Neural Computing and Applications (2023) 35:699–717
https://doi.org/10.1007/s00521-022-07797-y

ORIGINAL ARTICLE

Classification of Covid-19 misinformation on social media based on neuro-fuzzy and neural network: A systematic review

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Received: 1 March 2022 / Accepted: 6 September 2022 / Published online: 20 September 2022

Abstract
The spread of Covid-19 misinformation on social media had significant real-world consequences, and it raised fears among internet users since the pandemic has begun. Researchers from all over the world have shown an interest in developing deception classification methods to reduce the issue. Despite numerous obstacles that can thwart the efforts, the researchers aim to create an automated, stable, accurate, and effective mechanism for misinformation classification. In this paper, a systematic literature review is conducted to analyse the state-of-the-art related to the classification of misinformation on social media. IEEE Xplore, SpringerLink, ScienceDirect, Scopus, Taylor & Francis, Wiley, Google Scholar are used as databases to find relevant papers since 2018–2021. Firstly, the study begins by reviewing the history of the issues surrounding Covid-19 misinformation and its effects on social media users. Secondly, various neuro-fuzzy and neural network classification methods are identified. Thirdly, the strength, limitations, and challenges of neuro-fuzzy and neural network approaches are verified for the classification misinformation specially in case of Covid-19. Finally, the most efficient hybrid method of neuro-fuzzy and neural networks in terms of performance accuracy is discovered. This study is wrapped up by suggesting a hybrid ANFIS-DNN model for improving Covid-19 misinformation classification. The results of this study can be served as a roadmap for future research on misinformation classification.

Keywords Misinformation classification · Covid-19 · Neuro-fuzzy · Neural network · ANFIS · DNN

1 Introduction

People all around the globe are affected by coronavirus disease 2019 (Covid-19), the fifth outbreak after the 1918 influenza pandemic [1, 2]. Social media platform was utilized by many news agencies, organizations as well as society to distribute information and misinformation about the infectious virus during the pandemic. It is reported that Covid-19 conversation about illness increased among healthcare professionals and consumers [3, 4]. Moreover, since quarantine was started in all around the world, people rely on the internet and social media to find information. Various social network platforms such as Facebook, Google Scholar, TikTok [5], and Twitter, Centres for Disease Control and Prevention (CDC), World Health Organization (WHO), medical publications, and medical associations tried to update and disseminate information across many media. Information Network for Epidemics was designed by WHO as a platform to announce Public Health Emergency after the outbreak of Covid-19. WHO worked to give evidence-based responses to counteract misinformation spread across platforms and guarantee that anybody searching for "coronavirus" on social media or Google is directed to the WHO website or CDC, which provides trustworthy information [4].

Misinformation is deceptive information that is intentionally misleading or incorrect [6]. It has also been reported that misinformation is influencing the spreading of deadly diseases [7]. Individual citizens' behaviours, which is driven by the accuracy of the knowledge they have, are critical to the global response for health crises' progress. Moreover, misinformation regarding science, technology, and health is neither new nor novel to Covid-19. Many

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journalists, policymakers, and academics have supported WHO and underlined that misinformation regarding the epidemic poses a severe risk to public health and public action amid an unprecedented global health catastrophe [8–12]. The existing studies of Covid-19 misinformation mostly focused on detection and verification approaches [13–19], whereas there are very few studies that covers the most efficient methods for the classification Covid-19 misinformation. There is no consistent definition in the literature for the most efficient hybrid method of neuro-fuzzy and neural networks for classification. The existing related studies [20–24] did not emphasize on finding the most efficient hybrid model of neuro-fuzzy and neural network which can used for the classification of Covid-19 misinformation on social media. Furthermore, the exiting studies lack in discussion and justification of the strengths and limitations of ANFIS as neuro-fuzzy network for classification.

Therefore, this paper aims to compare state-of-the-art techniques such as neuro fuzzy, neural network, Machine Learning, and natural learning process which can be used for the classification Covid-19 misinformation. Hence, this study conducts a systematic literature review to discover suitable methods which can be used to classify Covid-19 misinformation on social media and to identify the most efficient techniques that can be used for proposing a hybrid classification model.

1.1 Misinformation on social media

The term "misinformation" can refer to both persons who have false beliefs and deceptive information that is purposefully false or inaccurate [6]. Therefore, it is crucial to distinguish between a lack of knowledge (or ignorance) and a high degree of confidence [6]. Additionally, it has been claimed that false information is having an impact on the spread of dangerous illnesses [7]. The effectiveness of the global response to this health crisis depends critically on how each individual citizen behaves, guided by the accuracy of the knowledge they possess. Moreover, misinformation regarding science, technology, and health is neither new nor novel to Covid-19. Many journalists, policymakers, and academics have supported WHO and underlined that misinformation regarding the epidemic poses a severe risk to public health and public action amid an unprecedented global health catastrophe. The focus of the currently conducted studies on Covid-19 disinformation is mostly on detection and verification [25–30]. There is not many research based on the Covid-19 misleading classification.

1.2 Neuro-fuzzy (NF)

Fuzzy logic is a method of computation that is founded on a degree of validity rather than the traditional true or false dichotomy (1 or 0). Natural language cannot be translated into 1 or 0 in a machine [31]. It might be helpful to consider fuzzy logic as the true way rationality operates, with binary or Boolean logic as a subset. Fuzzy reasoning seems to be more in line with how the brains operate. Neural networks, expert systems, and other artificial intelligence techniques use a similar mechanism. Fuzzy logic is critical for the advancement of human-like AI capabilities, also known as artificial general intelligence. It is considered as the depiction of abstract human cognitive ability in software so that, when confronted with an unknown problem, the AI system can solve it. In this paper, adaptive neural-based fuzzy inference system (ANFIS) technique, which is one of the most common NF methods, is explored.

1.2.1 Adaptive neuro-based fuzzy inference system (ANFIS)

The adaptive neural-based fuzzy inference system (ANFIS) model and its principles are based on Takagi–Sugeno–Kang model (TSK), or Sugeno fuzzy model [32], in which a rule Rk is defined as:

$$\text{Rule 1. if } (x_1 \text{is } A_1) \text{ and } (x_2 \text{is } B_2), \text{ Then } (y_1 = a_{10} + a_{11}x_1 + a_{12}x_2), \quad (1)$$

$$\text{Rule 2. If } (x_1 \text{is } A_2) \text{ and } (x_2 \text{is } B_2), \text{ Then } (y_2 = a_{20} + a_{21}x_1 + a_{22}x_2) \quad (2)$$

The ANFIS model is applied in many fields to solve complicated problems. It utilizes a hybrid learning rule that combines back-propagation gradient descent and the least-squares approach to identify a series of parameters. It can be used to construct a series of fuzzy IF–THEN rules with suitable membership functions to create the input–output pairs that were previously defined. ANFIS has been used in hydrological modelling by several scholars. ANFIS's five-layer architecture comprises two types of nodes: (1) fixed and (2) adaptable. In general, the first layer is known as the fuzzification layer, where the input value has its membership functions for each input, and the *a–f* is the value set and antecedent parameter. The second layer is the rule layer. It represents the firing strength for each rule generated in the first layer. The third layer is the normalization layer. It contains a certain ratio and calculates the firing strength. The defuzzification layer is in the fourth layer which is also known as the conclusion parameter. The last layer is the sum layer where the layer comes out with the final output.

Layer 1, also known as fuzzy sets, is the output of a node in this layer as shown in the following equation:

$$O_i^1, i = \mu_{Ai}(x) = \exp\left\{-\left[\left(\frac{x - C_i}{\sigma_i}\right)^2\right]\right\}, \quad i = 1,2 \text{ or } O_i^1 = \mu_{Bi-2}(y),\ i = 3,4 \tag{3}$$

where x = node input, and $\{\sigma_i,\ b_i,\ c_i\}$ = starting parameters. In other words, node i is known as a membership function, i.e. triangle, trapezoidal, or Gaussian, etc. For example, μ_{A1}, μ_{A2}, and μ_{B1}, μ_{B2} are the membership functions of Gaussian shape with two parameters centre (c) and width (σ).

