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Machine Learning Approaches for Combating Fake News on social media: Approaches, Advancement, Taxonomy and Future Directions

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ABSTRACT
Widespread of Social Network Sites (SNS) and the simplicity of used has gradually changed the generation and spread of information nowadays. However, cheap access to News does not equal an increased level of people's awareness. In contrast to the traditional media channels, social networks also bring about faster and wider dissemination of intentionally false information (fake news). Viral spread of fake news has severe consequences on the behavior's, attitudes and beliefs of the people, and ultimately can seriously harm the democratic processes. Reducing fake news negative impact through early detection and control of extensive spread presents the main challenge facing researchers nowadays. In this survey paper, we extensively analyze a wide range of different solutions for the early detection of fake news in the existing literature. More precisely, we examine Machine Learning (ML) models for the identification and classification of fake news, fake news detection on SNS. Finally, we present some open research challenges.

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INTRODUCTION

Micro blogging is a real time platform enabling users to share short digital contents such as text, links, images, or videos. Social media is an umbrella word for microblogs Dong and Yang (2020). Social media such as Twitter, Facebook, YouTube, Instagram, WhatsApp, Snapchat, LinkedIn, etc. resulted in the generation of large metadata for data mining and simulation modeling through users (Ghani, Hamid, Hashem, & Ahmed, 2019).The microblogging has attracted increase attention among users, organizations and scholars in various fields despite the fact that it is a new communication media compared to the traditional media (Earl, James, Ramo, & Scovill, 2021). The appeal of microblogging stems from its unique message features such as portability, instant messaging and user-friendliness; which enables real time communication with little or no content restrictions (Medina & Diaz, 2016).

Research Motivation

Recently Fake news detection has drawn huge attention from researchers across the world. Social media platforms have become a popular bridge among users (Fazil & Abulaish, 2018; Vosoughi, Mohsenvand, & Roy, 2017) d(Nasir, Khan, & Varlamis, 2021),in most of the literature reviewed there is no generalization across different dataset (Nasir et al., 2021) Recently, reviews on fake news detection using Machine Learning Algorithms, (Li, 2020) uses multiple-level convolutional neural network-based fake news detection system, which is combined to perform fake news detection in that MCNN extracts article representation and WS calculates the weight of sensitive words for each news. (Zervopoulos,2022) regarding the classification of fake news concerning the Hong Kong protests with the use of traditional machine learning (ML) algorithms is extended.

More specifically, three diverse feature sets, focusing on purely linguistic content (unlike most previous approaches that rely at least partly

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on user account information), are derived from the previously constructed dataset, which contains tweets in both English and Chinese, that are attempting to spread fake and real news originating from malicious users and trusted journalists, respectively.(Ajao, 2018) used hybrid model of deep learning LSTM and CNN for text and image Classification by automatic identification of features within Twitter post. Multi-level convolutional neural network (MCNN), which introduced the local convolutional features as well as the global semantics features, to effectively capture semantic information from article texts which can be used to classify the news as fake or not (Li, 2020).

The reason for Hybridizing two algorithms GRU-CNN is that convolutional neural network can extract local features of text but cannot capture structure information or semantic relationships between words, and a single CNN model's classification performance is low, whereas GRU can effectively extract semantic information and global structure relationships of text. To address this problem, we propose a news text classification method based on the GRU_CNN model. The fusion between the models of CNN and GRU according to their advantages (CNN is good at extracting local vector features of vulnerability text and GRU is good at extracting global features related to the context of vulnerability text). The merger of the features extracted by the complementary models can represent the semantic and grammatical information more accurately (Wang, 2022).

Social Media Platforms

The emergence of social network is already a major support of everyday life, and its use and significance within research and education is already indicated in occupational quality (Maclean, Jones, Carin-Levy, & Hunter, 2013). Technology is constantly changing our ideas of online social networking, and this opinion piece sets out to introduce, define, and consider the application of Twitter within occupational therapy research and education. In this section, we discussed the social media platform considered for this research.

Twitter

Twitter is a widely used free social networking tool that allows people to share information, in a real-time news feed through posting brief comments about their experiences and thoughts (Maclean et al., 2013). Public messages sent and received via Twitter or 'tweets' are limited to no more than 140 characters and can include links to blogs, web pages, images, videos and all other material online. Despite the brevity imposed by this media tool, Twitter use is extensively used in a wide variety of circumstances and, according to (Bouzid & Ilham, 2020) 'thousands of academics and researchers at all levels of experience and across all disciplines already use Twitter daily'. After setting up a twitter account (www.twitter.com), users establish a profile and a Twitter 'name' for instance, @OTprofile and can then send and receive tweets, accessed through any computer or mobile networked device.

Once a tweet is sent, it appears in the user's Twitter 'feed' and in the feed of anyone who is following them. Searching can also be used to find relevant tweets. This can be by keywords, often identified by user-defined hash tags, identified by an initial '#' symbol (for example #occupation or #journal). Hash tags help to locate particular areas of discussion (Maclean et al., 2013) and some hashtags that are used as professionally relevant to occupational therapy. As a communication tool, Twitter allows the free exchange of ideas nationally and globally, between people interested in similar areas of expertise, as well as providing the opportunity to engage in critical debate.

Table: 1 Summary for detecting fake news on Twitter Platform

Approach	Dataset	Result	Limitation	Platform
RNN and CNN for fake news detection	Weibo (Ma et al., 2016) Twitter15	Outperforms a state of-	Problem with computational	Twitter

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Approach	Dataset	Result	Limitation	Platform
(Y. Liu & Wu, 2018)	and Twitter16 (Ma, Gao, & Wong, 2017), user Profiles	the-art model in terms of both effectiveness and efficiency	efficiency and interpretability (Zhou & Zafarani, 2019)	
Diffusion of network information for classification (Vosoughi, Roy, & Aral, 2018)	126,000 stories, 3 million users, 4.5 million tweets, retweets, users	Fake news spreads rapidly and deeply and is more novel than true news	Information cascades (Constantinides, Henfridsson, & Parker, 2018)	Twitter
LSTM-RNN for fake news detection (Wu & Liu, 2018)	3,600 fake news, 68,892 real news, network information	Trace miner: classifying social media messages	Only considers network information	Twitter
Bow-Tie and D-core decomposition for user analysis (Garcia, Mavrodiev, Casati, & Schweitzer, 2017)	40 million users, 1.47 billion follower links	Global metrics are more predictive than local	Theory-driven approach (Hasani-Mavriqi, Kowald, Helic, & Lex, 2018)	Twitter

