IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 2 July 2023, accepted 13 July 2023, date of publication 24 July 2023, date of current version 2 August 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3298441

RESEARCH ARTICLE

Deep vs. Shallow: A Comparative Study of Machine Learning and Deep Learning Approaches for Fake Health News Detection

TRIPTI MAHARA[1], V. L. HELEN JOSEPHINE[2], RASHMI SRINIVASAN[2], POORVI PRAKASH[2], ABEER D. ALGARNI[3], AND OM PRAKASH VERMA[4], (Senior Member, IEEE)

[1]Department of Research and Business Analytics, Prin L.N. Welingkar Institute of Management Development and Research, Bangalore, Karnataka 560100, India
[2]School of Business and Management, Christ University, Bangalore, Karnataka 560029, India
[3]Department of Information Technology, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, P.O. Box 84428, Riyadh 11671, Saudi Arabia
[4]Department of Instrumentation and Control Engineering, Dr. B. R. Ambedkar National Institute of Technology Jalandhar, Jalandhar, Punjab 144011, India

Corresponding author: Tripti Mahara (triptimahara@gmail.com)

This research was funded by Princess Nourah bint Abdulrahman University Researchers Supporting Project number (PNURSP2023R51), Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia.

ABSTRACT Internet explosion and penetration have amplified the fake news problem that existed even before Internet penetration. This becomes more of a concern, if the news is health-related. To address this issue, this research proposes Content Based Models (CBM) and Feature Based Models (FBM). The difference between the two models lies in the input provided. The CBM only takes news content as the input, whereas the FBM along with the content also takes two readability features as the input. Under each category, the performance of five traditional machine learning techniques: - Decision Tree, Random Forest, Support Vector Machine, AdaBoost-Decision Tree and AdaBoost-Random Forest is compared with two hybrid Deep Learning approaches, namely CNN-LSTM and CNN-BiLSTM. The Fake News Healthcare dataset comprising 9581 articles was utilized for the study. Easy Data Augmentation technique is used to balance this highly imbalanced dataset. The experimental results demonstrate that Feature Based Models perform better than Content Based Models. Among the proposed FBM, the Hybrid CNN - LSTM model had a F1 score of 97.09% and AdaBoost-Random Forest had a F1 Score of 98.9%. Thus, Adaboost-Random Forest under FBM is the best-performing model for the classification of fake news.

INDEX TERMS Fake news, healthcare, classification, deep learning, machine learning, readability features.

I. INTRODUCTION

The Internet has revolutionized the way we access and share information. Although the Internet has brought significant benefits, it has also enabled the rapid spread of misinformation and fake news. The term fake news has become an increasingly buzzword in this era. It is nothing but manipulated information that is incorrect and that cannot be verified. It is "news that is intentionally and verifiable false" [1] and is spread with the intention of misleading users. The fake news is not something new. The "Great Moon Hoax" was one of the historical examples of a series of articles published in the New York Sun about the discovery of life on the moon way back in 1835 [2]. However, high internet penetration has led to widespread information dissemination from diverse sources such as online newspapers, blogs, social media, magazines, and various forums, making it difficult to identify the reliability of published news [3]. For instance, the 2016 U.S. presidential elections created a buzz around fake news [4]. According to Ipsos survey conducted by the Center of International Governance Innovation (CIGI) in over 25 countries, 86% of users admitted that they had been exposed to fake news, and they initially believed that the news was true [5]. In a survey by Microsoft, 60% of Indians have seen fake news online, compared to the global average of 57% [6]. The political domain has maximum instances of

The associate editor coordinating the review of this manuscript and approving it for publication was Nuno M. Garcia.

fake news, but the spread has now widened to various other domains. For instance, news of the Australian wildfire that spread in January 2020 created a lot of misinformation about the event [7]. The COVID-19 pandemic added fuel to the fire of spreading fake news regarding the origin and spread of the virus to remedies and cures. Medical professionals found it very difficult to manage the spread of fake news while handling the virus. World Health Organisation (WHO) warned of a 'infodemic' along with the global pandemic as lots of false information was getting circulated about the cause, spread, treatment and prevention of the virus [8]. For instance, a US citizen who heard that chloroquine could potentially treat COVID passed away after consuming medicine [9]. The spread is not only for a newly found virus or bacteria, but also for existing diseases such as cause and cure of cancer, autism, dementia, and urological conditions [9], [10], [11], [12], [13]. With very high Internet penetration, over 70% of adults use the Internet to search for healthcare-related information that might not always result in correct information.

The impact of fake news in the health sector can lead to more negative impacts than in other domains, as it involves human life. The spread of fake news can lead to negative outcomes, such as decreased trust in healthcare providers, harm to patients, and increased healthcare costs. A comprehensive review discovered that inaccurate and misleading health-related content causes people to experience mental, social, political, and/or economic hardship. For instance, a single piece of fake news related to medicine resulted in at least 800 fatalities and 5,800 hospital admissions [14].

Thus, this study focuses on identifying fake news in the healthcare domain. To address this, two categories of models, Content Based Models (CBM) and Feature Based Models (FBM), have been proposed. CBM uses the textual content of the articles as the input, whereas FBM, along with content, considers two readability features for model building. For each category, the performance of various machine learning models was compared with the two proposed hybrid Deep Learning models (CNN-LSTM and CNN-BiLSTM) for better accuracy.

The remainder of this paper is organized as follows. Section II comprises literature review, followed by the methodology in Section III. Section IV constitutes Model Building, followed by Model Evaluation Metrics in Section V. Results and Discussions are presented in Section VI, followed by Analysis of the Models Built in Section VII. Conclusion is presented in Section VIII.

II. BACKGROUND STUDY

Politics, Tourism and Marketing are the three most researched whereas health care is the least researched domains for fake news classification [15]. As the significance of identifying fake news in healthcare is more significant than any other domain due to its impact, this research focuses on this domain and presents the literature for the same.

Based on methodology used, research in this domain can be categorized as using either traditional machine learning or Deep Learning approaches for fake news classification.