Layer 2 is the layer that decides the firing strengths of different rules, and the output of node i is shown in the following equation:

$$O_i^2 = \omega_i = \mu_{Ai}(x_1).\mu_{Bi}(x_2), \quad i = 1,2. \tag{4}$$

Layer 3 is where the normalization occurs. The node in this layer normalizes the rule firing strengths and the output of node i is shown in the following equation:

$$O_i^3 = \overline{\omega}_i = \frac{\omega}{\sum_{j=1}^{2} \omega_i} i, \quad i = 1,2. \tag{5}$$

Layer 4 is the layer that computes the weighted outputs from the rules using Eq. (6). Each node in this layer represents a consequent part of the fuzzy rule. The linear coefficient of rule consequent is trainable.

$$O_i^4 = \overline{\omega}_i y_i = \overline{\omega}_i(a_{i0} + a_{i1}x_1 + a_{i2}x_2), \tag{6}$$

where $\{a_{i0}, a_{i1}, a_{i2}\}$= subsequent parameter set.

Layer 5 is where the nodes perform defuzzification of the consequent part of rules by summing outputs of all the rules. In this later, a singular node calculates the overall output of the system as shown in the following equation.

$$O_i^5 = \sum_{i=1}^{n} \overline{\omega}_i y_i \tag{7}$$

The final output can be revised as shown in Eq. (8), which is the formula of the linear combination of the resultant parameters.

$$\begin{aligned} y &= \frac{\omega_1}{\omega_1 + \omega_2} y_1 + \frac{\omega_2}{\omega_1 + \omega_2} y_2 \\ &= \overline{\omega}_1 y_1 + \overline{\omega}_2 y_2 \\ &= (\overline{\omega}_1)a_{10} + (\overline{\omega}_1 x_1)a_{11} + (\overline{\omega}_2 x_2)a_{12} + (\overline{\omega}_2)a_{20} + (\overline{\omega}_2 x_2)a_{22} \end{aligned} \tag{8}$$

Figure 1 illustrates an overview of the ANFIS model with 5 layers.

The ANFIS network's efficiency is considered adequate, though it has some significant flaws in which the most notable one is the curse of dimensionality and the computation expense. The number of rules needed in ANFIS is entirely determined by the length of the input vector, and the formula is Rules = (MF) input, where MF denotes the number of membership functions indicating the fuzzy partitions input. When there are a lot of inputs, the number of parameters that need to be evaluated goes up. As a consequence, the least square estimate would have to deal with very large matrices, resulting in a significant increase in computation time [33, 34]. There are three approaches recommended for parameter preparation and numerical effort, namely "reduce rule-base, reduce the number of parameters, and effective training methods." The ANFIS rules are minimized to reduce the number of parameters and computational effort while maintaining reasonable accuracy. Important contributions of ANFIS from the current literature are listed in this section.

1.3 Neural network (NN)

Deep learning is a new term for a type of artificial intelligence known as neural networks, which has been popular for over four decades. Warren McCulloch and Walter Pitts, the scholars from University of Chicago who joined MIT as founders in 1952, suggested neural networks for the first time in 1944 [35]. The simple architecture of basic NN consists of an input layer, hidden layer, and output layer. NN is designed to solve complicated problems which cannot be easily solved by humans [36].

1.3.1 Deep neural network (DNN)

A DNN includes a series of multiple layers. Each layer contains a set of neurons with the input activations from the previous layer, being passed on to the neurons of the subsequent layers for simple computation. The network's neurons work together to execute a dynamic nonlinear mapping from input to output. This mapping is obtained from data by adjusting the weights of each neuron using a method called error backpropagation [37]. Deep neural network (DNN) has one input, one output, and several hidden layers.

A neural network estimates the relationship between the input value of x and the output value of y by combining many computational units known as neurons. The objective of a NN, like those of other optimization methods such as simulated annealing, is to minimize the difference between the prediction data y and the target data y by optimizing a predefined loss function. Since NN are becoming more complex, they are now commonly referred to as DNNs. Figure 2 depicts a typical DNN architecture. In general, a DNN is made up of an input layer, many hidden layers, and an output layer. Each layer is typically made up of a large number of neurons.[1]

[1] https://towardsdatascience.com/a-laymans-guide-to-deep-neural-networks-ddcea24847fb.

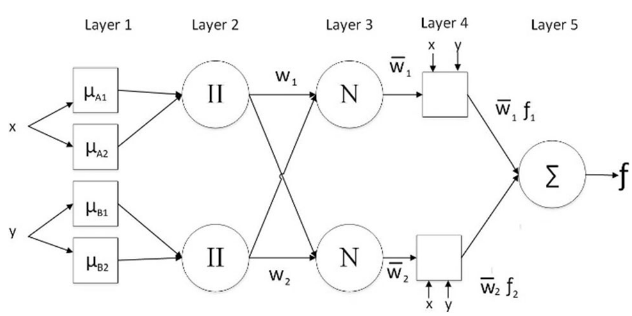

Fig. 1 ANFIS architecture

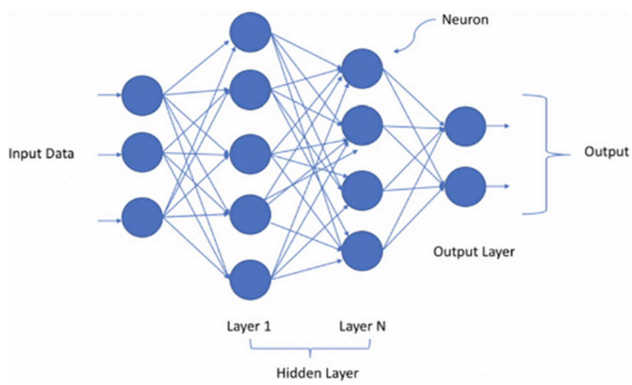

Fig. 2 A DNN with multiple hidden layers

DNN enables various layers of abstraction to adjust the number, scale, and composition of each layer, as well as the extraction of high-level features from reduced features to construct a hierarchical representation [38]. In general, a single layer contains multiple nodes in which each node is connected by a fixed collection of weight from previous layers. Weight collection is an important step that takes place during the learning process. The values of each layer can be calculated from prior layer nodes by assigning variables to the inputs and feeding them via the network to get the final output. On the other hand, the value of each hidden node in the network is calculated by computing a linear combination of node values from previous layers and then applying a nonlinear activation function. After applying an activation function to a node, its value is calculated as the maximum of the linear combination of the node from the previous layer [39].

1.4 Problem statement

With the emergence of Covid-19 pandemic, misinformation was spread in social media and different webpages. Thus, Covid-19 misinformation classification became an important area of research to inform people about true information, misinformation, or fake news during the pandemic [40]. To classify Covid-19 misinformation, machine learning techniques were used in many studies. In addition, there are many NF and neural network techniques for analysing Covid-19 misinformation. Nevertheless, due to the recency of Covid-19 pandemic, there is a lack of study to introduce the best techniques which can classify Covid-19 misinformation. The disparate research developed and referenced prompted the need for a systematic literature review (SLR) on NF and NN-based classification.

Therefore, this study aims to conduct a SLR to find the best NF and NN techniques for the classification of Covid-19 misinformation. This study reviews, organizes and summarizes the methods which can be used to classify Covid-19 misinformation. As conclusion, this study finds the best classification method with highest accuracy. Furthermore, this study highlights emerging obstacles and research holes, which will benefit both scholars and newcomers in this field.

