are essential for spotting bogus news on the internet. But for a quick response, each of these software programs need specialized study. Additionally, political concerns are the main emphasis of all these fact-checking programs. In addition, a user generated a lot of content that was shared, liked, and remarked on in an online social network platform. Through numerous posts, numerous fraudulent personas distribute false information on the social network site [12]. Due to the volume of information in all these shared articles, it is challenging to identify fake news on social media platforms. The bogus news that circulates around the network appears to be invisible. Machine learning is a component of artificial intelligence that aids in creating systems with the ability to learn and carry out various tasks [13].In comparison to a manual approach, utilizing a machine learning system to identify fake news has benefits [14].Feature engineering is used in the manual technique[15].The majority of manual fact-checking techniques for identifying false news are restricted to the text of articles without any clear references to sources, writers, or meta data. The development of artificial intelligence (AI) has made it simpler to automate the detection of fake news [16]; [17], which has improved prediction speed and accuracy [18]. Additionally, it has a strong ability to manage big data [19].

The other sections of the paper are as follows: Section 2 talks about Research Methodology. Section 3, discusses on Social Media Platform. Section 4, Presents Machine Learning. Section 5, Conclusion and Future Direction.

II. OVERVIEW OF SOCIAL MEDIA PLATFORMS

The rise of social networks has already had a significant impact on daily life, and occupational quality has already shown how important they are for research and education. This opinion piece aims to introduce, define, and consider the use of Twitter within occupational therapy research and teaching. As technology is continually changing how we think of online social networking, it is important to keep up with these changes. We will just consider Facebook in this paper

A. Facebook Overview

We give a brief summary of Facebook's features in this section. Based on the Facebook Timeline layout as it existed in October 2012 [20], this summary. On the website Facebook.com, users can register for an account. The new user selects a password and gains account access after giving some personal information (name, date of birth, gender, and email address). Facebook chooses to have a very uniform user account design. Numerous elements remain in the same location on the screen regardless of whose account it is, making it simple to identify and locate the information one is looking for. This account's home and profile pages are both crucial. The place where users introduce themselves is the profile page, commonly known as "the wall." At the top of the website, a large cover photo is complemented by a little profile picture. Below the cover photo, the user's name is displayed along with some basic details and a few links for friends, photographs, and "likes." The section where "status updates" are displayed is below that. Users are free to put whatever they like in their status, and friends can react on it by text or by liking it, which is displayed just below the status.

Users are informed of their friends' status changes and other activities (such as joining groups or becoming fans of things they enjoy) on the home page, often known as the "news feed." As a result, it continuously and chronologically displays the highlights of what friends have been up to lately. Table 1 below provides a summary of some Facebook algorithms that are used to detect fake news.

B. News Feed

Users are informed of their friends' status changes and other activities (such as joining groups or becoming fans of things they enjoy) on the home page, often known as the "news feed." The highlights of what friends have been up to over the last few hours are thus automatically and chronologically reflected [20]. The new user can start looking for friends and sending friend requests after creating a profile. Once the request is approved, Facebook links the two people by enabling them to view each other's profile pages and adding their updates to one another's news feeds. Facebook serves as an online platform for seeing and being seen, or to "presume": producing and consuming simultaneously [21].

C. Overview of Computational Algorithms Used in Fake News Detection

➢ *Overview of Machine Learning Algorithms*

The study of how computers can learn without being taught is known as machine learning (ML), which is a subset of artificial intelligence [22]. It has developed from artificial intelligence, particularly from computational learning theory and pattern recognition. A ML method is used to select the best function from a list of potential functions and to explain how the features of a dataset relate to one another. Optical character recognition (OCR), prediction, and computer vision applications all employ It [22].

In general, the nature and qualities of the data, as well as the success of the learning algorithms, determine the effectiveness and efficiency of a machine learning solution. Techniques such as classification analysis, regression, data clustering, feature engineering and dimensionality reduction, association rule learning, or reinforcement learning are available in the field of machine learning algorithms to efficiently construct data-driven systems.