Facebook Overview

In this section we provide a short overview of the features of Facebook. This overview is based on the Facebook Timeline layout as it was available in October 2012(Farahbakhsh et al., 2017). Individuals can create an account on the website Facebook.com. After providing some personal information (name, date of birth, gender, email address), the new user chooses a password and gets account access. Facebook opts for a highly standardized layout of user accounts. Regardless of whose account it is, many features appear on the same place on the screen, making it easy to recognize and find the data one is searching for. There are two important pages on this account: home and profile. The profile page, also often called 'the wall', is where users present themselves. A small profile picture adds to a large cover photo at the top of the page, below which the name of the user is presented along with some basic information and a few buttons referring to friends, photos, and "likes." Below that is the area where "status updates" appear.

Users can post anything they want in their status, and friends can respond to this statement by text comments or by liking it shown directly below the status. On the home page, also often called "news feed," users are informed on the status updates and other activities (joining groups or becoming fan of something they like) from their friends. It thus automatically and chronologically reflects the highlights of what friends have been doing in the past hours.

News Feed

On the home page, also often called "news feed," users are informed on the status updates and other activities (joining groups or becoming fan of something they like) from their friends. It thus automatically and chronologically reflects the highlights of what friends have been doing in the past hours (Farahbakhsh et al., 2017). Once a profile is created, the new user can start looking for friends and send friend requests. When accepted, Facebook connects the two individuals by allowing them to see each other's profile page and by adding their activities to one another's news feed. Facebook thus functions as an online application to see and to be seen (Stroud, 2008) or to "presume": producing and consuming at the

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same time (Le & Tarafdar, 2009) & (Le & Tarafdar, 2009).

Table: 2 Detecting Fake News on Facebook Platform

Approach	Dataset	Result	Limitation	Platform
Bayesian inference for fake news detection (Tschiatschek, Singla, Gomez Rodriguez, Merchant, & Krause, 2018)	4,039 users, 88,234 edges, users and spammer	Outperforms NOLEARN and RANDOM algorithms	Trustworthiness of news sources are ambiguous	Facebook
Stochastic epidemic model for fact-checking (Tambuscio, Ruffo, Flammini, & Menczer, 2015)	Network with 1,000 nodes, Spreading rate, forgetting probability	Define a fact-checking probability for hoaxes	Does not consider the heterogeneity of agents	Facebook
Random forest classifier for fake news detection (Potthast, Kiesel, Reinartz, Bevendorff, & Stein, 2017)	1,627 articles, Writing Style	Distinguished hyper partisan and mainstream	Not applicable for fake news detection	Facebook
LR, BCS algorithm for classification (Tacchini, Ballarin, Della Vedova, Moret, & de Alfaro, 2017)	15,500 posts, 909,236 users, likes	Classification accuracy 99% for hoaxes and non-hoaxes	Limited conspiracy theories in data set (Shu, Mahudeswaran, Wang, Lee, & Liu, 2020)	Facebook

Instagram

Instagram, a mobile application is a computer-based software made to help individuals who utilize a smart phone to do a specific task (Makarim, Dimyati, & Kurniullah, 2020). Instagram is an online networking that is now well known worldwide (Binmasudi, 2018). Moreau then records that this application has 800 million users from over the world. Instagram originates from two words, Insta and Gram (Memon, Sharma, Mohite, & Jain, 2018)

Instagram Features

Instagram has experienced a complete transformation and it is still growing with new features (Makarim et al., 2020). With the increasing features available on Instagram such as Instagram has now more fun. Instagram users can share their stories on Instagram Story that can be seen for 24 hours (Yanuar, Azman, Nurrahmi, & Kamara, 2021)

On Instagram, besides uploading photos and videos, users can also edit their photos and videos before uploading them; this is because Instagram has a filter feature that can edit photos or videos by giving certain effects to our choice so that photos that have been posted will look more beautiful and attractive. Filters in Instagram are one of the important points in building a brand image (Janavi, Soleimani, Gholampour, Friedrichsen, & Ebrahimi, 2021).

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Table 3: Detecting fake news on Instagram platform

Approach	Dataset	Result	Limitation	Platform
Random tree, J48, SVM, RBF, MLP, Hoeffding tree, and Naïve Bayes for classification(Sheikhi, 2020a)	10000 from real dataset on Instagram	bagging decision tree-based algorithm produced better performance than the other five classification algorithms	most fake accounts do not contain many posts or mostly have zero or one post by this trick, they can sometimes bypass Instagram's limitations	Instagram
machine learning algorithms like Naive Bayes, Logistic Regression, Support Vector Machines and Neural Networks are applied.(Akyon & Kalfaoglu, 2019)	1002 real account and 201 fake account has been gathered after extensive manual labeling, including accounts from different countries and fields.	SVM and neural network based methods achieved the most promising performance	Longer time for training and testing data	Instagram
We applied major clustering methods including K-means, Gaussian Mix-tures Model, and Spectral Clustering algorithms (Zarei, Farahbakhsh, & Crespi, 2020)	We collected 4.8K comments, and 2.6K likes across 566 posts created from 3.8K impersonators during 7month	We obtained valuable knowledge by using various text analysis techniques which explains better the behaviors of impersonators.	They didn't use machine learning algorithm as classifiers for comment which fails to predict at first whether the content of the text is fake or not and second, evaluate whether the publisher of that comment is impersonator or not.	Instagram
We use Naive Bayes Classifier, a Bayesian approach of Machine Learning algorithm has applied to identify the fake news.(Adiba, Islam, Kaiser, Mahmud, & Rahman, 2020)	dataset is collected from Kaggle which is the largest community of data scientist	Naive Bayes has significant impact on accuracy	Not suitable in handling large text	Instagram

Fake News Analysis

People heavily dependent on social media for getting information and spend a substantial amount of time interacting on it. In 2018, the Pew Research Center revealed that 68 percent of Americans used social media to obtain

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information (Shearer & Mitchell, 2021). On average, 45 percent of the world's population spend 2 hours and 23 minutes per day on social media and this figure is constantly increasing (Asano, 2017) . The biggest problem with information available on social media is its low quality. Unlike the traditional media, at the moment, there is no regulatory authority checking the quality of information shared on social media(Shu, Wang, & Liu, 2019). The negative potential of such unchecked information became evident during the 2016 US presidential election1. In short, it is of paramount importance to start considering fake news as a critical issue that needs to be solved(Allcott & Gentzkow, 2017).