1.5 Research contribution

Several studies were found which focused on Covid-19 misinformation detection, prediction, verification, pre-training, and classification. However, a rigorous and structured literature review that can list various problems, techniques, and presents unmet needs, as well as future direction is missing. Therefore, this SLR covers the techniques that can be utilized for misinformation classification specially related to Covid-19. This paper reviewed the articles which are published between July 2018 and May 2021. The main contributions of this study are to address the following research questions:

RQ1: Which techniques/methods are used for the misinformation classification? Which studies are related to Covid-19?
RQ2: What are the most efficient methods that can be used for Covid-19 misinformation classification using NF and NN techniques?
RQ3: What are the strengths and limitations of the current NF and NN approaches to classify Covid-19 misinformation?

This study adopted the systematic literature review (SLR) method from some of the existing studies [41, 42], and some guidelines are followed from [43–45]. The proposed SLR in this study is structured as follows: Sect. 1 introduces the concept, the problem statement, the goals, and contributions of this paper. Section 2 focuses on cutting-edge methods and approaches. Section 3 addresses general methodology and adheres to research process rules by formulating research questions, sample collection, and quality evaluation, respectively. Section 4 contains a concise presentation of the results and debate, supplemented by a lengthy review as well as containing a comprehensive presentation of the results and discussion, accompanied by a systematic review in Sect. 5. Section 6 wraps up the article with future instructions.

2 Related work

The spread of Covid-19 misinformation creates severe issues in society. Consequently, many researchers have attempted to identify the most effective method for detecting, classifying, and predicting misinformation. The total number of 35 papers were found from the database search which were related to Covid-19 misinformation classification. Those papers utilized neuro-fuzzy (NF), neural network (NN), natural language processing (NLP), machine learning techniques, and hybrid models for the classification of misinformation. Table 1 lists the existing relevant studies, their tackled problems, methods, dataset, as well as the database that the papers are retrieved from.

2.1 Adaptive neuro-fuzzy inferences system

A generic ANN model can only approximate the output parameters but cannot state what kind of connections exist between the input and output parameters. This is one of the main disadvantages of the neural network model which led to the creation of neuro-fuzzy systems. A survey was conducted by [46] using ANFIS and ANN states that a combination of neural network and fuzzy logic can improve the quality of detection as well as minimize setup time. Another study by [47] addressed the implementation of NF and rule-based models in real-world results with high accuracy and appropriate level of interpretability construction. A study by [48] proposed a hybrid NF and feature reduction model for data classification. The result of this study shows that the performance of the NF-FR model has improved significantly, and it is effective for removing redundant and noisy data. Moreover, [49] proposed a fog-based ANFIS, particle swarm optimization, and grey wolf optimizer (PSOGWO) model used for prediction. Furthermore, [50] integrated particle swarm optimization into a micro-genetic algorithm to optimize the extreme learning adaptive neuro-fuzzy inference system (ELANFIS) for predicting the mental workload of knowledge workers.

Based on a recent study by [34], ANFIS is an effective prediction model for NF structures as well as other machine learning techniques. In this study [51], the third layer that normalizes rule intensity is omitted. Nevertheless, the techniques like ANFIS employs a hybrid learning algorithm. To suggest effective training methods, several researchers trained ANFIS parameters with metaheuristic algorithms, either to hybridize it with least-squares or gradient descent, or by training all parameters with the metaheuristic algorithm alone. Another article [52] has proposed a “hybrid of particle swarm optimization (PSO) and the least square approach to refine ANFIS premise and associated parameters.”

Reference [53] has utilized cat swarm optimization (CSO) algorithm with gradient descent to train the membership function parameters and consequent parameters of ANFIS. Reference [54] suggested a modified “artificial bee colony” (ABC) algorithm to optimize all ANFIS parameters. Reference [55] suggested genetic algorithm to optimize the premise parameter of ANFIS. However, there is a drawback which introduces another layer to the ANFIS system for enhancing the computational effort after the membership function layer. This method modifies the membership functions depending on the “error measure.” After that, the trivial rules are trimmed using an “error threshold.” Moreover, to train classifiers on text data, a study by [56] presented fuzzy rules as it is suitable for ambiguous and imprecise classification. The complicated cases are classified into one or more categories.

Reference [57] used a technique known as hierarchical hyperplane clustering synthesis (HHCS), which incrementally adds rules to the ANFIS rule-base before the desired precision is reached. This study achieves interpretability by generating the best ruleset. But traditional parameter tuning algorithms such as gradient descent and least square estimation are also used in this method. Furthermore, analogous to the previously mentioned approach, this analysis adds to the complexity of ANFIS structure. ANFIS rule-based is minimized using Karnaugh Map when modelling traffic signal controllers [58] in addition to cluster analysis. In this approach, rules are mapped into a K-Map to provide a minimal mapping that accurately reflects reducing rules. [59] trained ANFIS method to enhance brain images for classification. This paper also compares CNN [60], Deep CNN [61], Modified AdaBoost [62], and ANFIS among which the latter classification algorithm shows the highest accuracy, sensitivity, and specificity.

Another research by [63] proposed an optimized algorithm for ANFIS with the implementation of a GA algorithm to find an answer for physical work rate classification. Using ANFIS in this model has decreased the error rate and provided high precision and simplicity. Moreover, [48] used a hybrid NF and feature reduction (NF-FR) model. For all patterns, the proposed NF-FR model employs a feature-based class pertinence fuzzification technique. They compared the proposed model NF-FR against the ANN, NF, and ANNFR machine learning models. Using the informative dissolved gas analysis method (DGAM) based on training with ANFIS method, an effective technique for diagnosing and classifying power transformer problems is proposed that improves robustness and the classification accuracy [64].

Table 1 Summary of reviewed papers

Study	Year	Problem tackled	Method				Dataset	Database/Library
			NF	NN	NLP	Machine learning		
[55]	2018	Classification	✔	X	X	X	Medical dataset	Taylor & Francis
[59]	2018	Classification	✔	X	X	X	Brain images	ScienceDirect
[21]	2018	Detection	X	✔	X	X	Twitter	Google Scholar
								(Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics)
[20]	2018	Classification	X	✔	✔	X	Liar, Kaggle	Wiley
[65]	2018	Classification	✔	X	X	X	Twitter	SpringerLink
[47]	2019	Classification	✔	X	X	X	–	ScienceDirect
[73]	2019	Identification & Classification	X	✔	X	DSSM	LIAR	Taylor & Francis
[24]	2019	Classification	X	✔	X	X	Sentimental Text	IEEE
[66]	2019	Classification	✔	X	X	X	Twitter	Google Scholar (International Journal of Intelligent Engineering & Systems)
[88]	2019	Classification	X	X	X	SVM, KNN, Naïve Bayes, AdaBoost, Bagging	Twitter	Taylor & Francis
[56]	2019	Classification	✔	X	X	X	Social Media	IEEE
[64]	2020	Classification	✔	X	X	X	Power transformers faults	ScienceDirect
	2020	Detection						
[23]	2020	Detection	X	✔	X	X	Kaggle	ScienceDirect
[48]	2020	Classification	✔	X	X	X	–	Google Scholar
								(*Advances in Fuzzy Systems*)
[67]	2020	Classification	✔	✔	X	X	–	IEEE
[86]	2020	Detection	X	X	X	Stochastic gradient descent	Data set of Bengali language	IEEE
[87]	2020	Detection	X	X	X	23 Machine Languages	BuzzFeed, Political News, ISOT Fake news	ScienceDirect
[71]	2020	Detection	X	✔	X	X	Facebook, Twitter, Weibo	SpringerLink
[49]	2020	Prediction	✔	X	X	X	–	IEEE
[68]	2020	Classification	✔	X	X	X	Medical dataset	IEEE
[25]	2020	Detection	X	X	X	DT, kNN, LR, LSVM, MNB, BNB, NN, ERF, and XGBoost	Twitter	IEEE
[89]	2020	Detection & Prediction	X	X	X	Logistic Regression, Support Vector Classification, and Naïve Bayes	Twitter	Scopus
[13]	2021	Verification	X	X	X	ML	Twitter, Reddit, Bing	ScienceDirect
[28]	2021	Detection	X	X	✔	X	CNN, WHO, CDCP	ScienceDirect
[29]	2021	Classification	X	X	X	Random Forest	Twitter	Scopus
[30]	2021	Detection	X	X	X	ML procedures	–	IEEE
[74]	2021	Detection	X	✔	X	SVM	FakeDataNews	Wiley
[72]	2021	Classification	X	✔	X	SVM	Mendeley Data	ScienceDirect
[80]	2021	Detection	X	X	✔	X	Thai Text	Scopus