A HealthLies dataset consisting of facts and fake information on various diseases such as cancer, Covid, Zika virus, Ebola, and AIDS was built, and the performance of various machine learning models was compared with the BERT Model. The results indicated that BERT outperformed all other traditional models [16]. A classifier to detect fake news for autism was built using a Random Forest Classifier with F1 score of 85% [17]. The performance of traditional machine learning algorithms such as Naive Bayes, Nearest Neighbor, Random Forest, Logistics Regression, Adaboost, Neural Network was compared with four Deep Learning approaches: - CNN, RNN, GRU, and RNN. The results show that deep learning algorithms perform better than traditional machine learning algorithms for the COVID 19 dataset [18]. Cross-SEAN, an approach for fake news detection and semi-supervised models for text classification that learns from significant external facts and partially generalizes to newly emerging false news, was proposed and compared with seven cutting-edge techniques. The results showed that it performed 9% better than the best baseline with a 0.95 F1 Score on CTF, a large-scale COVID-19 Twitter dataset [19]. In [20], the performance of traditional machine learning algorithms, such as Multinomial Naïve Bayes, Support Vector Machine, Logistic Regression and Random Forest, considering topical, structural, and semantic patterns was compared to identify fake news. Both traditional and Deep Learning methods were compared for the Covid-19 dataset to identify fake news. The results showed that Deep learning-based models are better able to detect fake news [21]. A classifier using Random Forest to identify fake news for COVID-19, after incorporating linguistic and sentiment features, was built [22]. A Random tree-based classifier was built to identify ZIKA Virus related fake tweets using feature selection with a F1 score of 94.5% [23].

Relatively more work has been done in other domains compared to the healthcare domain. For example, in [24], researchers proposed a two-phase approach called WELFake, which uses word embedding over linguistic variables to identify false news using supervised machine learning models. In the first stage, linguistic features were applied to check the authenticity of news content. In the second stage, voting classification was performed when linguistic feature sets were combined with word embedding. The WELFake model achieved an accuracy of 96.73%, which was higher than the maximum accuracies of the CNN and BERT models, which were 92.48% and 93.79%, respectively, for articles related to the political domain. The performance of traditional machine learning models (Binomial Linear Regression, Naïve Bayes Classifier) was compared with Deep Learning models (CNN, LSTM) and an accuracy and F1 score of approximately 94% and 98% respectively was obtained with a Deep Learning Model [25]. A comprehensive survey of the existing fake news identification techniques, along with a comparison of traditional techniques (Naïve Bayes and Random Forest) with Deep Learning based methods, like Passive Aggressive and LSTM was conducted. The results of this study show that LSTM has the highest accuracy of 92% [26]. A Content Based transfer learning approach to detect fake news was proposed and achieved an accuracy of 92% [27]. Very limited work has been conducted on building hybrid models. For instance, LSTM and CNN were used together to propose a hybrid model for identifying fake news [28], [29].

As observed, few studies using limited techniques have been conducted in the healthcare domain for fake news identification, although more models have been built for other domains. Hence, this research bridges this gap by building a fake news classifier specifically for the healthcare domain with high accuracy.

III. METHODOLOGY

The proposed research methodology presented in Fig 1 consists of building Content Based and proposed Feature Based models using machine learning and Deep Learning techniques. In the first case, only the content (i.e., fake news) is used to build the models, whereas, for the Feature Based models, additional readability features are provided as input along with the content to build models and their performance is compared.

A. DATA COLLECTION

There are numerous open datasets available for the study of fake news in the political domain, but datasets in the healthcare domain are exceedingly infrequent and small. One prominent publicly available dataset is the HealthLIES dataset that contains 12,267 sentences, which are labelled as either true or false based on whether they contain factual health information or misinformation, respectively. The HealthLIES dataset was created by collecting sentences from various online sources, including social media, news articles, and health-related websites [30]. In addition, there is a compiled dataset focusing on fake news in the healthcare industry, named the Fake News Healthcare (FNH) dataset [31]. This dataset comprises 9581 labelled news articles, with 1816 classified as fake and 7765 as genuine. The dataset also includes additional information such as the URL, article title, and article length. The fake and genuine news samples in the FNH dataset were collected from credible websites such as CNN, BBC News, and The Atlantic for genuine news samples, whereas sources like theonion.com and PolitiFact were utilized for fake news samples. The FNH dataset was selected for this research because of the additional information available that will be utilized for model building.

B. DATA AUGMENTATION

The FNH is a highly imbalanced dataset with two classes: True and Fake. True news accounted for 76.4% of the data, whereas fake news was 23.6%. When comparing the number of documents that contain real news to those that include fake news, the ratio of imbalance for the FNH dataset was 4:1. This type of imbalance in the dataset affects the accuracy of the results and is not feasible for building accurate models. Hence, data augmentation techniques are required to overcome this problem by randomly duplicating samples from the minority class to provide a balanced and effective dataset. Data augmentation is performed to balance the dataset by generating synthetic data from the available data [32]. This is a popular technique in the computer vision domain; however, it becomes more difficult in Natural Language Processing (NLP) because it involves understanding the grammatical structure of the text [33]. The Easy Data Augmentation (EDA) technique is one of the most widely used augmentation methods for textual data [34]. In this technique, ''n' words, other than stop words, are selected from the sentence and replaced with their random synonyms using WordNet. EDA was deployed for data augmentation in this research. After augmentation, the final dataset consisted of 7625 fake articles and 7765 genuine articles.

C. DATA PRE-PROCESSING

After balancing the dataset, the next step was to obtain a valid set of tokens for each article. This was achieved by removing the numbers and special characters. Stop words and punctuation marks are not removed, as they provide more context to the text while incorporating word embedding for feature extraction. Finally, lemmatization was performed to obtain the root words. This preprocessing resulted in a list of valid tokens.

D. FEATURE EXTRACTION

Term Frequency- Inverse Document Frequency (tf-idf) and GloVe Word Embeddings are used for feature extraction in traditional machine learning and deep learning models, respectively. Readability features were extracted for FBM.

1) TF-IDF

It is a widely used measure to create document vectors. This vector converts words into numbers based on the importance of a term within and across documents with respect to the available corpus [35].

2) WORD EMBEDDING

The valid tokens obtained after preprocessing must be converted into number vectors using word embedding. Words that have the same context and meaning will be close to each other, as word embedding takes into consideration the semantic and syntactic information of the word [36]. In this study, GloVe (Global Vectors), a very popular pre-trained word embedding technique, was used to obtain the matrix [37]. It was trained using a dataset of six billion words with a vocabulary of 400 thousand words.