In spite of the overwhelming evidence supporting the need to detect fake news, there is no universally accepted definition of fake news. According to (Lazer et al., 2018), "fake news is fabricated information that copycats news media content in form but not in organizational process or intent". In a similar way, fake news is defined as "a news article that is intentionally and verifiable false"(Shu, Sliva, Wang, Tang, & Liu, 2017)

Some articles also associate fake news with terms such as deceptive news (Allcott & Gentzkow, 2017), satire news (Rubin, Chen, & Conroy, 2015), clickbait(Chen, Conroy, & Rubin, 2015), rumors (Zubiaga, Aker, Bontcheva, Liakata, & Procter, 2018), misinformation (Kucharski, 2016), and disinformation (Kucharski, 2016). Hence, these terms are used interchangeably in this survey.

Fake news benchmark dataset

There are a lot of different public datasets for fake news on social media. In this section, we presented the popular datasets used by researchers in developing models to detect fake news. The different fake news datasets are explained indicating the suitability of each dataset for a particular research and limitations. In Table 4 the summary of the fake news datasets description with sources are presented for researchers to easily identify the sources of the fake news datasets, research suitability and limitations.

1. **Buzz Feed News:** BuzzFeed News is a collection of title and links to an actual story or a post that is considered fake news. This data-set is useful for testing linguistic methods. However, multimedia content is not part of this data-set, therefore certain analysis is not possible on text-only data-set (Parikh & Atrey, 2018).
2. **LIAR:** LIAR is a bench-marking framework made available by University of California, Santa Barbara researchers. This dataset is also linguistic-based dataset and only contains text data and has similar limitations like the BuzzFeed News data-set (Howard et al., 2017).
3. **PHEME**: This data-set includes rumored Tweets, collected and annotated within the journalism use case of the project (Zubiaga, Kochkina, Liakata, Procter, & Lukasik, 2016). It contains Twitter conversations which are initiated by a rumored Tweet. Also, it is linguistic based data-set. It contains about 330 conversations (297 in English and 33 Germany).
4. **CREDBANK:** The only dataset that contained social media data and allows users to perform analysis on the Twitter data. This dataset signs off on all the categories except the visual data. It misses out on having multimedia data, but still makes it a very compelling choice for researchers who are also focused on fake news detection on social media (Mitra & Gilbert, 2015).
5. **Complete dataset:** composed of 15,500 posts from 32 pages (14 conspiracy and 18 scientific), with more than 2,300,00 likes by 900,000+ user. Among the posts, 8,923 (57.6%) are hoaxes 6,577 (42.4%) hoaxes (Bessi et al., 2015).
6. **FAKENEWSNET:** is an ongoing data collection project for fake news research. It consists of headlines and body texts of fake news articles based

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on BuzzFeed and PolitiFact. It also collects information about the social engagements of these articles (Shu, Mahudeswaran, & Liu, 2019).

Table 4: Summary of fake news database

Dataset	Main Input	Data Size	# of class	SNS	Modality	URL
LIAR	Short claim	12,836	6	Politifact	Text	https://www.cs.ucsb.edu/~william/data/liar_dataset.zip
FEVER	Short claim	185,445	3	Wikipedia	Text	http://fever.ai/
BUZZFEEDNEWS	FB Post	2,282	4	Facebook	Text	https://www.kaggle.com/mrisdal/fake-news/data
BUZZFACE	FB Post	2,263	4	Facebook	Text	https://github.com/gsantia/buzzface
SOME-LIKE-IT-HOAX	FB Post	15,500	2	Facebook	Text	https://arxiv.org/cs
PHEME	Tweet	330	2	Twitter	Text	https://www.pheme.eu/software-downloads/
CREDBANK	Tweet	60 million	5	Twitter	Text	https://github.com/compsocial/CREDBANK-data
FAKENEWSNET	Article	602,659	2	Twitter	Text	https://github.com/kaiDML/FakenewsNet
BS DETECTOR	Article	-	3	Facebook	Text	https://www.producthunt.com/posts/b-s-detector
FakeNewsCorpus	FB Post	9,400,000	10	Open source	Text	https://github.com/several27/FakeNewsCorpus
Breaking!	FB Post	700	2 to 3	BS Detector	Text	
FA-KES	FB Post	804	2	15 news outlet	Text	https://zenodo.org/record/2607278#.X3oK8WgzaUk
NELA-GT-2018	FB post	713,000	8	194 news outlet	Text	https://dataverse.harvard.edu/dataset/dvn/ULHCB

Machine learning

Machine Learning (ML) is a subset of AI and is a field of work that addresses how computers can learn without being programmed (Khallaf, 2021). It has evolved from artificial intelligence, specifically pattern recognition and computational learning theory. A ML algorithm is used to choose the best function among a set of possible ones and to explain the relationship between features of a dataset. It is used in applications for computer vision, optical character recognition (OCR), and prediction (Khallaf, 2021)

Machine learning Techniques

In this paper, we talk about six categories of Machine Learning algorithms: Supervised learning, Unsupervised learning, Semi-supervised learning, multi-task learning, Federated Learning and Reinforcement learning (Sarker, 2021), as shown in Fig. 1. In the\ following, we briefly discuss each type of learning technique with the scope of their applicability to solve real-world problems.