Table 1 (continued)

Study	Year	Problem tackled	Method				Dataset	Database/Library
			NF	NN	NLP	Machine learning		
[69]	2021	Classification	✔	X	X	X	Medical dataset	Google Scholar *(Journal of Physics: Conference Series)*
[90]	2021	Classification	X	✔	X	X	Academic dataset	ScienceDirect
[91]	2021	Classification	✔	X	X	X	Medical dataset	Wiley
[26]	2021	Detection & Prediction	X	✔	✔	X	Twitter	Scopus
[27]	2021	Detection	X	✔	X	X	Twitter	Scopus

An experiment was carried out on a limited Twitter sample training set, and it has not been compared to the most recent top of the line for study conducted by [65], which used ANFIS to solve three separate classification problems: (1) sentence-level subjectivity detection, (2) text sentiment analysis, and (3) user intention identification in a natural language call routing system. The major purpose of the study by [65] is to prevent the use of human annotation or lexical expertise. In this study, the membership degree of each term is determined using trimmed ICF (inverse-class frequency). The fuzzification processes used entail computing the maximum membership degree about the classes for each term, as well as the mean of maxima for all classes.

A study by [66] suggested a hybrid ANFIS for sentiment analysis of political Twitter data that incorporates nonlinear SVM. Unigrams and bigrams models are employed in the feature extraction step. Because the author utilized only one fuzzy MF, ANFIS receives only the words or a pair of words as input.

2.2 Deep neural network

Another outstanding paper by [67] implements a combination of ANFIS and DNN for classification problems with an accuracy of 97.99%. [49] proposed a hybrid method of ANFIS + PSOGWO for Parkinson's disease prediction and results in an accuracy of 87.5%. Reference [68] implemented ANFIS method to classify brain images and results in 99.6% accuracy. Reference [69] carried out a comparison review among ANN, FIS, and ANFIS models to identify the method with the highest accuracy. As a result, ANN, FIS, and ANFIS output 92.3, 88, and 96%, respectively. A paper by (Srinath & Gayathri, 2021) carried out classification using soft computing methods along with ANFIS algorithm which results in an accuracy of 99.4%.

Reference [70] introduced a rumour detection based on recursive neural networks (RvNN) which improved performance in very large margins compared to current models in the year 2018. A detection model was introduced by [23] based on CNN to detect fake news with 98.36 accuracy. A survey carried out by [71] shows that using neural network methods is an effective and scalable technique to identify misinformation in social media. [25] conducted a study identifying the best method to detect Covid-19 misinformation. Among all methods there are ten machine learning algorithms, seven feature extraction techniques, and one NN method that showed the most efficiency in detecting Covid-19 misinformation. [72] implemented deep learning models to classify fake news and DNN models outperform out of all. [27] proposed semi-supervised neural network model to detect Covid-19 fake news that achieves a 0.95 F1 Score on CTF, outperforming the best baseline by 9%.

A paper was released by [20] that automatically classifies fake news with a combination of DNN and NLP with 82.4% success rate while the DNN and NLP model alone achieved 81 and 72%, respectively. [73] proposed a framework using a combination of DSSM and RNN to identify and classify fake news with 99% accuracy. A different approach was used by [22] which compares GNN, Bert, and Bag of Words (BoW) models to detect Covid-19 fake news and 5G conspiracy theories for the identification of misinformation spreaders using the Twitter dataset. This study concludes that GNN performance is better due to the higher accuracy. [74] introduces a hybrid model with a combination of RNN and SVM with an accuracy of 91.2%. Finally, a combination model of CNN and Bert was proposed by [26] with an accuracy of 68.78%.

A study done by [24] implemented a DNN model to classify the implicit emotion. To assess the trend of the users' implicit emotion text, a classification model based on DNN, LSTM, Bi-LSTM, and CNN was proposed.

2.3 Natural language processing

Reference [75] developed LIAR dataset, consisting of 12,800 manually labelled short statements of many topics from PolitiFact that implements surface-level linguistic patterns with hybrid CNNs. [76] introduced FEVER, a large dataset used for fact extraction and verification against textual sources, which implements the evidence-based technique. The highest level of accuracy is reached with FEVER on labelling a claim with supporting proof of 31.87%.

Bert is developed by [77] using natural language processing (NLP) to produce deep learning semi-supervised methods for the detection of misinformation. Another study by [78] improved Bert to produce Roberta by optimizing BERT pretraining approach. Furthermore, [79] developed DistilBERT which is another improved version of Bert. It is a 40% smaller, 60% faster, less expensive, and lighter pretraining method which aims to work on a wide range of counterparts and retain 97% of language understanding capabilities than Bert. Nonetheless, in order to combat Covid-19 misinformation, [28] have proposed a model based on DistilBERT and SHAP. [80] proposed a Covid-19 fake news detection model using NLP.

Researchers have been working on developing NLP algorithms for Covid-19 misinformation classification. A corpus is required to construct the algorithm. As a result, the members of the NLP community generated the Fake-Covid [81], ReCOVery [82], CoAID [30], and CMU-MisCOV19 [83] datasets.

2.4 Machine learning

Machine learning is used for various purposes such as detection, classification, prediction, clustering and so forth [84, 85]. Other techniques using machine learning are widely implemented to detect, classify, and predict misinformation. A model created by [86] proposed a stochastic gradient descent technique with 87% accuracy. Moreover, another paper by [87] used 23 machine learning techniques such as BayesNet, JRip, OneR, decision stump, ZeroR, stochastic gradient descent (SGD), CV parameter selection (CVPS), randomizable filtered classifier (RFC), logistic model tree (LMT), locally weighted learning (LWL), classification via clustering (CvC), weighted instances handler wrapper (WIHW), ridor, multi-layer perceptron (MLP), ordinal learning model (OLM), simple cart, attribute selected classifier (ASC), J48, sequential minimal optimization (SMO), bagging, decision tree, IBk, and kernel logistic regression (KLR) to detect fake news in social media. The paper concludes that the decision tree obtained the best mean values in terms of accuracy (74.5%), precision (74.1), and F-measure (75.9). Using five types of classification method, including SVM, KNN, NB, AdaBoost and Bagging, a study proposed by [88] classified twitter dataset related to renewable energy into positive, neutral or negative. To extract the features from the supplied datasets, the authors of this paper used the information gain function and CfsSubsetEvaluation [88].They use WEKA Tool and R-Studio to accomplish their recommended strategy. The SVM algorithm outperforms other ML algorithms when used in conjunction with the CfsSubsetEvaluation function, according to the results of the experiments. [89] managed to identify rumour from Twitter with 84% accuracy. Additionally, [13] implemented ML and allowing humans to "vote" on news content. A paper by [29] proposes a model using random forest algorithm, sentiment analysis and dynamic topic modelling to characterize and classify four COVID-19 conspiracy theories. Finally, [30] introduced a modified deep neural network to propose CoAID-DEEP which is an automatic Covid-19 misleading information on Twitter achieving the accuracy of 98.57%.