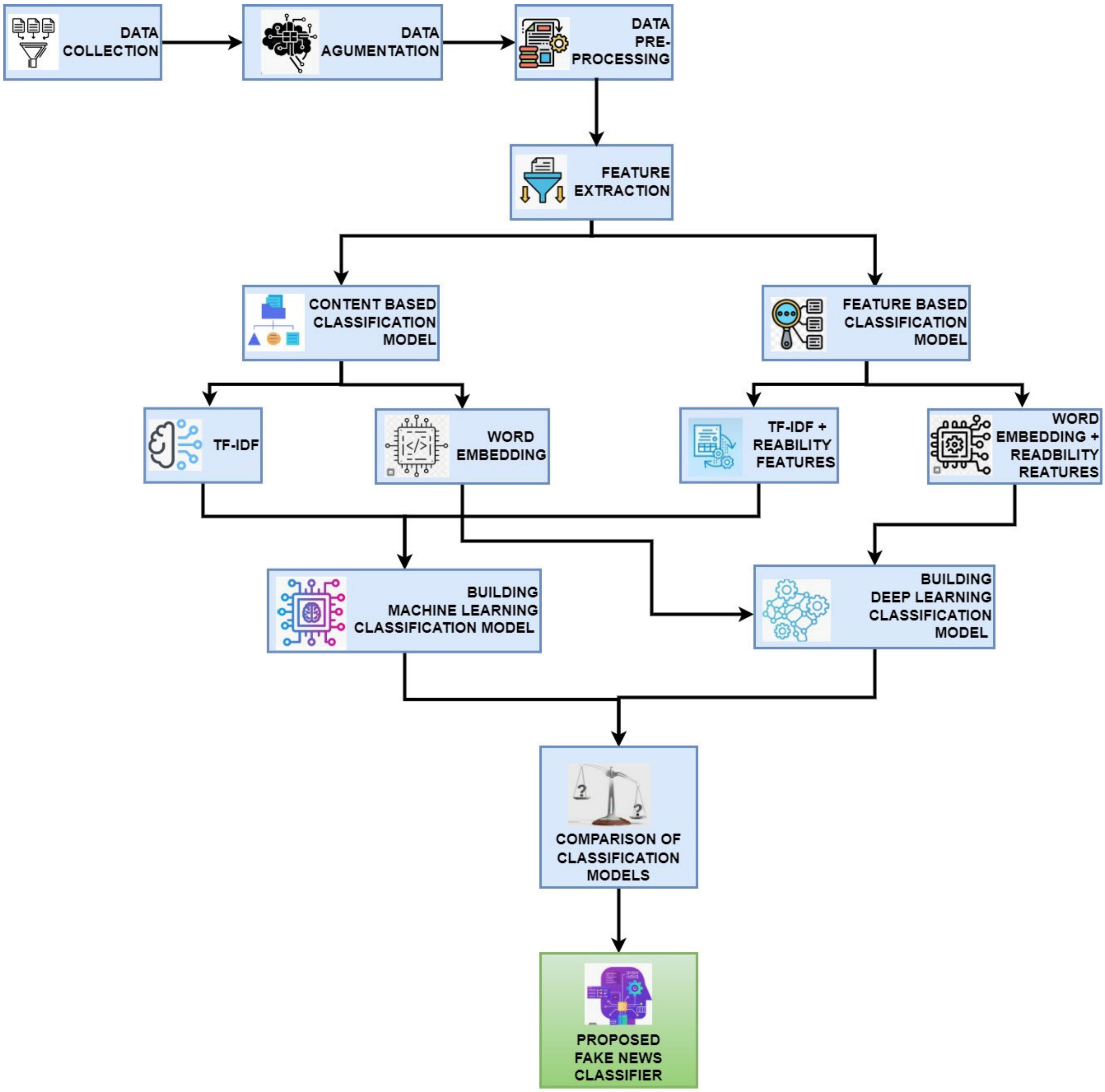


FIGURE 1. Proposed methodology.

3) READABILITY FEATURES

Fake news in healthcare can be particularly dangerous as it can mislead people to make decisions that can have negative consequences on their health. By using readability metrics, such as Simple Measure of Gobbledygook (SMOG) score and Type-Token Ratio (TTR), we can assess the readability of healthcare-related content and identify potentially fake news articles that are difficult to comprehend or contain a high proportion of rare or unique words [38].

SMOG and TTR are particularly important in the healthcare domain because of the specialized language and terminology used in the medical literature. Medical terminology can be complex and difficult for common man to understand, making it easier for fake news to spread and mislead people. Hence, these features can help identify articles that are intentionally obfuscating information or using jargon to appear authoritative while making it difficult for readers to understand the information, primarily during patient care.

a: SMOG SCORE

SMOG is a readability index that measures the complexity of a piece of text by analyzing the number of polysyllabic words. A polysyllabic word contains two or more syllables.

Algorithm to calculate SMOG Score:

Step 1: From the news, three samples of ten-word sentences were chosen.

Step 2: Count the number of polysyllables in the sentences (words with three or more syllables).

Step 3: Determine the grade using the formula -

$$\text{grade} = 1.0430\sqrt{\text{number of polysyllables x} \frac{30}{\text{Number of sentences}}} + 3.1291 \quad (1)$$

where: polysyllable count = The number of words of more than two syllables in a sample of 30 sentences.

b: TYPE TOKEN RATIO

The Type-Token Ratio (TTR) is a valuable metric used to determine the level of complexity of a document by assessing its lexical diversity. It calculates the ratio of the number of unique words (types) to the total number of words (tokens) in a particular language segment. TTR ratio closer to 1 indicates that the segment has a higher degree of lexical richness.

$$TTR = \frac{\text{numberoftypes}}{\text{numberoftokens}} \times 100 \quad (2)$$

Both SMOG and TTR scores are provided along with both the Tf-idf vector and the vector obtained after applying GloVe to build the FBM.

IV. MODEL BUILDING

This section proposes building classifier models under two categories: Content Based Models and Feature Based Models, as depicted in Fig 1. For both categories, the performance of traditional machine learning algorithms is compared with the proposed Deep Learning Algorithms to identify the best classifier for fake news identification.

A. TRADITIONAL MACHINE LEARNING MODELS

Decision Tree, Random Forest, Support Vector Machine, AdaBoost Decision tree, and AdaBoost Random Forest models were built to analyze the performance of both the CBM and FBM categories.