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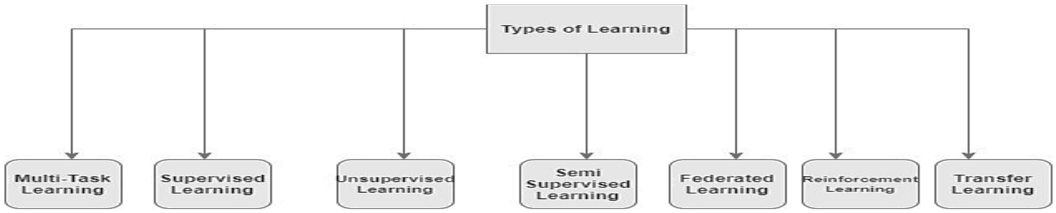

Figure 1: Machine Learning Categories

Supervised

Supervised learning is typically the task of machine learning to learn a function that maps an input to an output based on sample input-output pairs (Han, 2011). It uses labeled training data and a collection of training examples to infer a function. Supervised learning is carried out when certain goals are identified to be accomplished from a certain set of inputs (Sarker, 2020), i.e., a *task driven approach*. The most common supervised tasks are "classification" that separates the data, and "regression" that fits the data. For instance, predicting the class label or sentiment of a piece of text, like a tweet or a product review, i.e., text classification is an example of supervised learning.

Semi-supervised learning

Semi-supervised learning can be defined as a hybridization of the above-mentioned supervised and unsupervised methods, as it operates on both labeled and unlabeled data (Sarker, 2020) Thus, it falls between learning "without supervision" and learning "with supervision". In the real world, labeled data could be rare in several contexts, and unlabeled data are numerous, where semi-supervised learning is useful (Mohammed, 2016). The ultimate goal of a semi-supervised learning model is to provide a better outcome for prediction than that produced using the labeled data alone from the model. Some application areas where semi-supervised learning is used include machine translation, fraud detection, labeling data and text classification.

Unsupervised learning

Unsupervised learning analyzes unlabeled datasets without the need for human interference, i.e., a *data-driven process* (Han, 2011. This is widely used for extracting generative features, identifying meaningful trends and structures, groupings in results, and exploratory purposes. The most common unsupervised learning tasks are clustering, density estimation, feature learning, dimensionality reduction, finding association rules, anomaly detection, etc.

Reinforcement learning

Reinforcement learning is a type of machine learning algorithm that enables software agents and machines to automatically evaluate the optimal behavior in a particular context or environment to improve its efficiency (Kaelbling, 1996), i.e., an *environment-driven approach*. This type of learning is based on reward or penalty, and its ultimate goal is to use insights obtained from environmental activists to take action to increase the reward or minimize the risk (Mohammed, 2016). It is a powerful tool for training AI models that can help increase automation or optimize the operational efficiency of sophisticated systems such as robotics, autonomous driving tasks, manufacturing and supply chain logistics, however, not preferable to use it for solving the basic or straightforward problems.

Federated Learning (FL)

This is a distributed learning paradigm that addresses data isolation problem via collaborative training. In this paradigm, training is an act of collaboration between multiple clients (such as research institutions) without requiring centralized local data while providing a certain degree of user-level privacy (McMahan, 2017) (Jin, 2015).

Multi-Task learning (MTL)

It is a classical field in machine information provided by multiple related tasks than single task model. MTL is motivated by the fact that during human learning activities, the learned

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skills and knowledge from one task can be helpful to another one. MTL has been widely applied to many applications such as computer vision (Wang, 2011), (Zhang, 2016), Bioinformatics, web applications, natural languages processing (Wu, 2015)and so on. More specifically, face detection and alignment are performed simultaneously to improve the precision of both tasks. Compared with transfer learning, MTL treats each task equally such that the performance of all the tasks is improved, while the aim of transfer learning is to promote the performance of the target task with the assistance of source tasks. However, the performance of the existing multi-task approaches would largely degenerate when dealing with the polluted data, i.e., outliers (Zhang, 2020).

Transfer Learning

Transfer learning allows transferring the trained knowledge of the neural network in terms of parametric weights to the new model. Transfer learning boosts the performance of the new model even when it is trained on a small dataset (Gaur, 2020). Transfer learning is used to improve a learner from one domain by transferring information from a related domain. We can draw from real-world non-technical experiences to understand why transfer learning is possible. Consider an example of two people who want to learn to play the piano. One person has no previous experience playing music, and the other person has extensive music knowledge through playing the guitar. The person with an extensive music background will be able to learn the piano in a more efficient manner by transferring previously learned music knowledge to the task of learning, the need for transfer learning occurs when there is a limited supply of target training data (Weiss, 2016).

Deep Learning

Deep learning has gained popularity because of advancement in computing capability by the advent of graphics processing unit (GPU), reduced hardware cost, and improved network connectivity (Zang, 2019). Proliferation of training data and the current research progress in machine learning and information processing are also contributing factors to prominence of deep learning (Khan, 2019). Unlike in traditional machine learning where domain expert is needed to assist in feature extraction, deep learning can learn features automatically from a dataset. Instead of using manually generated collection of rules to obtain features of data, deep learning possesses the ability to learn the essential features automatically at the training phase (Wani, 2020).

Deep learning uses a number (tens to even hundreds) of consecutive layers with each layer giving more significant representation of input data(Wani, 2020). It has been applied in challenging fields of machine learning like image classification, voice recognition, handwriting transcription, natural language processing, self-driving cars and many more. Fig. 2 presents the taxonomy of the deep learning architecture as seen below.