The artificial neural network, which is a member of a larger family of machine learning techniques that may be used to intelligently evaluate data, is also where deep learning originated. So, it can be difficult to choose a learning algorithm that is appropriate for the target application in a given domain. The rationale is that different learning algorithms serve different purposes, and even results from algorithms in the same general category can differ depending on the peculiarities of the input data. In order to apply machine learning algorithms in a variety of real-world application areas, such as IoT systems, cybersecurity services, business and recommendation systems, smart cities, healthcare and COVID-19, context-aware systems, sustainable agriculture, and many more [23], it is crucial to understand the principles underlying different machine learning algorithms. The taxonomy is shown in Figure 1 below.

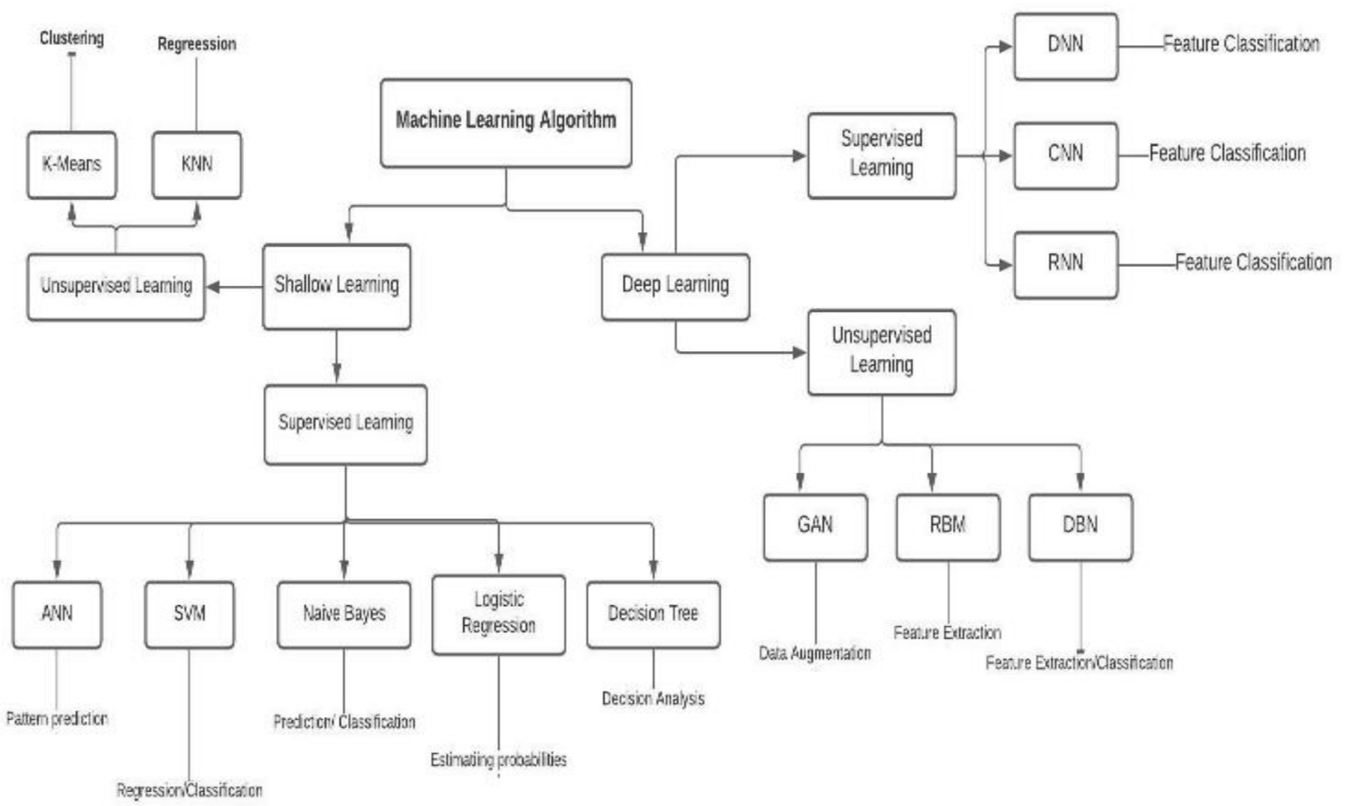

Fig 1 Taxonomy of Machine Learning Algorithms [24]