1) DECISION TREE

A decision tree is a modelling technique that employs a hierarchical tree structure to develop regression or classification models. It recursively partitions a dataset into progressively smaller subsets while constructing a decision tree. The final tree includes the decision and leaf nodes, where each leaf node corresponds to a classification or decision. The root node sits at the top of the decision tree, and represents the best predictor. When dividing data using entropy, the process is known as "Information Gain." Decision trees can process both numerical and categorical data and are non-parametric, enabling them to handle large and complex datasets effectively without imposing a complicated parametric framework.

$$\text{Gain(T, X)} = \text{Entropy (T)} - \text{Entropy (T, X)} \quad (3)$$

where, T = target variable

X = Feature to be split on

Entropy (T, X) = Entropy calculated after the data is split on feature X.

2) RANDOM FOREST

Random Forest is a supervised learning technique that constructs an ensemble of decision trees using the "bagging" approach. This method combines multiple learning models to improve the overall output. Using replacement when sampling the data, approximately one-third of the samples are used to test the model, known as out-of-bag samples. The impurity of the dataset can be assessed using the Gini index, with the root node selected as the feature. Scikit-learn computes the Gini Importance of each node for each decision tree, assuming that the tree is binary, with only two child nodes.

3) SUPPORT VECTOR MACHINE

A Support Vector Machine (SVM) is a classification technique that seeks to identify a hyperplane in an N-dimensional space that separates the data points into distinct categories. The size is determined by the number of features, and the objective is to establish an optimal decision boundary or line for accurate classification of new data points. The optimal decision boundary is referred to as the "hyperplane." In situations where there are numerous features, such as in text classification tasks, the linear kernel is highly effective. The linear kernel functions are faster than most of the other kernel functions. This equation defines the decision boundary of the SVM.

$$f(x) = w^T X + b \quad (4)$$

where, w is the weight vector that must be, X is the data that must be classified and b is the linear coefficient estimated from the training data.

4) ADABOOST ALGORITHM

AdaBoost is an ensemble learning technique that enhances the accuracy of classifiers by combining multiple classifiers. AdaBoost classifier constructs a strong and robust classifier by amalgamating several weak classifiers, resulting in a highly accurate and reliable classifier. The primary principle of AdaBoost is to set classifier weights and train the data samples in each iteration to enable accurate predictions for uncommon observations. Any machine learning approach that accepts training set weights can serve as a fundamental classifier in AdaBoost.

$$H(x) = sign\left(\sum_{t=1}^{T} a_t h_t(x)\right) \quad (5)$$

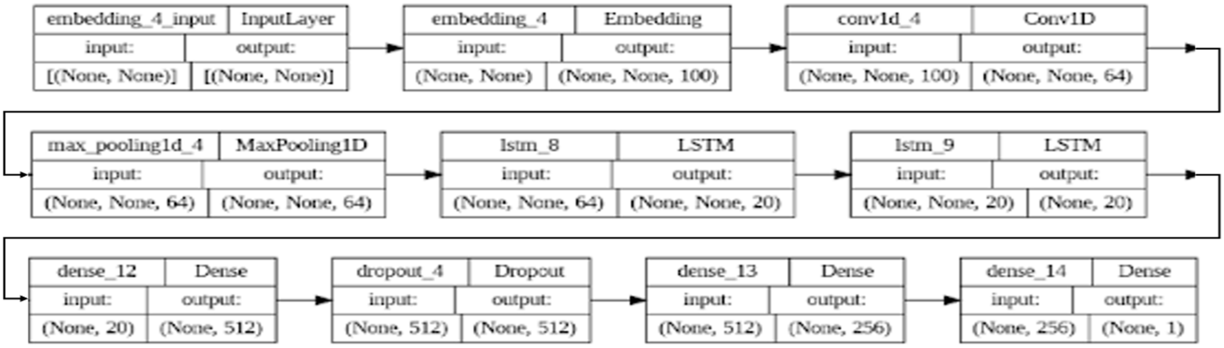


FIGURE 2. **CNN-LSTM model.**

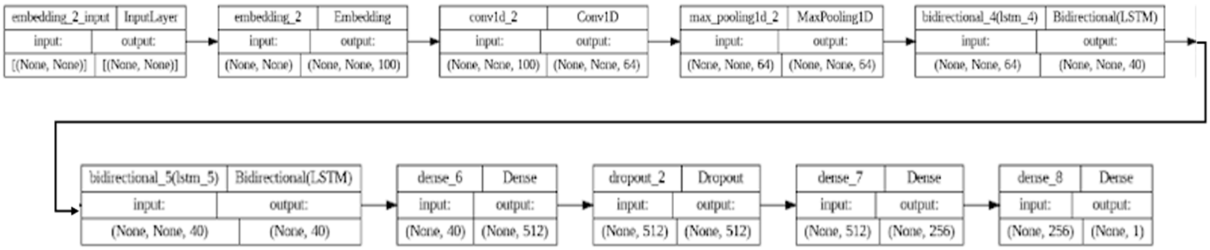


FIGURE 3. **Hybrid CNN-BiLSTM model.**

AdaBoost is subject to two essential requirements. First, the classifier must be trained interactively on various weighted training instances. Second, it aims to achieve an excellent fit for these instances in each iteration by minimizing training errors. It can be used either with Decision Tree or Random Forest. Both are ensemble learning models.

B. DEEP LEARNING MODELS

In this category, two deep learning-based models, Hybrid CNN-LSTM and Hybrid CNN-BiLSTM, are proposed to build a fake news classifier.

1) CNN-LSTM MODEL

A hybrid model comprising both CNN and LSTM is proposed in this study, as depicted in Fig 2. The first layer is the embedding layer, followed by a one-dimensional CNN layer (Conv1D). This layer is used to extract local features using 64 filters with a kernel size of 5 using the ReLU activation function. This results in large feature vectors, which become the input to the MaxPooling 1D layer with a window size of four. This enables the dimension reduction of the feature vectors. The pooled feature maps are input into two LSTM layers that output long-term dependent features of the input feature maps while preserving the memory. Each LSTM layer comprises 20 neurons with an output dimension of 20, utilizing a linear activation function. The trained feature vectors are eventually classified using a dense layer that maps the output space dimension to one, indicating the classification label (fake or not fake) using the sigmoid activation function. The model is trained using the Adam optimizer with a learning rate of 0.01 and cross entropy as the loss function.