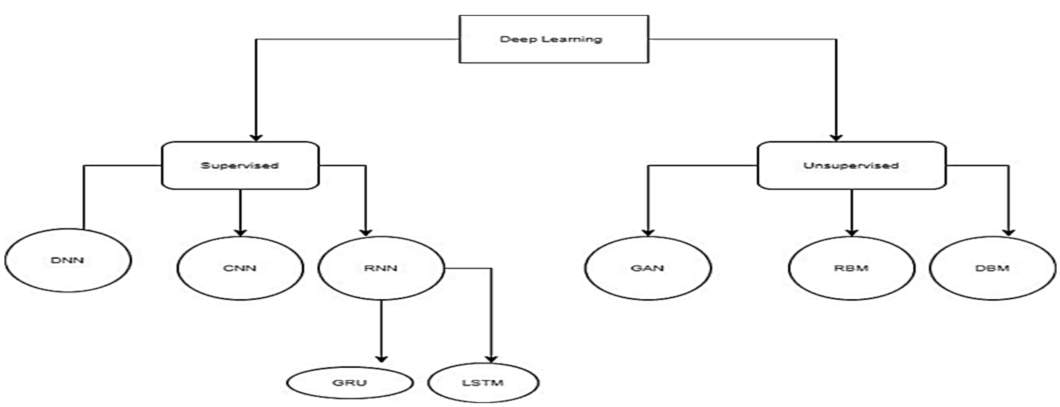

Figure 2: Taxonomy of Deep Learning Algorithm

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Deep learning is a subset of machine learning. It is a neural network with a large number of layers and parameters. Most deep learning methods use neural network architectures. Therefore, it is also referred to as deep neural networks. In short, deep learning uses a cascade of multiple layers of nonlinear processing units for feature extraction and transformation. The lower layers close to the data input learn simple features, while higher layers learn more complex features derived from lower layer features. The architecture forms a hierarchical and powerful feature representation. It means that deep learning is suited for analyzing and extracting useful knowledge from both large huge amounts of data and data collected from different sources (Shinde, 2018). Generally, DL models contain three types of layers: input later (received data), hidden layer (extracts patterns), and output layer (produces the results).

Deep learning architectures

There are multiple architectures that can be implemented when it comes to deep learning. Each of these architectures has its uses and compatibilities with certain applications. For the purpose of this paper, a definition of the most commonly used types of networks in construction is presented next

Convolutional neural network

Convolutional neural networks (CNN) are special neural networks that are used for data processing. These data are interpreted as matrices. The data belonging to the time series data in the form of a 1-D matrix (values of regular time intervals) or data can be in a 2-D matrix (pixel images). CNNs are very successful in practice. The name of these networks suggests that there is a mathematical operation called convolution. The convolutional networks are in simple neural networks that use a convolution of possible multiple numerical data in one of their layers (Krešňáková, 2019). The notion of convolution in mathematics is defined as:

$$S(i,j) = (K * I)(i,j) = \sum_m \sum_n I(m,n)K(i-m, j-n) \ldots\ldots\ldots\ldots(1)$$

Where the local operator (kernel, filter) **K** is applied, for example, to a digital image **I**

Convolutional neural network (CNN) is designed to mimic the human visual system (HVS). Consequently, CNNs have made great achievements in the computer vision field (Sharif Razavian, Azizpour, Sullivan, & Carlsson, 2014) (Krizhevsky, Sutskever, & Hinton, 2012) (Lawrence, Giles, Tsoi, & Back, 1997). A CNN is stacked with alternate convolutional and pooling layers (see Figure 3). The convolutional layers are used to extract features, and the pooling layers are used to enhance the feature generalizability. The CNN work on 2-dimensional (2D) data so the input data must be translated into matrices.

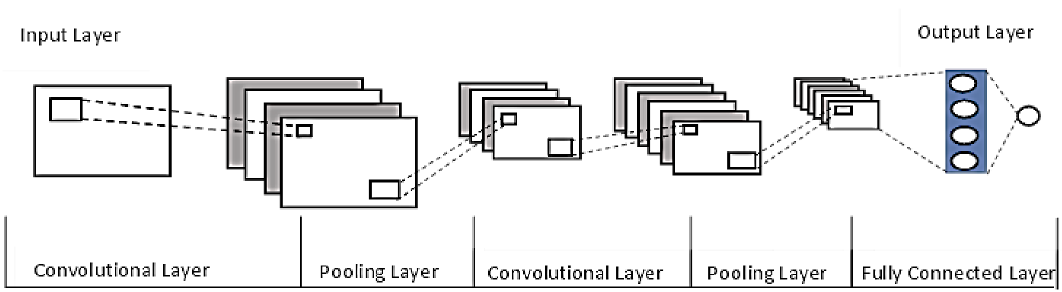

Figure 3: Structure of Convolutional Neural Network

Deep forward neural networks

Known as *feedforward neural networks* or *multilayer perceptron's* are basic models of deep learning. The goal of forward neural networks is to approximate the function $f*$. For example, $y = f*(x)$ maps the x input to y. The

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forward neural network defines the mapping $y = f(x;\ \theta)$ and finds the value of the parameters θ, which leads to the best approximation of the function. The basic model of a neuron is called perceptron. Perceptron receives input signals $\bar{x} = (x1, x2, \ldots, xn+1)$ via synaptic scales that form the vector $\bar{w} = (w1, w2, \ldots, wn+1)$. Perceptron output is given as a scalar product of the weight and vector, transformed by the activation function (Krešňáková, 2019)

$$\text{output} = f(\bar{w}.\bar{x}) = f\left(\sum_{i=1}^{n+1} w_i x_i\right) \ldots\ldots\ldots\ldots(2)$$

The basic model of perception shown in figure ……below

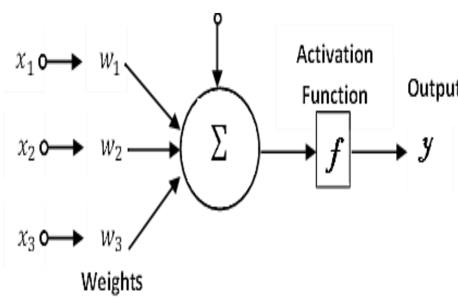

Figure 4: Structure of Deep Forward Neural Network

Recurrent neural networks

Recurrent Neural Networks (RNNs) are an extension to feed-forward networks and additionally allow the use of the previous output as a current input. They are mainly used for time-series and sequential data. RNNs have also been used for tracking objects and humans in videos. A variation or modified version of RNN are LSTMs, which have an additional memory set that enables the processing of information with memory gaps. They are able to learn temporal and sequential patterns from sequences of data (Khallaf, 2021). In this paper we will discuss about GRU in detail.