➢ *Shallow Machine Learning*

Shallow algorithms compared to the Deep learning models Deep learning is a subfield of machine learning, and in most application scenarios, the results of deep learning models outperform those of classic machine learning (or shallow model) methods. According to [24], the following characteristics most clearly illustrate the distinctions between shallow and deep models:

- Running time: The running time takes into account both training and testing time. Deep models take substantially longer to train and test than shallow models do because of their high level of complexity.
- The number of parameters: Learnable parameters and hyper parameters are the two different sorts of parameters. The hyper parameters are manually set prior to training, while the learnable parameters are generated during the training phase. Deep models require more time to train and optimize than shallow models since there are

many more learnable parameters and hyper parameters in deep models than in shallow models.

- Feature representation: Before introducing the data into the conventional methods, feature engineering is a crucial step because the input to standard machine learning models is a feature vector. Deep learning models, on the other hand, are independent of feature engineering and are capable of learning feature representations from unprocessed data. Deep learning techniques have a significant advantage over conventional machine learning techniques since they may be applied end-to-end.
- Learning capacity: Deep learning models have intricate architecture and a large number of parameters (often millions or more). As a result, deep learning models are better at fitting data than shallow learning models. In contrast to shallow algorithms, deep learning models also have a higher risk of overfitting and need significantly more training data. The impact of deep learning models is superior, though.
- Interpretability. A key aspect of deep learning is that the models are "black boxes" and the outcomes are essentially incomprehensible [25]. However, traditional machine learning methods with strong interpretability include the decision tree and naive Bayes.

Table 1 The Pros and Cons of the Shallow Models

Algorithms	Advantages	Disadvantages	Improvement Measures
ANN	Strong fitting abilities and the capacity to work with nonlinear data [24].	Overfitting prone; prone to become caught in a local optimum; time-consuming model training	enhanced optimizer, activation, and loss functions
SVM	Gain knowledge from a simple train set; powerful generation ability	do poorly on tasks involving huge data or numerous classifications; kernel function parameters are sensitive.	Particle swarm optimization (PSO)-assisted parameter optimization
KNN	apply to voluminous data; appropriate for nonlinear data; exercise swiftly; robust to data noise reduction.	Long test times; low accuracy for the minority class; and sensitivity to the parameter K	trigonometric inequality reduced comparison times; Particle swarm optimization (PSO) [26] optimized parameters; Synthetic minority oversampling method (SMOTE)-balanced datasets [27]
Naïve Bayes	robust to noise; capable of incremental learning	Perform poorly with data related to attributes.	Latent variables were imported to loosen the independent assumption
LR	Quickly trainable and simple; automatically scales features	perform poorly with nonlinear data; Suitable to oversizing	[28] Imported regularization to prevent overfitting
Decision Tree	Automatic feature selection; powerful interpretation	Classification outcome tends toward the majority class; disregard the data's correlation	SMOTE-balanced datasets; latent variables added
K-means	Strong scalability; simple, quick training; able to fit large data	perform poorly with nonconvex data; capable of startup; aware of the K parameter	Enhancement to the initialization process [29].