3 Research method

There are many existing studies related to Covid-19 misinformation; however, most of them focused on detection and verification while only few studies cover the classification of Covid-19 misinformation. In addition, there are not many studies which covers the classification of Covid-19 misinformation using ANFIS. Therefore, this study conducts a systematic literature review (SLR) to discover the classification of Covid-19 misinformation on social media based on neuro-fuzzy, neural network and specially ANFIS. A SLR is characterized as the preparation, assessment, and reporting of available studies related to specific research area, subject, issue, or field of interest. Such a review aims to recognize established approaches to the use of a specific technology for identifying the future problems and holes in recent research and for providing a guide for properly conducting new research in this field [42]. The SLR in this paper is carried out by adopting the method from [41] in which there are three stages of planning, conducting, and reporting. The more refined version of SLR steps in this study is as follows:

(1) Prepare a set of study questions.
(2) Select a few experiments that are appropriate and conduct a pilot project.

(3) Conduct a web search (IEEE Xplore, SpringerLink, Science Direct, Scopus, Taylor & Francis, Wiley, Google Scholar) to find related information.
(4) Keep a record of every quest strategy.
(5) Study evaluation and collection.
(6) Examining and presenting the findings.
(7) Discuss the review's overall conclusion and shortcomings.
(8) Give suggestions.

The goal of the proposed SLR is to review and summarize the current findings on misinformation classification, as well as to identify possible gaps and future current research in this field.

3.1 Search strategy

A well-planned search strategy is the key in an SLR to extract the relevant results. Therefore, a considerable exploration for the analysis paper was conducted to answer the projected analysis queries. We tend to use the steps counselled by [92] to organize the search terms utilized in this SLR as follows:

(1) Derive vital search terms from the analysis queries by distinguishing population, intervention, outcome, and context.
(2) Enlist the keywords within the relevant papers.
(3) Suggests different spellings and synonyms for search terms with the assistance of a wordbook.
(4) Use mathematician AND to concatenate the search keywords for confined analysis.
(5) Use OR to construct search keywords from search terms with similar meanings.

3.2 Search string

The resultant search strings for the SLR conducted in this paper are as follows:

COVID-19: “Corona” OR “Coronavirus” OR “Covid” OR “Covid-2019” OR “Novel Coronavirus Illness” OR “Wuhan coronavirus” OR “Coronavirus diseases” AND.
MISINFORMATION: “Disinformation” OR “False News” OR “Rumours” OR “False Rumour” OR “False Information” OR “Untruth” AND.
SOCIAL MEDIA: “Online” OR “Social Platform” OR “Social Site” OR “Social Web” OR “Multimedia” OR “Media” OR “Media Platform” OR “Public Network” AND.
ARTIFICIAL INTELLIGENT: “Neuro-fuzzy” OR “Neural Network” OR “Adaptive Neuro-based Fuzzy Inference System” OR “ANFIS” OR “Deep Neural Network” OR “DNN” AND.
DETECTION: ‘‘Observation’’ OR ‘‘Identification’’ OR ‘‘Spotting’’ OR ‘‘Recognition’’ OR ‘‘Diagnosis’’ OR ‘‘Sensing’’ AND.
CLASSIFICATION: “Categorization” OR “Grouping” OR “Grading” OR “Ranking” OR “Organization” OR “Sorting” OR “Systematization” AND.
PREDICTION: ‘‘Forecasting’’ OR ‘‘Divination’’ OR ‘‘Augury’’ OR ‘‘Projection’’ OR ‘‘Prognosis’’ OR ‘‘Guess’’.

After applying the search string, the total number of 1091 articles were retrieved from the selected databases. Some words may not be relevant to the topic, but the terms added to the search fully utilize the outcome. Nonetheless, the papers are filtered based on the relevancy to Covid-19 misinformation classification and those irrelevant papers are removed from the list. The keywords used for searching in the selected databases are listed in Table 2.

The decisions were made as part of the quest strategy (Table 3). Only selected libraries and databases such as IEEE Xplore, SpringerLink, ScienceDirect, Scopus, Taylor & Francis, Wiley, Google Scholar were used to search for the proposed SLR in this paper. In addition, only journal articles and conference papers were included in this SLR, and other papers were excluded. It was avoided to exclude articles that lack the selected keywords in their title or abstract but are still applicable to the literature. Finally, the literature search was filtered based on the publication dates from June 2018 to May 2021.

3.3 String refinement

It is critical to verify the search results returned from specified search engines once the string has been created. The result should include potential articles for primary research. If no identified papers are returned, or if only a few are, the search string must be modified. To fine-tune the search string, it is needed to optimize both synonyms and the search parameters in each search engine.

It is required to check the effect of inclusion and exclusion of synonyms, publication type, year limit, language, research area, and specific journals, etc., on an individual basis until satisfied with the results. Table 4 shows the returned papers after applying various filtering with the final search string to the searched databases.

There are a few limitations that are imposed separately, and some limits that are implemented to a search engine, such as English language, year (2018–2021), and article form (conference, journal, magazine, and workshop). All through the query evolution phase, IEEE Explorer generated quite a few results relative to other search databases.

Table 2 Keyword and synonyms

Keyword	Synonyms
Covid-19	Corona, Coronavirus, Covid, Covid-2019, Novel Coronavirus Illness, Wuhan coronavirus, Coronavirus diseases
Misinformation	Disinformation, False News, Rumours, False Rumour, False Information, Untruth, Falsity, Misreport, Misstatement, Deception
Social Media	Online, Social Platform, Social Site, Social Web, Multimedia, Media, Media Platform, Public Network
Artificial Intelligent	Neuro-fuzzy, Neural Network, Adaptive Neuro-based Fuzzy Inference System, ANFIS, Deep Neural Network, DNN
Detection	Observation, Identification, Spotting, Recognition, Diagnosis, Sensing
Classification	Categorization, Grouping, Grading, Ranking, Sorting, Systematization
Prediction	Forecasting, Divination, Augury, Projection, Prognosis, Guess

Table 3 Search strategy decisions

Searched library	IEEE Xplore, SpringerLink, ScienceDirect, Scopus, Taylor & Francis, Wiley, Google Scholar
Searched papers	Journal papers, conference papers
Search applied on	Available full-text articles
	Attempt to avoid excluding articles that lack keywords in their title or abstract but are still applicable to the literature
Publication period	Since June 2018

Table 4 Search limits on searched databases

Library	Limits	Returned papers
IEEE	2018–2021, English, Conference, Journals, Keywords	15
Science Direct	2018–2021, English, Conference, Journals, Computer Science	43
Scopus	2018–2021, English, Conference, Journals, Computer Science, Keywords	22
Spring	2018–2021, English, Conference, Journals, Keywords	86
Taylor & Francis	2018–2021, English, Conference, Journals, Computer Science, Keywords	17
Wiley	2018–2021, English, Conference, Journals, Computer Science, Keywords	30
Google Scholar	2018–2021, English, Conference, Journals, Keywords	196
Total		409

ScienceDirect has a restriction that no upwards of 8 Boolean connectors per area can be used in a search. Therefore, there were not many return results. For the journal articles, the Scopus search engine was used, and the conference papers cap culminated in 22 papers. For further refine the search for Springer by topic (Computer Science) from recommended articles was done which result in fine-tuned papers. Taylor & Francis has fewer results with 17 papers. Wiley was searched with keywords and the outcome was 30 papers. Lastly, Google Scholar had many options. Therefore, an advance option was implemented to get filtered results of 196 papers. Figure 3 shows the percentage of the papers covered by the research libraries.

3.4 Study selection

The combined search technique yielded 409 potential papers. The research papers were eliminated based on three commonly implemented selection criteria which are the title, abstract, introduction, and conclusion analysis as well as full paper and quality assessment. Therefore, based on title and abstract 130 papers were eliminated in the primary phase. The second phase is analysed based on the introduction and conclusion with 167 papers rejected. The remaining 112 were further revised, and 78 papers were rejected in the final phase based on full test, quality assessment and critically evaluating the content of the paper. The remaining 34 papers are included in the SLR.