Long short-term memory

The long short-term memory (LSTM) is a variant of RNN developed to provide solution to vanishing gradient problem associated with the RNN. The LSTM has three layers; input layer, recurrent hidden layer, and output layer. The architecture of LSTM consists of memory blocks where a memory block is formed by memory cells sharing common input gate and output gate which control the flow of error and weight conflicts in the memory cell. A memory cell consists of a self-connected constant error carousel (CEC), the CEC activation functions indicate the state of a cell. With the aid of the CEC, multiplicative gates (input and output gates) learn to open and close constant flow of error hence solving the issue of vanishing gradient.

Forget gate was incorporated in memory block to prevent limitless growth of internal cell values especially when dealing with incessant time series data that has been segmented earlier. This allows the memory block to automatically reset when the information flow gets outdated and CEC weight is substituted with the forget gate activation (Jauro, 2020).
Given an input sequence $x = (x1, x2, \ldots, xr)$ and an output sequence $y = (y1, y2, \ldots, yr)$, LSTM iteratively performs computation expressed as: $t = 1$ *to* T

$$i_t = \sigma(W_{ix}x_t + W_{im}m_{t-1} + W_{ic}c_{t-1} + b_i) \ldots\ldots\ldots(3)$$

$$f_t = \sigma(W_{fx}x_t + W_{fm}m_{t-1} + W_{fc}c_{t-1} + b_f \ldots\ldots\ldots(4)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot g(W_{cx}x_t + W_{cm}m_{t-1} + c) \ldots\ldots\ldots(5)$$

$$o_t = \sigma(W_{ox}x_t + W_{om}m_{t-1} + W_{oc}c_t + b_o) \ldots\ldots\ldots(6)$$

$$m_t = o_t \odot h(c_t) \ldots\ldots\ldots(7)$$

$$y_t = \varphi\left(W_{ym}m_t + b_y\right) \ldots\ldots\ldots(8)$$

Gated Recurrent Unit (GRU)

The hidden layer of the GRU-RNN model is a gated recurrent unit (GRU), which is an improvement on the hidden layer of the traditional RNN, its schematic diagram and structure are shown in Fig. 5 and Fig.6. A GRU consists of an update gate, a reset gate and a temporary output.

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The related symbols are explained as follows:

1. xt represents the network input at instant t;
2. h~t and ht are information vectors, respectively represent the temporary output and the hidden layer output at instant t;
3. zt and rt are gate vectors, respectively represent the output of the update gate and the reset gate at instant t;
4. Wr, Wz, W and Wo represent the weight matrices of the reset gate, the update gate, the temporary output, and the output layer respectively;
5. br, bz, bh~ and bo represent the different biases corresponding to the different weight matrices. (Jiao, 2020) *SOCt* represents the output of the GRU-RNN model;

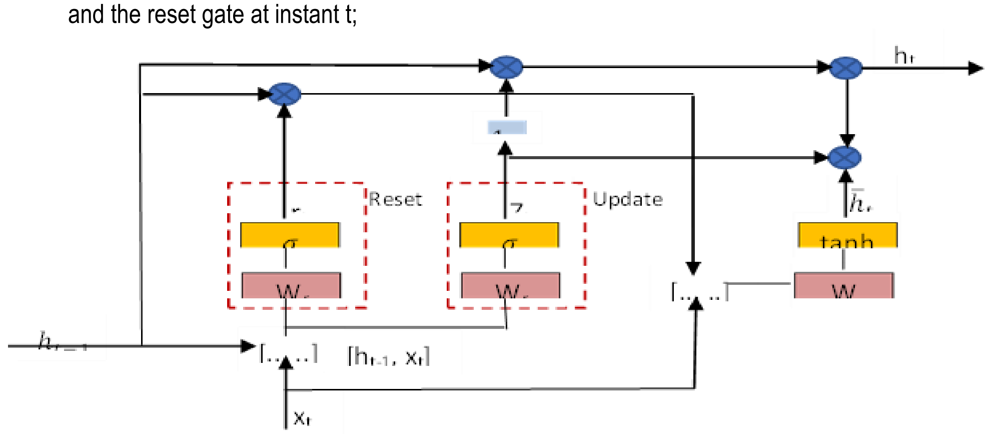

Figure 5: Schematic diagram of GRU

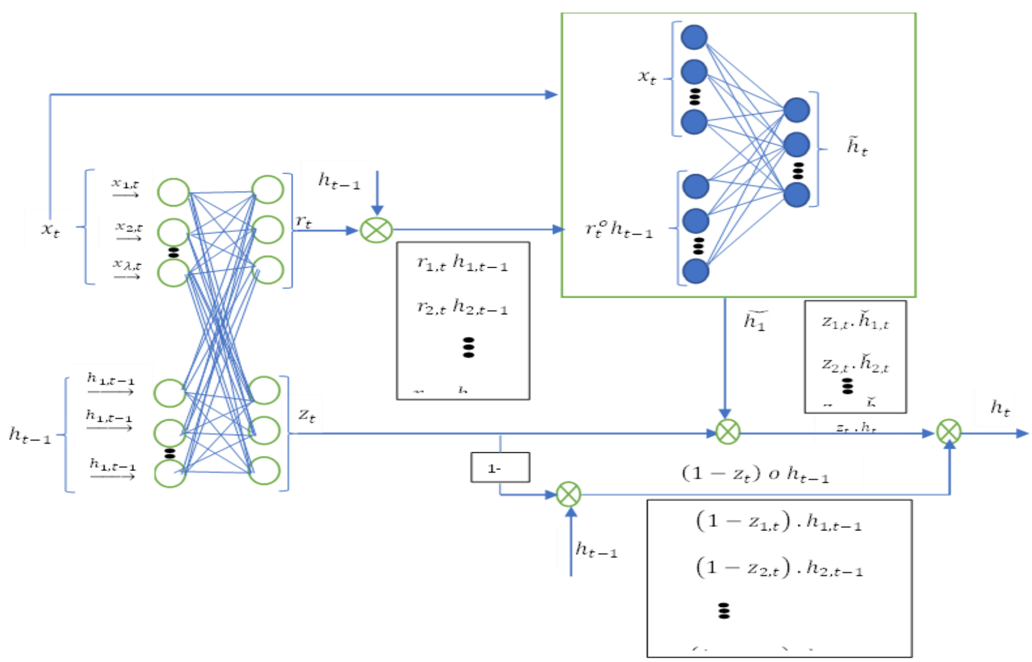

Figure 6: The Structure of GRU

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$\sigma(x)$ and tanh(x) represent the sigmoid and tanh activation functions, respectively. Their specific expressions are:

$$\sigma(x) = \frac{1}{1+\exp(-x)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (9)$$

$$\frac{d\sigma}{dx} = \sigma(x)[1-\sigma(x)], \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (10)$$

$$\tanh(x) = \frac{\exp(x)-\exp(-x)}{\exp(x)+\exp(-x)} \ldots\ldots\ldots\ldots\ldots\ldots (11)$$

$$\frac{d\,tanh}{dx} = 1 - tanh^2(x) \ldots\ldots\ldots\ldots\ldots\ldots\ldots (12)$$