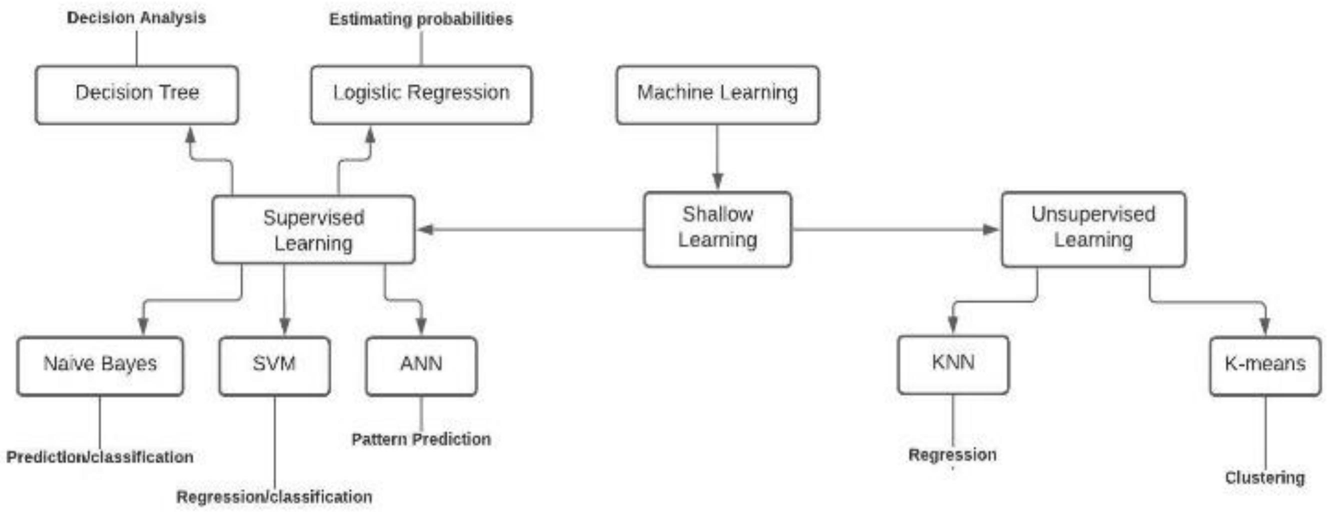

Fig 2 Taxonomy of Shallow Algorithms

➢ *Deep Learning*

Because of the development of graphics processing units (GPU), lower hardware costs, and enhanced network connectivity, deep learning has become more and more popular[30]. Deep learning is becoming more popular due to the proliferation of training data as well as current advancements in machine learning and information processing research [31]. Deep learning can automatically learn features from a dataset, in contrast to classical machine learning, where a domain expert is required to help in feature extraction. Deep learning has the capacity to automatically pick up the crucial features during the training phase rather than employing a manually created collection of rules to gather data features [32].According to [32], deep learning employs a number (tens or even hundreds) of successive layers, each of which provides a more significant representation of the input data. It has been used in difficult machine learning applications like as image classification, speech recognition, handwriting transcription, natural language processing, self-driving automobiles, and many others. The taxonomy of the deep learning architecture is shown in Fig. 3 as follows.