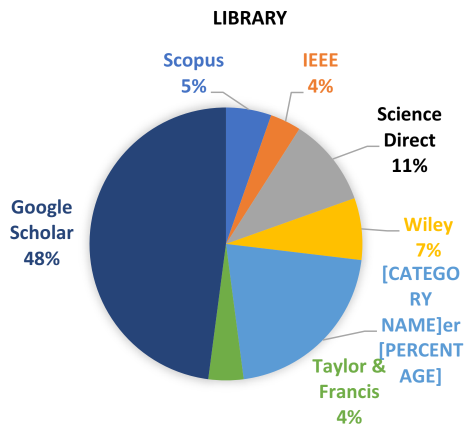

Fig. 3 (%) Distribution of the papers by research library

The frequency distribution of the approved papers over the years is shown in Fig. 4.

3.4.1 Exclusion and inclusion

The exclusion and inclusion criteria for selecting the articles for this study are listed in Table 5. Therefore, this systematic literature review only contained the papers that met the inclusion requirements.

This literature review covers the period from 2018 to 2021 on papers relevant to misinformation classification using deep learning. This is due to limited coverage of NF, and NN model application for misinformation classification. Another main reason why this SLR focuses on papers from 2018 is to cover more papers relevant to classification techniques to identify the most efficient method for classifying Covid-19 misinformation. Covid-19 started in 2019 but classification of misinformation was done before 2019. Therefore, papers from 2018 were included in which various techniques used for classification of different types of misinformation on social media.

4 Result and analysis

The outcome and discoveries are introduced in this part which are separated from the reviewed articles to respond to the research questions of this study. All the research

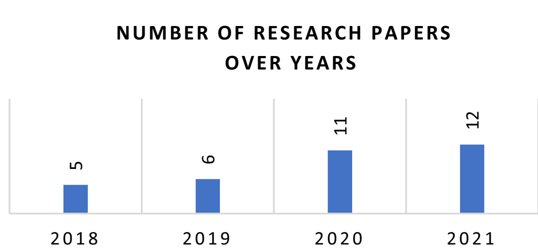

Fig. 4 Number of researched papers over the years

questions are discussed with significant investigations featured during the SLR process.

4.1 Misinformation classification techniques/methods over the last 4 years (RQ1)

To respond to RQ1, there are 4 significant techniques as follows which are widely implemented to produce the results with the best accuracy over the past few years.

- Neuro-Fuzzy.
- Neural Network.
- Natural Language Processing.
- Machine Learning Techniques.

In this review, we classified logistic regression, support vector classification, naïve Bayes, SVM and generative pre-trained transformer 2 (GPT2), decision tree, stochastic gradient descent as machine learning techniques. The methods that have been implemented for misinformation detection and prediction are like classic state-of-the-art classification methods, which are also used for comparison in terms of performance. In this literature, classification methods have been widely used as illustrated in Fig. 5.

The main objective of this SLR is to provide a clear picture for those who want to contribute to Covid-19 misinformation classification. Many researchers and beginners would like to know which technique can produce higher accuracy for classification methods. In this part, we cover some of the most innovative classification techniques that have been implemented recently. Nevertheless, providing an accurate answer is difficult as each research has its classification background. Figure 6 shows the distribution of techniques covered in this SLR for the classification of Covid-19 misinformation. Most of the reviewed papers used NF techniques (38%), 32% of the papers utilized NN, while NLP and machine learning techniques were covered in 24 and 4% of the papers, respectively. The bar chart shown in Fig. 6 includes the studies from 2018 to 2021.

In this SLR, mixed findings were discovered during the pilot research. Because many of the articles lacks in dataset description and comparing the results, it was difficult to conclude the notable techniques they have discussed. Nonetheless, to compare the performance of the proposed model by various researchers, the accuracy index has been selected in this SLR as shown in Fig. 7.

To answer RQ1, Fig. 7 shows the most utilized technique for misinformation classification over the past 4 years is NF. The second used technique is NN followed by machine learning. Finally, NLP is used the least for classifying misinformation. NF, NN, and ML are also widely used for detection and prediction of misinformation. Before the pandemic, misinformation detection was mostly

Table 5 Exclusion and inclusion criteria

Exclusion criteria	Inclusion criteria
The article is written in a language other than English	Papers that are written in the English language
The complete article or journal is unavailable	Paper is completely available
The paper has little to do with Deep Learning and detecting, classifying, or Predicting misinformation	The paper is related to machine learning and detecting, classifying, or Predicting misinformation
Later than 2018	The most detailed and frequent repeated articles of the same sample were included

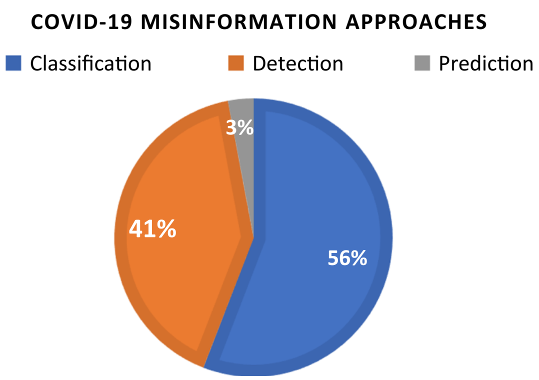

Fig. 5 (%) Distribution of Covid-19 misinformation approaches

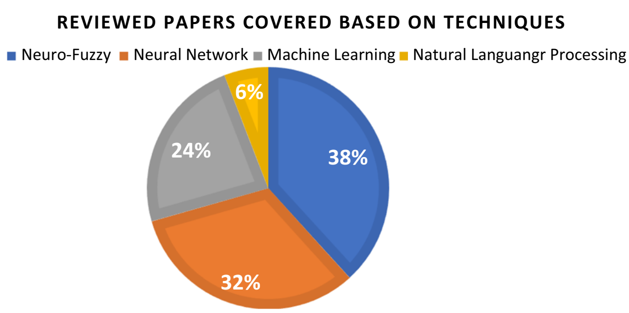

Fig. 6 (%) Distribution of reviewed papers covered based on techniques

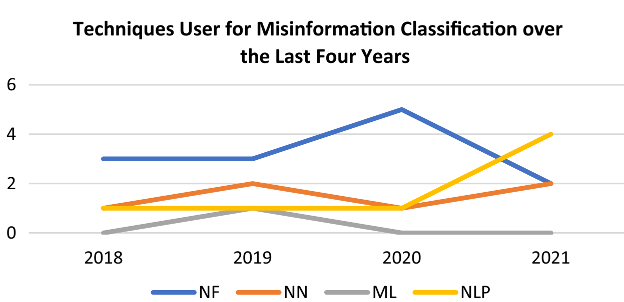

Fig. 7 Techniques used for misinformation classification over the last 4 years

focused on political issues, online news, Wikipedia, and many more.

4.1.1 Studies related to Covid-19 misinformation classification (Rq1a)

After the outbreak of Covid-19 pandemic, more misinformation was circulating on social media platforms than actual true information. Therefore, society and many organizations were confused and were struggling to identify the true information. Hence starting from 2019, many researchers race to find the proper models that provides the highest accuracy for classifying Covid-19 misinformation. The existing studies by [13, 25–30, 80, 89] focused on detecting Covid-19 misinformation. In terms of the best approach, suggestions, and future work, this study has recognized a few excellent and notable techniques for Covid-19 misinformation classification.