2) HYBRID CNN-BILSTM MODEL

The architecture of the model is the same as that of the hybrid CNN-LSTM model. The only change incorporated is the usage of the Bi-directional LSTM layer instead of the LSTM layers, as depicted in Fig 3. It has several layers, starting from the word-embedding layer to the CNN layer, followed by the max pooling layer, the Bi-directional LSTM layer, and the dense layer to obtain the classification. In bi-directional LSTM, the input flows in both directions, having information about both the past and present. Therefore, it can produce a more meaningful output.

V. MODEL EVALUATION METRICS

The model performance was evaluated using four metrics, namely: Accuracy, Precision, Recall and F1 Score, as shown in Table 1. To evaluate the model, four estimation parameters-True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) were used. A true positive outcome occurs when the model correctly predicts the positive class, whereas a true negative result occurs when the model accurately describes the negative class. On the other hand, a false positive result occurs when the model inaccurately estimates the positive class, whereas a false negative outcome occurs when the model incorrectly predicts the negative class.

VI. RESULTS AND DISCUSSIONS

CBM and FBM utilizes Machine Learning and Deep Learning approaches are executed in the Google Colab environment owing to the availability of GPU for heavy computation. The code was written in Python using

TABLE 1. Model evaluation metrics.

Metric	Definition	Formula
Accuracy	This refers to the fraction of accurately predicted fake news articles out of the total number of fake news articles.	$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$
Precision	This ratio represents the proportion of accurately predicted fake news articles to the total number of predicted positives.	$$Precision = \frac{TP}{TP+FP} \quad (7)$$
Recall	It is a measure of the proportion of actual positive cases that were correctly identified by the model as positive.	$$Recall = \frac{TP}{TP+FN} \quad (8)$$
F1 Score	The testing accuracy of the model is calculated by taking the harmonic mean of precision and Recall.	$$F1\ Score = \frac{2 * Precision * Recall}{Recall + Precision} \quad (9)$$

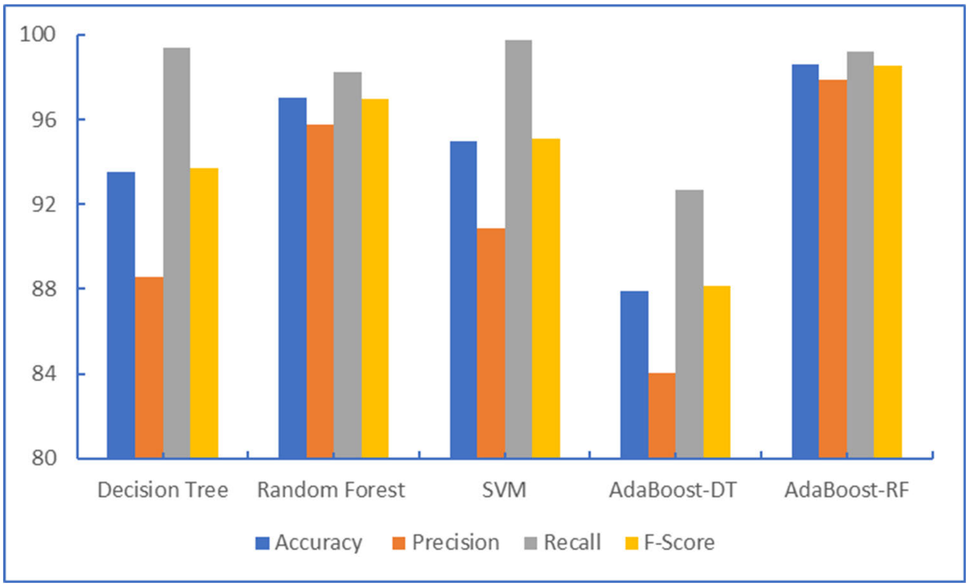


FIGURE 4. Comparing the performance of traditional machine learning models under content based models.

Keras, pandas, Numpy, Scikit-learn, and Matplotlib packages. For the Deep learning models, GloVe word embedding with 100 dimensions was utilized. A sequential model consisting of several layers of neurons available in Keras was used to build the Deep Learning based models.

A. MACHINE LEARNING MODELS

The results of five machine learning algorithms, Decision Tree, Random Forest, Support Vector Machine, AdaBoost-Decision Tree (DT), and AdaBoost- Random Forest (RF) under CBM were implemented to check their performance in classifying fake news. The results are shown in Fig 4. The performances of all five machine learning algorithms were compared under FBM. Here, the readability features are also taken as input along with the content, and the results are presented in Fig 5.

B. DEEP LEARNING MODELS

The performances of CNN-LSTM and CNN-BiLSTM were analyzed for both the CBM and proposed FBM. For the FBM,the GloVe Embedding technique is applied to the contents along with SMOG score and TTR to generate the input vectors.

Hyperparameter tuning was performed for both categories of the models by evaluating the performance of CNN-LSTM and CNN-BiLSTM algorithms for different activation functions including ReLU, tanh, Sigmoid, and Softmax for various training-test splits (80:20, 90:10, 70:30). To determine the most relevant activation function, the data

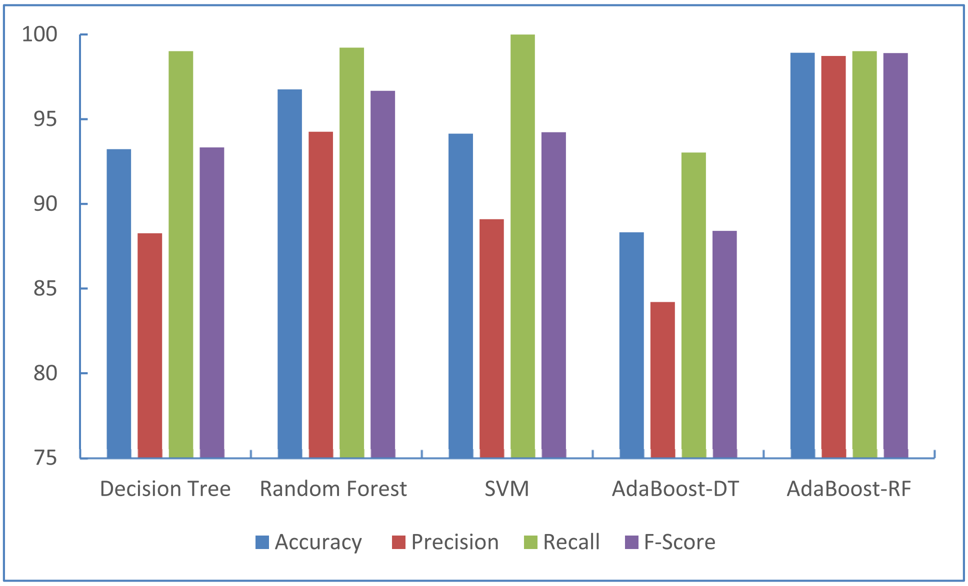


FIGURE 5. Comparing the performance of traditional machine learning models under feature based category.