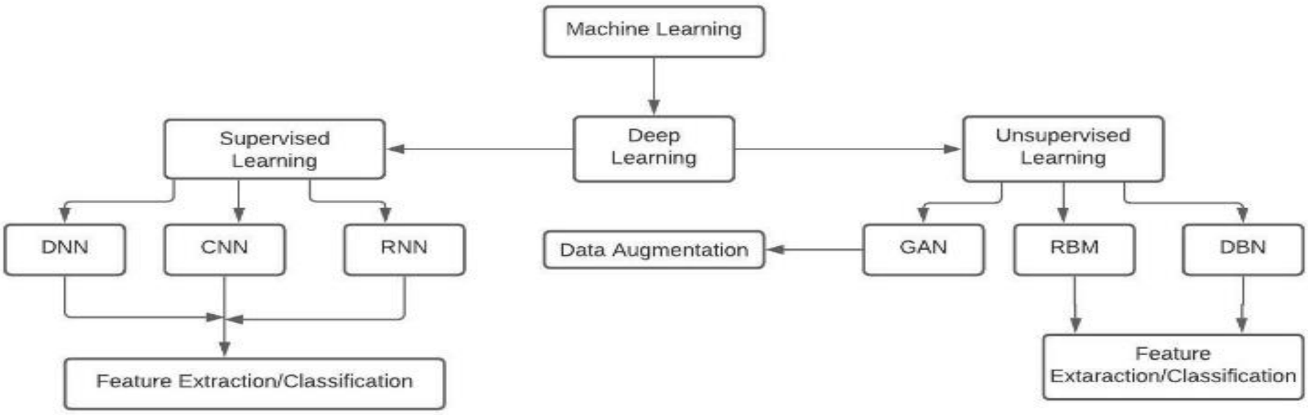

Fig 3 Taxonomy of Deep Learning Algorithms

D. Related Work

Deep Learning Algorithms and Shallow Machine Learning Algorithms are the two types of machine learning algorithms that can be used to detect fake news. We only have two data processing layers in shallow learning, with the second layer being linear. Therefore, we only take a linear combination (2) of a number of functions of type (1). In contrast, deep learning uses a number of nonlinear layers for data processing. The process of identifying fake news has been referred to by many different names, including disinformation, rumor, and spam. Each paper adopts its own definition of these words that contradicts with or overlaps with other papers' definitions of the terms, just as each individual may have their own intuitive definition of similar notions. For this reason, we specifically state that the focus of our research is identifying news information on Facebook social media that is phony, real, or contrived. Due to terminology differences, Table 3 lists existing work in broad categories based on which of the four qualities (Language, Dataset, Platform, and Algorithm) were taken into account. Text analysis of rumors, spam, and fake news has been the subject of a significant amount of research. This research has centered on textual traits [33].[34] employed KNN, SVM, LR, DT, and Nave Bayes instead of LSTM in their study on classifying fake news on Facebook. The strategy predicts outcomes more correctly in deep learning contexts compared to machine learning environments; however, feature engineering was its main drawback. The results show that the proposed Hybrid CNN-RNN approach is far more accurate than any prior methods. [35] proposed Hybrid CNN-RNN for false News detection. [36] also conducted a number of comparative experiments with various hyper parameter values and proposed a text categorization approach based on CNN, LSTM, and FF. Additionally, they provided parameter tuning guidance and have some expertise configuring hyper parameters. Although they have shown better performance, CNN and LSTM require a lot of processing power to train on big amounts of data. The dependability of news sources is unknown, however [37] employs Bayesian inference to identify fake news; as a result, the findings indicate superior to RANDOM and NOLEARN algorithms. The researchers suggested combining deep learning algorithms (CNN-GRU) to classify fake news using a corpus of Facebook text. The models of CNN and GRU were reviewed for a possible fusion based on their strengths (CNN excels at extracting local vector features of vulnerability text, whereas GRU excels at extracting global features related to the context of vulnerability text). In order to better precisely capture the semantic and grammatical information, the characteristics retrieved by the complimentary models might be combined [38].

➢ *Application of Shallow Machine Learning Algorithms used in Fake News*

Based on the work of[39], Nave Bayes and SVM were proposed and compared with neural networks for the classification of false information on Twitter, but their work was only done in English. In addition, [40] and [34] propose LR, KNN, SVM, L, DT and Nave Bayes were compared with L and LSTM it's shows improvement in term of accuracy using the deep learning over machine learning, but machine learning is faced with feature engineering. A summary of the various works is shown in Table 2.