4.2 The most efficient methods for misinformation classification using NF and NN techniques (RQ2)

Utilizing NN, [20] proposed a hybrid model of DNN and NLP techniques. The proposed model achieved 81% accuracy. In addition, [25] classified Covid-19 misinformation using DT, KNN, LR, LSVM, MNB, BNB, NN, ERF, and XGBoost techniques and compared their performance. NN classifier showed the best outcome of 99.89 and 99.60% for F1-Score and Geometric-mean, respectively. Recently, [72] improved CNN to propose a novel method called Deep 1D-CNN. The proposed model achieves very good performance with 97.9% accuracy. Table 6 lists the performance evaluation and description of reviewed papers that implemented NN techniques.

In this section, evaluation performance of NLP and ML techniques is combined in Table 7. An evidence-based method was introduced by [76]. The model increased the accuracy of fake news verification to 50.91%. The outstanding model in the year 2020 was a model proposed by [87]. The paper used 23 supervised machine learning algorithms. Among the 23 ML algorithms, decision tree produced the highest accuracy value of 96.8%. Another interesting approach by [30] introduced a hybrid modified

Table 6 Performance evaluation of neural network method

Study	Problem tackled	Method	Performance	Description
[20]	Classification	DNN + NLP	Accuracy: 81%	Combination model of DNN + NLP to identify fake or genuine information
[21]	Detection	RvNN	Accuracy: 0.737	Improve fake news detection based on bottom-up and top-down structured neural network
[22]	Detection	GNN + NLP	ROC: 0.95%	Improves model with implementation of GNN
[23]	Detection	Deep CNN (FNDNet)	Accuracy: 98.36	The CNN-based model improves existing fake news detection
[24]	Classification	DNN	Accuracy: 84.37	Compares sentimental text classification of DNN and CNN models
[25]	Detection	DT, kNN, LR, LSVM, MNB, BNB, NN, ERF, and XGBoost	Accuracy: 99.63	Compares misleading information on Covid-19 using stated methods and NN provides the best accuracy
[26]	Detection	CNN + BERT	F-Score: 68.24	Covid-19 detection system using CNN and BERT
[93]	Classification	DNN, ANN	Accuracy: 95.84	DNN classification model outperformance ANN model and achieves better accuracy
[72]	Classification	DNN, LSTM, BI-LSTM, GRU, BI-GRU, ID-CNN, SVM, Naïve Bayes	Accuracy: 97.900	Predicts the validity of news and 1D-CNN outperforms
[27]	Detection	Cross-SEAN	Accuracy: 94	Covid-19 datasets with labelled true or false tweets

Table 7 Performance evaluation of NLP and ML methods

Study	Problem tackled	Method	Performance	Description
[76]	Detection	Evidence-based	Accuracy: 50.91%	Introduction of a publicly available dataset for verification
[86]	Detection	Stochastic Gradient Descent	Accuracy: 87%	Fake news detection system based on news headlines
[87]	Detection	Supervised ML Techniques	DT: Acc:0.968 Precision: 0.963 Recall: 0.973 F-M: 0.968	23 ML algorithms implemented to detection fake news and Decision Tree provides the best performance
[89]	Detection	Logistic Regression, Support Vector Classification, and Naïve Bayes	LR: Accuracy: 84%	Covid-19 rumours detection and logistic regression provides the best accuracy
[28]	Detection	DistilBERT	Accuracy: 97.2	Covid-19 misinformation detection using NLP and explains why the news is false
[88]	Classification	SVM, KNN, Naïve Bayes, AdaBoost, Bagging	Accuracy: 89.01	Classifies Tweets into three categories based on sentiments
[29]	Classification	Random Forest	F1 scores between 0.347 to 0.857	Classifies four Covid-19 conspiracy theories
[30]	Detection	LSTM, GRU, Decision Tree (DT), Logistic Regression (LR), K Nearest Neighbour (KNN), Random Forest (RF), Support Vector Machine (SVM), and Naive Bayes (NB)	GRU: Accuracy: 98.29	provides a framework to detect Covid-19 misinformation using modified LSTM + GRU

model of LSTM and GRU, which aims to detect Covid-19 misinformation. The proposed model achieved the accuracy of 98.29%.

Over the past four consecutive years, the NF technique outperforms NN, NLP, and many machine learning techniques. In this part of SLR, two papers that are published in 2018 were reviewed among which the paper by [59] achieved the best performance for the proposed NF method. This paper performed a comparison experiment between ANFIS, CNN, deep CNN, and DGAM. The proposed model which is the ANFIS model was used to classify brain MRI images and was compared with existing state-of-the-art experiment results. Moreover, [64] proposed a model based on ANFIS with the accuracy of 99.62%. The model improved the robustness of ANFIS technique and amplified the classification accuracy results. Furthermore, [91] implemented ANFIS for data classification with the accuracy of 99.4%, specificity, and sensitivity of 99.7%. Table 8 shows the list of papers which utilized NF for in their proposed classification model. In addition, the problem, proposed method, performance, and evaluation of the method for those papers are shown in the table.

Based on the overall performance evaluation of different classification methods, NF provides the best accuracy results. Figure 8 illustrates the accuracy performance of different classification techniques used by various researchers. Therefore, to answer RQ2, the most efficient method for the classification of Covid-19 misinformation is NF including ANFIS, NN, ML and NLP, respectively.

4.3 The strength and limitations of the current neuro-fuzzy and neural network approach to classify Covid-19 misinformation (RQ3)

The strengths and limitations of ANFIS as neuro-fuzzy network are listed in Table 9. The robustness of the findings provided by ANFIS can be ascribed to its success [94]. ANFIS is as generalizable as NNs and other machine learning approaches [95]. ANFIS can take crisp input, express it in the form of membership functions and fuzzy rules, and then create crisp output from the fuzzy rules. This makes room for applications that require precise inputs and outputs. It is a very promising technique that has yet to be explored in a variety of different nonlinear, complicated approximation and control issues.

ANFIS has a significant processing cost because of its complicated structure and gradient learning. This is a severe barrier for applications that require a high number of inputs. ANFIS model has higher accuracy than the other NF model types which compensates for its less interpretable structure [46].

Table 8 Performance evaluation of neuro-fuzzy method

Study	Problem tackled	Method	Performance	Description
[55]	Classification	ANFIS	Accuracy: 97.9, MSE: 3.188	ANFIS is used to decrease error rate, give high precision and simplicity
[65]	Classification	ANFIS	Accuracy: 92.16	Implements ANFIS method for text classification
[66]	Classification	ANFIS + Nonlinear SVM	Accuracy: 90	Proposed a method of Classification of the political tweets using ANFIS and nonlinear SVM
[59]	Classification	ANFIS	Accuracy: 99.30 Specificity: 99.71 Sensitivity: 70.25 Precision: 82.09	ANFIS model outperforms CNN, Deep CNN, DGAM classification
[64]	Classification	ANFIS	Accuracy: 99.62	ANFIS improves robustness and increases classification accuracy
[48]	Classification	Neuro-Fuzzy	Accuracy: 95.59 Precision: 0.9629 Recall: 0.9544 F-M: 0.9569	NF-FR handles imprecise and problems with uncertainty
[67]	Classification	ANFIS + DNN	Accuracy: 97.99 MSE: 0.0401	ANFIS solves DNN problem of transparency
[49]	Prediction	ANFIS + PSOGWO	Accuracy: 87.5	Hybrid model of ANFIS and PSOGWO produces better outcomes
[68]	Classification	ANFIS	Accuracy: 99.6 Specificity: 99.7 Sensitivity: 98.1 Precision: 98.5 F-M: 97.9	Applied ANFIS in tumour classification
[69]	Classification	ANFIS	Accuracy: 96 Specificity: 94 Sensitivity: 99	ANFIS outperforms ANN, FIS in classifying breast ultrasound images
[91]	Classification	ANFIS	Accuracy: 99.4 Specificity: 99.7 Sensitivity: 99.7	Implementation of ANFIS model can improve the classification

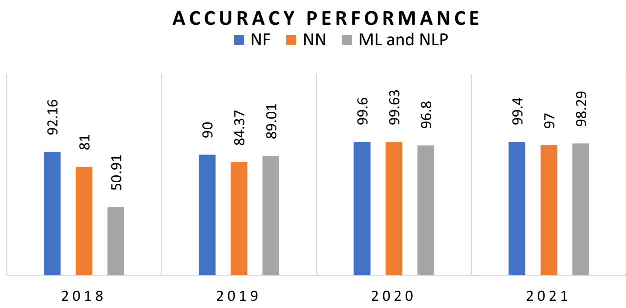

Fig. 8 Accuracy as performance measure of different techniques

The restrictions of ANFIS are broadly defined as follows: (a) the kind and quantity of membership functions; (b) the placement of a membership function; and (c) the curse of dimensionality [96]. Furthermore, the trade-off between interpretability and accuracy is considered a critical issue. The computational cost of ANFIS is high due to complex structure and gradient learning.