TABLE 2. Hyper-parameter tuning: Results of different activation functions for different models.

	F1-Score			
Activation Function	Content Based Models		Feature Based Models	
	CNN-LSTM	CNN-BiLSTM	CNN-LSTM	CNN-BiLSTM
ReLU	**96.19**	**96.44**	**97.09**	**96.94**
Tanh	96.17	96.12	95.86	95.91
Sigmoid	94.45	95.4	95.52	85.91
Softmax	72.71	96.12	95.31	95.92

TABLE 3. Hyper parameter tuning: results of various train-test split ratio with ReLU as activation function.

	F1-Score			
Training-Test Split Ratio	Content Based Models		Feature Based Models	
	CNN-LSTM	CNN-BiLSTM	CNN-LSTM	CNN-BiLSTM
90-10	96.17	96.12	95.86	95.91
80-20	**96.19**	**96.44**	**97.09**	**96.94**
70-30	94.45	95.4	95.52	85.91

was split in 80-20% (training-test ratio), and the results are presented in Table 2. It is evident that for the four models in both the Content Based and Feature Based categories, the F1-score with ReLU as an activation function was better than the other activation functions.

Therefore, ReLU was selected as the activation function for further experiments. Considering ReLU as the activation function, the performances of all the models were tested with different training-test split ratios (80-20, 90-10, 70-30). As observed, in Table 3, the 80-20 split gave the highest F1-score for all models under both categories. Finally, CBM and FBM were built with ReLU as an activation function with an 80-20% training-test split with a batch size of 200. The models were trained using the Adam optimizer with a learning rate of 0.01 using cross entropy as the loss function.

The performance of CNN-LSTM and CNN-BiLSTM for both CBM and FBM are compared and presented in Fig 6 and Fig 7, respectively.

VII. ANALYSIS OF THE MODELS BUILT

The F1 score is a useful metric that considers both Precision and Recall, providing an overall measure of the model's performance. It considers model's accuracy in predicting true positives and its ability to identify actual positives, which are both critical factors in detecting fake news. Thus, for each category, the model with the highest F1 score was considered the best. In each category, the best-performing model was identified, and its performance is depicted in the graph presented in Fig 8. The experimental results demonstrate that Feature Based Models perform better than traditional models.

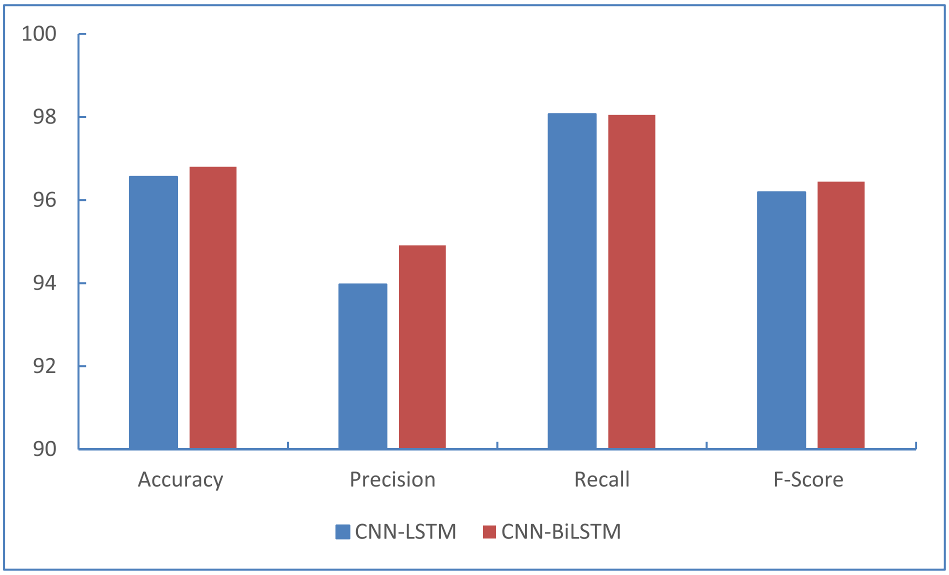


FIGURE 6. Comparing the performance of proposed deep learning models under content based category.

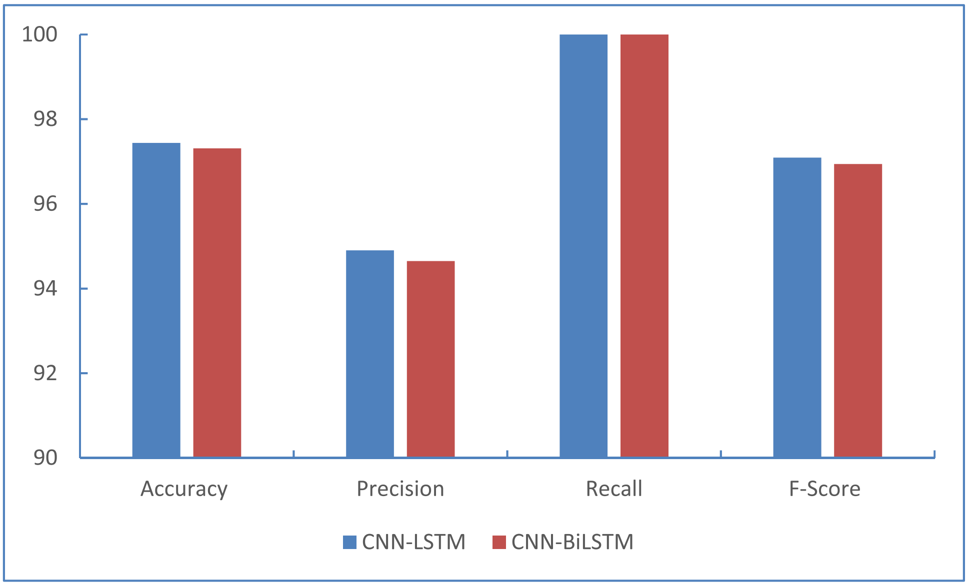


FIGURE 7. Comparing the performance of proposed deep learning models under feature based category.