Table 2 Summary of Shallow Machine Learning Algorithms used in Fake News

Reference	Language	Dataset	Social media platform	Algorithm proposed	Comparative algorithm	Results	Limitation
(Atodiresei et al., 2018)	English	NoSQL dataset	Twitter	Naïve Bayes and SVM	Neural network	The result is very trustworthy for fact-checking.	It only functions with Twit in English.
(Aldwairi & Alwahedi, 2018)	English and Arabic	Clickbaits from SNS	SNS	LR	L	Outstanding performance in identifying potential false news sources	On SNS, only two languages are allowed.
(Sahoo & Gupta, 2021)	English	Over 15,000 news articles from various Facebook users, including true and false news	Facebook	KNN,SVN,LR,DT and Naïve Bayess	LSTM	Utilizing both user profiles and the false news feature, the method predicts outcomes more accurately in deep learning environments than in machine learning environments.	feature engineering
Reference	Language	Dataset	Social media platform	Algorithm proposed	Comparative algorithm	Results	Limitation

➢ *Application of Shallow Machine Learning Algorithms used in Fake News*

Recently, a lot of individuals have tried utilizing machine learning algorithms to identify bogus news. [35] created a hybrid CNN-RNN where the result indicates higher improvement in accuracy than any other technique, but the model cannot generalize across dataset [18] implemented fake news using DNN, but it had the limitation of taking a long time to train and test. In 2020, Agarwal et al. When CNN-RNN was compared to SVM and GRU, its performance was superior, however the suggested method for classifying articles as trustworthy or unreliable without considering their sources is shown in table 4 below.

Table 3 Deep Learning Algorithm used in Fake News

Reference	Language	Dataset	Social media platform	Algorithm proposed	Comparative Algorithm	Results	Limitation
(Nasir et al., 2021)	English	FA-KES and ISOT	Twitter	Hybrid CNN-RNN Approach	LSTM	The findings demonstrate that the suggested Hybrid CNN-RNN method is much more accurate than any previous methods.	These models frequently perform well on a particular dataset but are difficult to generalize.
(Kaliyar et al., 2021)	English	BuzzFed and PolitiFact	SNS	DNN	SVM	DNN offers improved performance.	There is a lot of testing and training.
(Agarwal et al., 2020)	English	Kaggle fake news dataset	SNS	CNN and RNN	SVM and GRU	RNN and CNN combined do better.	The suggested approach focuses on categorizing articles as legitimate or fraudulent without taking into account their sources.
(Krešňáková et al., 2019)	English	Dataset obtained from the Kaggle competition	OSN	FF,CNN,LSTM		CNN and LSTM have demonstrated improved performance.	High computational cost for large-scale data training

Table 4 Detecting Fake News on Facebook Platform

Approach	Dataset	Result	Limitation	Platform
Using Bayesian inference to identify Fake news (Tschiatschek et al., 2018).	88,234 edges, users, 4,039 users, and spammer	superior to RANDOM and NOLEARN algorithms	The reliability of news sources is unclear.	Facebook
Fact-checking stochastic epidemic model (Tambuscio et al., 2015),	1,000-node network, spreading rate, and forgetting likelihood	Establish a hoax fact-checking likelihood	Does not take into account the diversity of agents	Facebook
(Potthast et al., 2017) "Random forest classifier for fake news detection".	1,627 pieces of content, writing	hyper-partisan and mainstream distinction	Not applicable for	
LR, BCS algorithm for classification(Tacchini et al., 2017).	15,500 posts, 909,236 users, likes	99 percent accuracy in classifying hoaxes and real stories	Few conspiracy ideas are present in the data set (Shu et al., 2020).	Facebook

III. MATERIALS AND METHOD

This section's major goal is to make sure the systematic literature review process is followed in order to minimize bias and make sure the topic matter is adequately covered. This section discusses the method used to review the literature on Machine learning applications in Fake News detection. There are explanations of search terms, search methodology, data sources, databases, and inclusion and exclusion criteria. The systematic literature review followed the instructions in the computer science systematic literature review. The work is also used as a guide to conduct our systematic literature review[41].