In general, the DNN model is an ANN model with many layers in between the input and output layers [97]. The DNN model works more efficiently if more data are provided. The more the data, the higher the accuracy of the model will be achieved [98]. However, it only works well with big data, whereas the performance level is inefficient if there is less data. The DNN model has a high capability to capture nonlinear, high-dimensional features in big data. Moreover, the DNN model has efficient computation power although it is expensive. Furthermore, DNN model has black box nature. Therefore, the outcome is unpredictable. Table 10 shows the strength and limitation of DNN model summary.

5 Discussion and conclusion

The major goal of this SLR is to describe and summarize existing classification approaches that can be used for Covid-19 misinformation classification based on a hybrid NF-NN model. It specifically tries to address the stated research questions by extensively analysing the selected papers that were filtered using the inclusion, exclusion, and quality evaluation criteria. RQ1 aimed to identify suitable technique for the classification of misinformation specifically related to Covid-19. In RQ2, the most efficient NF and NN techniques are thoroughly described based on performance measures as well as the best methods. Finally, RQ3 highlighted the strength and limitations of the selected NF-NN methods such as ANFIS and DNN.

The first objective was to identify the most common techniques used to classify misinformation from the year 2018–2021. From the findings, we have identified that the number of studies on misinformation classification has significantly increased over the years, especially since the outbreak of Covid-19. Researchers have widened the scope of techniques implemented to classify misinformation. RQ1 is designed to classify misinformation approaches reported over the past four years as well as focus on Covid-19 misinformation studies since 2019.

For RQ2, general classification methods were reviewed along with the performance measure. RQ2 was taken a step back and not specifically based on misinformation. This is because we wanted to explore more possibilities of various techniques used for classification and compare their performance. In this SLR, the main ideology is based on NF and NN techniques. Therefore, papers based on NF and NN classification that provides the best performance measures were reviewed. Precisely, ANFIS [68] and DNN [93] algorithms both using medical dataset have provided the

Table 9 Strength and limitation of ANFIS model

Strength	Limitation
Results precise output	High computational cost
High accuracy than other Neuro-Fuzzy models	A significant bottleneck to applications with large inputs
Robustness of results	The location of a membership function
Highly generalization capability	The curse of dimensionality

Table 10 Strength and limitation of DNN model

Strength	Limitation
Works better with big data	Requires more data to work with than regular ML
Efficient computational power	Expensive computational as it has high complexity
The algorithm implemented runs faster	Black box nature

best accuracy performance in compared to the state-of-art techniques. In addition, it was proved that ANFIS and DNN are effective and efficient for data classification. The accuracy gap offered by existing approaches continues to be a problem for researchers. They intend to overcome the limitations of recent advancements in Covid-19 misinformation classification so that it may be used in practice.

Efficient Covid-19 misinformation classification allows machine learning to learn the vicinity of a misstatement to anticipate it in the future. Several approaches have been developed and applied in this respect, based on Covid-19 misinformation classification. For many years, detection algorithms have been utilized extensively for disinformation detection. Nonetheless, these techniques on their own were not dependable or feasible to be executed in the actual world.

RQ3 covers the various problems that the researchers may confront as well as potential solutions. It seeks to identify possible gaps so that a new researcher may readily comprehend and act on unmet requirements. Several possible areas for further research have been discovered during the SLR and pilot study processes. ANFIS stands out of all NF models because it gives the most accurate results. However, it has a high dimensionality problem. Research by [67] suggests that a hybrid model of ANFIS and NN models can cure the problem.

Moreover, in RQ3 we discussed the design and operation of ANFIS and DNN, as well as the benefits and drawbacks of these two widely used classifiers. ANFIS is good at handling nonlinear problems, but its applicability is limited to situations with less dimensional data. Deep learning approaches, such as DNN, outperform conventional methods for tackling classification problems with a large number of input characteristics because of their higher-level abstraction and feature abstraction capabilities. On the one hand, the DNN classifier's implementation has aided in the solution of big and difficult issues. In addition, due to the deep structure of DNN, it optimizes millions of parameters. As a result, DNN findings began to be criticized by professionals as being opaque and difficult to comprehend. Recently, scholars attempted to address DNN's weakness by employing fuzzy logic. Therefore, it is suggested to use a hybrid model of ANFIS and DNN for improving Covid-19 misinformation classification in future studies. The standalone model of ANFIS and DNN shows high accuracy. However, the hybrid model which combines ANFIS and DNN improves the accuracy for test classification.

Following the principles of Kitchenham and Charters by [92], we methodically unfold the essential features of misinformation classification mechanism in this work. Due to the occurrence of Covid-19 pandemic, this study tried to focus more on the techniques which can be utilized for Covid-19 misinformation classification. A thorough systematic literature review (SLR) of these approaches was done in this study utilizing 34 publications related to misinformation classification published between 2018 and 2021. Firstly, the SLR started with a focused scope on misinformation classification methods. Then, the studies with the focus on Covid-19 misinformation were highlighted. Next, a detailed comparison of NF, NN, NLP, and ML methods was provided based on implemented technique, and performance measurement.

Table 11 Comparison of ANFIS, DNN, and hybrid model of ANFIS with DNN

Techniques	ANFIS	DNN	ANFIS + DNN
Dimensionality	High	High	High
Robustness	High	Low	High
Generalization capability	High	High	High
Big data	Low	High	High
Accuracy	High	High	High
Computational cost	High	High	High
Complexity of black box nature	Low	High	Low

In short, the hybrid model of ANFIS and DNN will be implanted in this paper to classify Covid-19 misinformation in social media based on the level of risk. Table 11 shows an overview of the overall comparison of ANFIS, DNN, and the proposed hybrid model of ANFIS and DNN model. As mentioned, the limitation of the ANFIS model as mentioned earlier is that it struggles with high dimensionality as well as computational time and cost. Moreover, the ANFIS model does not work well with a big dataset while DNN can compute with a large set of data. ANFIS model has high robustness, while DNN has low robustness. As for generalization capability both ANFIS and DNN models are high. DNN suffers from the black-box nature. However, with the combination of ANFIS with DNN, it overcomes the black box problem.

Finally, this SLR was wrapped up by providing an insightful point of view on using ANFIS and DNN as the best model to classify Covid-19 misinformation on social media. Based on the results of this SLR, it can be concluded that although ANFIS and DNN's standalone model has a high level of accuracy for the classification of Covid-19 misinformation, the hybrid ANFIS-DNN can enhance classification accuracy. DNN can be studied further in the future, to provide an insight for improving the performance of misinformation classification.

Acknowledgements The authors are thankful to the School of Computer Sciences, and Division of Research & Innovation, USM for supporting this study from the Short-Term Grant (304/PKOMP/6315435) granted to Dr Pantea Keikhosrokiani.

Data availability statements Not applicable.

Declarations

Conflict of interest There is no conflict of interest.

Ethical statement Not applicable.

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