The function of the gate structure in a GRU is information selection and screening, that is, through multiplying the corresponding elements in gate vector ***zt***/***rt*** and in information vector ***h~t***/***ht*** 1 select information in ***h~t*** or ***ht*** 1. If the element in ***zt***/***rt*** is 1, the corresponding element in ***h~t***/***ht*** 1 is selected; Otherwise (0), the corresponding element in ***h~t***/***ht*** 1 is discarded (Jauro, 2020).

Other Deep learning algorithms where applied in Natural Language Processing by many people such as deep belief network (DBN) (Yang, Zheng, Wu, Niu, & Yang, 2019; Zhao, Zhang, & Zheng, 2017) for Pre-training and fine-tuning, Recurrent Neural Network used in sequential data analysis) (Graves & Jaitly, 2014; Graves, Mohamed, & Hinton, 2013; Sutskever, Vinyals, & Le, 2014),Long Short term Memory(L.S.T.M)for attack detection (Jauro, 2020), Generative Adversarial Network.(GAN) model includes two subnetworks, i.e., a generator and a discriminator.

The generator aims to generate synthetic data similar to the real data, and the discriminator intends to distinguish synthetic data from real data. Thus, the generator and the discriminator improve each other. GANs are currently a hot research topic used to augment data in attack detection, which partly ease the problem of IDS dataset shortages. Meanwhile, GANs belong to adversarial learning approaches which can raise the detection accuracy of models by adding adversarial samples to the training set (Hongyu Liu & Lang, 2019),Restricted Boltmann Machine(RBM) Applied for feature extraction (Hinton, 2012) and Deep Neural Network(DNN) was applied in the work of(Jauro,2020) for Pre-training and Fine-tuning same in (Hongyu Liu & Lang, 2019).

Shallow algorithms s compared to the Deep learning models

Deep learning is a branch of machine learning, and the effects of deep learning models are obviously superior to those of the traditional machine learning (or shallow model) methods in most application scenarios. The differences between shallow models and deep models are mainly reflected in the following aspects (Hongyu Liu & Lang, 2019):

Running time

The running time includes both training and test time. Due to the high complexity of deep models, both their training and test times are much longer than those of shallow models.

Number of parameters

There are two types of parameters: learnable parameters and hyperparameters. The learnable parameters are computed during the training phase, and the hyperparameters are set manually before training begins. The learnable parameters and hyperparameters in deep models far outnumber those in shallow models, consequently, training and optimizing deep models takes longer convergence time compared to the shallow algorithms.

Feature representation

The inputs to traditional machine learning models are a feature vector, and feature engineering is an essential step before feeding the data into the traditional algorithms. In contrast, deep learning models are able to learn feature representations from raw data and are not reliant on feature engineering. The deep learning methods can be executed in an end-to-end manner, giving the deep learning an outstanding advantage over traditional machine learning methods.

Learning capacity

The structures of deep learning models are complex and they contain huge number of

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parameters (generally millions or more). Therefore, the deep learning models have stronger fitting ability than the shallow models. However, deep learning models also face a higher risk of overfitting compared to the shallow algorithms, require a much larger volume of data for training. However, the effect of deep learning models is better.

Interpretability

Deep learning models are black boxes (Fong & Vedaldi, 2017; Ribeiro, Singh, & Guestrin, 2016; Scott & Lee, 2017), the results are almost uninterruptable which is a critical point in deep learning. However, some traditional machine learning algorithms, such as the decision tree and naïve Bayes, have strong interpretability.

Table 5: The pros and cons of the shallow models

Algorithms	Advantages	Disadvantages	Improvement Measures
ANN	Able to deal with nonlinear data; Strong fitting ability(Hongyu Liu & Lang, 2019)	Apt to overfitting; Prone to become stuck in a local optimum; Model training is time consuming	Adopted improved optimizers, activation functions, and loss functions
SVM	Learn useful information from small train set; Strong generation capability	Do not perform well on big data or multiple classification tasks; Sensitive to kernel function parameters	Optimized parameters by particle swarm optimization (PSO)
KNN	Apply to massive data; Suitable to nonlinear data; Train quickly; Robust to noise reduction in data.	Low accuracy on the minority class; Long test times; Sensitive to the parameter K	Reduced comparison times by trigonometric inequality; Optimized parameters by particle swarm optimization (PSO) (Syarif & Gata, 2017); Balanced datasets using the synthetic minority oversampling technique (SMOTE) (Pajouh, Dastghaibyfard, & Hashemi, 2017)
Naïve Bayes	Robust to noise; Able to learn incrementally	Do not perform well on attribute-related data	Imported latent variables to relax the independent assumption
LR	Simple, can be trained rapidly; Automatically scale features	Do not perform well on nonlinear data; Apt to overfitting	Imported regularization to avoid overfitting (Shah, Qian, Kumar, Ali, & Alvi, 2017)
Decision Tree	Automatically select features; Strong interpretation	Classification result trends to majority class; Ignore the correlation of data	Balanced datasets with SMOTE; Introduced latent variables
K-means	Simple, can be trained rapidly; Strong scalability; Can fit to big data	Do not perform well on nonconvex data; Sensitive to initialization; Sensitive to the parameter K	Improved initialization method (Peng, Leung, & Huang, 2018)

Deep learning algorithms used in fake news

Many researchers used different deep learning algorithm for fake news detection, (Nasir et al., 2021) used hybrid CNN-RNN on two datasets, such models work on specific dataset with significant performance but do not generalize across different dataset. (Kaliyar, Goswami, & Narang, 2021b) used DNN which show good performance but high time complexity in training and testing. Agarwal, Mittal, Pathak, & Goyal, 2020) CNN -RNN on kaggle dataset compare with SVM and GRU. (Krešňáková, Sarnovský, & Butka, 2019) FF, CNN, LSTM shows significant performance but generally deep learning algorithms are usual slow in convergence due to many Neural network and hyper parameters.