A. Article Inclusion/Exclusion Criteria

There were established inclusion and exclusion criteria to ensure that only the pertinent papers were extracted for examination. By examining the papers' titles, abstracts, conclusions, and entire contents, we were able to determine if they were among the articles that were relevant for the review or not.

B. Eligibility

We used a set of criteria on the articles we pulled from academic databases to ascertain the eligibility of the articles we chose. 1,237 papers in total were found during the initial search of all academic databases. 1,06 articles were discarded after duplicates were removed and titles were used as the basis for deletion. In the second stage, which took into account the abstract and conclusion, 839 items were eliminated. Only 45 papers ultimately passed the full content stage and were thus used for the review. The method for choosing articles is depicted in Figure 5.

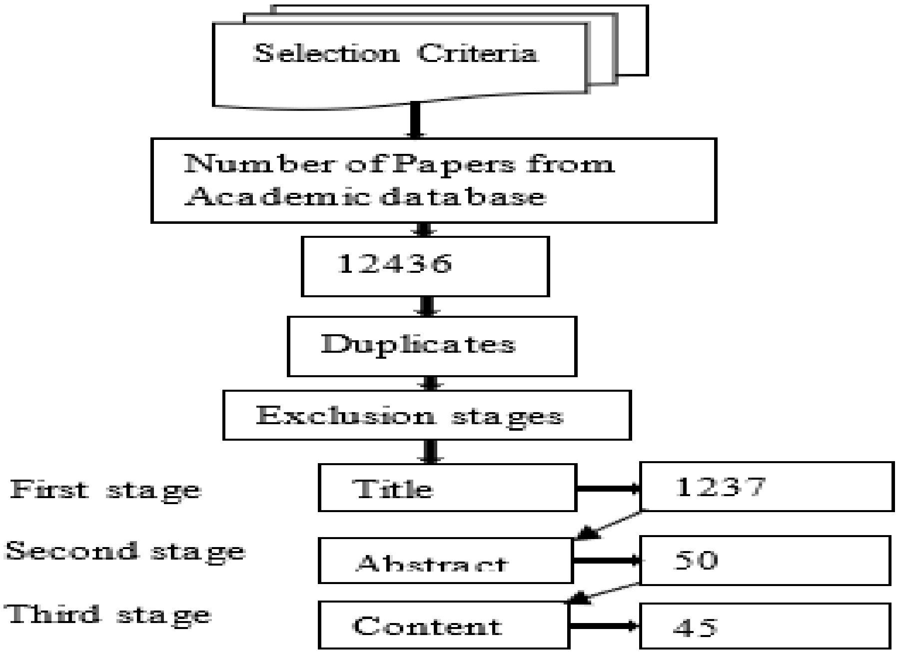

Fig 4 Article Exclusion Criteria

IV. RESEARCH FINDINGS AND CHALLENGES

According to the reviews, the following issues were found. Based on the work of [33], they used Nave Bayes to classify data with good accuracy but encountered (feature engineering) issues. High cost of labeling and training data, inability to handle huge datasets; [35] had greater classification accuracy but no dataset-wide generalization. Also [18] found considerable improvements but did not take into account chamber-based information and news context; [30]**;** Shows significant improvement on content based, propagation based & hybrid. Content based performed well in predicting fake news with limited prior knowledge but Limited high-quality data accessibility, high dimensionality data, diverse nature, unidentified factual data, and massive data size. [42];Classify fake News but limited high-quality data accessibility, high dimensionality data, diverse nature, unidentified factual data, and massive data size.

V. CONCLUSION

The adoption of machine learning approaches for battling fake news on Facebook has been the subject of an extensive literature review. The numerous machine learning techniques and their applications in the detection of fake news on Facebook social media have been discussed. It was discovered that various Machine Learning Algorithms had been used to address issues with Fake News identification on Facebook social media. This review can serve as a starting point for new researchers in the field and a benchmark for developing a hybrid learning algorithm for spotting false news on Facebook social media, specifically for combining text and image identification.

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