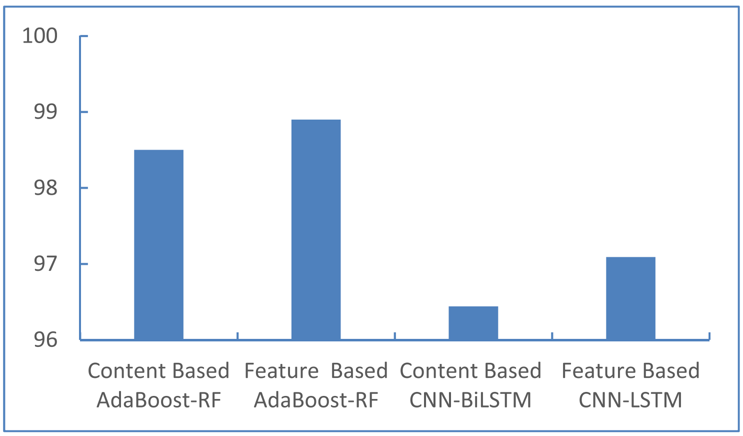


FIGURE 8. Comparing the best performing models of each category.

As observed, AdaBoost-RF outperformed all other Content and Feature Based Models. AdaBoost-RF had the highest F1 score when considering both categories. AdaBoost-RF has a F1 score of 98.5% in CBM, whereas Feature Based AdaBoost-RF has F1 score of 98.9%. Therefore, the proposed AdaBoost -Random Forest in the FBM category is the preferred model for classifying fake news.

VIII. CONCLUSION

Fake news is becoming a common phenomenon, and it is crucial to identify it, to curb the spread. The research proposed comparing various models under Content Based and Feature Based Model categories to identify the best performing model. The results reveal that Adaboost-RF under FBM is the best performing model even in comparison with Deep Learning Models. This is in line with Occam's Razor, where simple models are considered better than complex models because of the trade-offs among model simplicity, resource usage, and execution time [39].

ACKNOWLEDGMENT

The authors would like to acknowledge Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia for supporting this research.

REFERENCES

[1] H. Allcott and M. Gentzkow, "Social media and fake news in the 2016 election," *J. Econ. Perspect.*, vol. 31, no. 2, pp. 211–236, May 2017, doi: 10.1257/jep.31.2.211.

[2] I. K. Vida, "The 'great moon hoax' of 1835," *Hung. J. English Amer. Stud.*, vol. 18, nos. 1–2, pp. 431–441, 2012.

[3] A. M. Kaplan, "Social media, the digital revolution, and the business of media," *Int. J. Media Manage.*, vol. 17, no. 4, pp. 197–199, Oct. 2015, doi: 10.1080/14241277.2015.1120014.

[4] J. Albright. (2016). *The Election 2016 Micro-Propaganda Machine*. Accessed: May 2023. [Online]. Available: https://d1gi.medium.com/the-election2016-micro-propaganda-machine-383449cc1fba

[5] IPSOS. (2019). *Fake News: A Global Epidemic Vast Majority (86%) of Online Global Citizens Have Been Exposed to it*. Accessed: Mar. 2023. [Online]. Available: https://www.ipsos.com/en-us/news-polls/cigi-fake-news-global-epidemic

[6] BI. (2019). *India Has More Fake News Than Any Other Country in the World: Survey*. Accessed: Mar. 2023. [Online]. Available: https://www.businessinsider.in/india-has-more-fake-news-than-any-other-country-in-the-world-survey/articleshow/67868418.cms

[7] G. Rannard. (2020). *Australia Fires: Misleading Maps and Pictures go Viral*. [Online]. Available: https://www.bbc.com/news/blogs-trending-51020564

[8] Z. Thomas. (2020). *WHO Says Fake Coronavirus Claims Causing 'Infodemic'*. BBC. Accessed: Mar. 2023. [Online]. Available: https://bbc.in/2xUcaAh

[9] Z. Barua, S. Barua, S. Aktar, N. Kabir, and M. Li, "Effects of misinformation on COVID-19 individual responses and recommendations for resilience of disastrous consequences of misinformation," *Prog. Disaster Sci.*, vol. 8, Dec. 2020, Art. no. 100119, doi: 10.1016/j.pdisas.2020.100119.

[10] S. Loeb, J. Taylor, J. F. Borin, R. Mihalcea, V. Perez-Rosas, N. Byrne, A. L. Chiang, and A. Langford, "Fake news: Spread of misinformation about urological conditions on social media," *Eur. Urol. Focus*, vol. 6, no. 3, pp. 437–439, May 2020.

[11] R. Bal, S. Sinha, S. Dutta, R. Joshi, S. Ghosh, and R. Dutt, "Analysing the extent of misinformation in cancer related tweets," in *Proc. Int. AAAI Conf. Web Social Media*, vol. 14, no. 1, 2020, pp. 924–928.

[12] S. Kumari, H. K. Reddy, C. S. Kulkarni, and V. Gowthami, "Debunking health fake news with domain specific pre-trained model," *Global Transitions Proc.*, vol. 2, no. 2, pp. 267–272, Nov. 2021.

[13] C. Melchior and M. Oliveira, "Health-related fake news on social media platforms: A systematic literature review," *New Media Soc.*, vol. 24, no. 6, pp. 1500–1522, Jun. 2022.

[14] A. Coleman. (2020). *'Hundreds of Dead' Because of COVID-19 Misinformation*. BBC News. [Online]. Available: http://bbc.com/news/world-53755067

[15] S. Rastogi and D. Bansal, "A review on fake news detection 3T's: Typology, time of detection, taxonomies," *Int. J. Inf. Secur.*, vol. 22, no. 1, pp. 177–212, Feb. 2023.

[16] G. Chaphekar and J. G. Jetcheva, "HealthLies: Dataset and machine learning models for detecting fake health news," in *Proc. IEEE 8th Int. Conf. Big Data Comput. Service Appl. (BigDataService)*, Newark, CA, USA, Aug. 2022, pp. 1–8, doi: 10.1109/BigDataService55688.2022.00008.