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Table 6: Some Deep Learning algorithm used in Fake News Detection

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 results show that the proposed Hybrid CNN-RNN method is significantly better than all other methods in accuracy.	such models tend to work well on a specific dataset, but do not generalize well
(Kaliyar, Goswami, & Narang, 2021b)	Englis	BuzzFeed and PolitiFact	SNS	DNN	SVM	DNN give better performance.	Training and testing time is high
(Agarwal, Mittal, Pathak, & Goyal, 2020)	English	Kaggle fake news dataset	SNS	CNN and RNN	SVM and GRU	The blend of CNN and RNN perform better	The proposed work is on the classification of articles into fake or real, not taking into consideration their sources.
(Krešňáková, Sarnovský, & Butka, 2019)	English	Dataset obtained from the Kaggle competition	OSN	FF,CNN,LSTM		CNN and LSTM proof to be more effective in performance	High computational cost on training largeData

Prominent Cases of Fake News

Fake news has generated a lot of issues across the world such as war(Atodiresei, Tănăselea, & Iftene, 2018) political instability (Figueira & Oliveira, 2017),Cybercrime (Cheng, Mitomo, Seo, & Kamplean, 2020),Economic Crisis (Paka, Bansal, Kaushik, Sengupta, & Chakraborty, 2021) and the likes as Seen in table7.

Table 7: Case studies on fake news

Reference	Case study	Negative Impact
(Atodiresei, Tănăselea, & Iftene, 2018)	Syrian War	It affects commerce, journalism and democracy all over the world, with huge collateral damages.

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Reference	Case study	Negative Impact
(Figueira & Oliveira, 2017)	2016 US election	It affects public trust on the electoral system
(Cheng, Mitomo, Seo, & Kamplean, 2020)	Thailand Cybercrime	Affects businesses and governance negatively
(Kaliyar et al., 2021b)	The Selection of New Air marshal in India	It affects the public emotionally and spread negative impact on the society.
(Paka, Bansal, Kaushik, Sengupta, & Chakraborty, 2021)	2013 tweet 'Breaking: Two Explosions in the White House and Barack Obama is injured', from a hacked Associated Press account	created a loss of $136 billion worth of stock value
(Zervopoulos, 2022)	Hongkong Protest	Destruction of properties and loss of lives

Vectorization

Vectorization is basically the art of getting rid of explicit for loops in your code(Stock, Pouchet, & Sadayappan, 2012). In the machine learning era, with safety deep learning in practice, you often find yourself training on relatively large data sets, because that's when deep learning algorithms tend to shine. Also, it's important that your code runs very quickly, otherwise, if it's running on a big data set, your code might take a long time to run then you just find yourself waiting a very long time to get the result . Vectorizing is the process of encoding text as integers i.e. numeric form to create feature vectors so that machine learning algorithms can understand our data(Sharma, Saran, & Patil, 2020) Vectorization method used in fake news detection are summarize on the table 8 below.

Table 8: Vectorization Method on Fake News Detection

Reference	Language	Domain	Vectorization	Feature extraction	Data collection method
(Adiba et al., 2020)	English	Politics	Word2vec/Doc2vec	Instagram API	Twitter Crawler
(W. Y. Wang, 2017)	English	Health	FastText embeddings	VGG16,ResNet50 And EfficientNet	Facebook/Twitter crawler
(Sheikhi, 2020b)	English	Business	Gensim	Instagram API	Web crawler
(Reis, Correia, Murai, Veloso, & Benevenuto, 2019)	English	Politics	Word2vec	Facebook API	Facebook crawler
(Atodiresei et al., 2018)	English	Politics	FastText	API called OpenCalais	Twitter crawler

Challenges of Fake News Detection on social media

The various challenges faced to work in this direction are as follows:

1. Data challenge (Z. Zhou, Guan, Bhat, & Hsu, 2019): Limited high-quality data accessibility, high dimensionality data, heterogeneous nature, Factual Data unidentifiable, massive data size.

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2. Extensive and significant feature extraction (Choudhary & Arora, 2021): Careful observation on news content features is needed this is still underexplored. Researchers either worked on syntactic or on semantic features of news content without even exploring the importance of features. Along this line, we have explored features to determine whether new features should be used or not.
3. Adequate Learning model: Indeed, the adequacy of the learning model depends on the targeted dataset. For example, learning of data which is collected through Realtime streaming for specific scenario news may require a memory-based learning model. On the other end, varying and diversified content can give better results for the semantic feature-based neural model. Henceforth, model competency is dependent on targeted dataset content and features (Choudhary & Arora, 2021).
4. The fake news challenge is a machine learning task which is a contribution between AI community, journalists and fact-checkers. It forms a basis for fighting fake news and aims to develop tools towards fake news detection. One of the tools is a stance detection tool which is the first interest of the challenge. The challenge is about predicting the stance of a news article (body of the article) towards its paired title or headline(Masood & Aker, 2018).

Conclusion/Future Work

Thorough literature surveys on the adoption of Machine Learning Approaches for Combating Fake News on social media have been conducted. Machine Learning Application in Fake News Detection on social media have been discussed and the various Machine Learning Techniques. Different Machine Learning Algorithm was found to have been applied to solve problems in Fake News detection on social media. The Machine Learning Algorithm that generates a lot of interest as shown from the reviewed works is the CNN followed by SVM. From the trend of publications, we believe that the adoption of Hybrid deep Learning Algorithm is gaining very high interest and is expected to continue because of the growing trend and the new opportunities for future Research. FUTURE WORK: This review can help new researchers in the field as an initial reading materials and benchmark for proposing a Hybrid Deep Learning algorithm for fake news detection on social media.

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