[17] Y. Zhao, J. Da, and J. Yan, "Detecting health misinformation in online health communities: Incorporating behavioral features into machine learning based approaches," *Inf. Process. Manage.*, vol. 58, no. 1, Jan. 2021, Art. no. 102390.

[18] W. H. Bangyal, R. Qasim, N. U. Rehman, Z. Ahmad, H. Dar, L. Rukhsar, Z. Aman, and J. Ahmad, "Detection of fake news text classification on COVID-19 using deep learning approaches," *Comput. Math. Methods Med.*, vol. 2021, pp. 1–14, Nov. 2021.

[19] W. S. Paka, R. Bansal, A. Kaushik, S. Sengupta, and T. Chakraborty, "Cross-SEAN: A cross-stitch semi-supervised neural attention model for COVID-19 fake news detection," *Appl. Soft Comput.*, vol. 107, Aug. 2021, Art. no. 107393, doi: 10.1016/j.asoc.2021.107393.

[20] S. Dhoju, M. M. U. Rony, M. A. Kabir, and N. Hassan, "Differences in health news from reliable and unreliable media," in *Proc. Companion World Wide Web Conf.*, May 2019, pp. 1–14.

[21] R. Garg and S. Jeevraj, "Effective fake news classifier and its applications to COVID-19," in *Proc. IEEE Bombay Sect. Signature Conf. (IBSSC)*, Nov. 2021, pp. 1–6, doi: 10.1109/IBSSC53889.2021.9673448.

[22] S. Khan, S. Hakak, N. Deepa, B. Prabadevi, K. Dev, and S. Trelova, "Detecting COVID-19-related fake news using feature extraction," *Frontiers Public Health*, vol. 9, Jan. 2022, Art. no. 788074.

[23] A. Ghenai and Y. Mejova, "Catching Zika fever: Application of crowdsourcing and machine learning for tracking health misinformation on Twitter," in *Proc. IEEE Int. Conf. Healthcare Informat. (ICHI)*, Park City, UT, USA, Aug. 2017, p. 518, doi: 10.1109/ICHI.2017.58.

[24] P. K. Verma, P. Agrawal, I. Amorim, and R. Prodan, "WELFake: Word embedding over linguistic features for fake news detection," *IEEE Trans. Computat. Social Syst.*, vol. 8, no. 4, pp. 881–893, Aug. 2021, doi: 10.1109/TCSS.2021.3068519.

[25] C.-M. Lai, M.-H. Chen, E. Kristiani, V. K. Verma, and C.-T. Yang, "Fake news classification based on content level features," *Appl. Sci.*, vol. 12, no. 3, p. 1116, Jan. 2022.

[26] D. Rohera, H. Shethna, K. Patel, U. Thakker, S. Tanwar, R. Gupta, W.-C. Hong, and R. Sharma, "A taxonomy of fake news classification techniques: Survey and implementation aspects," *IEEE Access*, vol. 10, pp. 30367–30394, 2022.

[27] B. Palani and S. Elango, "CTrL-FND: Content-based transfer learning approach for fake news detection on social media," *Int. J. Syst. Assurance Eng. Manage.*, vol. 14, no. 3, pp. 903–918, Jun. 2023.

[28] O. Ajao, D. Bhowmik, and S. Zargari, "Fake news identification on Twitter with hybrid CNN and RNN models," in *Proc. 9th Int. Conf. Social Media Soc.*, Jul. 2018, pp. 226–230.

[29] J. A. Nasir, O. S. Khan, and I. Varlamis, "Fake news detection: A hybrid CNN-RNN based deep learning approach," *Int. J. Inf. Manage. Data Insights*, vol. 1, no. 1, Apr. 2021, Art. no. 100007, doi: 10.1016/j.jjimei.2020.100007.

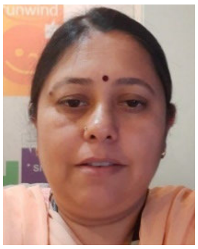
[30] E. Dai, Y. Sun, and S. Wang, "Ginger cannot cure cancer: Battling fake health news with a comprehensive data repository," in *Proc. 14th Int. AAAI Conf. Web Social Media*, 2020, p. 14.

[31] I. Agarwal, D. Rana, N. N. S. Daivik, and S. Teja, "Fake news on COVID-19 healthcare," *IEEE Dataport*, doi: 10.21227/k0qs-bz38.

[32] J. Lemley, S. Bazrafkan, and P. Corcoran, "Smart augmentation learning an optimal data augmentation strategy," *IEEE Access*, vol. 5, pp. 5858–5869, 2017, doi: 10.1109/ACCESS.2017.2696121.

[33] B. Li, Y. Hou, and W. Che, "Data augmentation approaches in natural language processing: A survey," *AI Open*, vol. 3, pp. 71–90, 2022.

[34] J. Wei and K. Zou, "EDA: Easy data augmentation techniques for boosting performance on text classification tasks," in *Proc. Conf. Empirical Methods Natural Lang. Process. 9th Int. Joint Conf. Natural Lang. Process. (EMNLP-IJCNLP)*, 2019, pp. 6382–6388.
[35] J. Ramos, "Using TF-IDF to determine word relevance in document queries," in *Proc. 1st Instructional Conf. Mach. Learn.*, vol. 242, no. 1, 2003, pp. 29–48.
[36] W. López, J. Merlino, and P. Rodríguez-Bocca, "Learning semantic information from internet domain names using word embeddings," *Eng. Appl. Artif. Intell.*, vol. 94, Sep. 2020, Art. no. 103823.
[37] J. Pennington, R. Socher, and C. Manning, "Glove: Global vectors for word representation," in *Proc. Conf. Empirical Methods Natural Lang. Process. (EMNLP)*, Stroudsburg, PA, USA, 2014, pp. 1532–1543, doi: 10.3115/v1/D14-1162.
[38] H. Laughlin, "SMOG grading—A new readability formula," *J. Reading*, vol. 12, no. 8, pp. 639–646, 1969.
[39] F. J. B. Stoffi, G. Cevolani, and G. Gnecco, "Simple models in complex worlds: Occam's Razor and statistical learning theory," *Minds Mach.*, vol. 32, no. 1, pp. 13–42, Mar. 2022.



TRIPTI MAHARA received the B.E. (CSE) degree from Sardar Patel University, in 1999, and the M. Tech. and Ph.D. degrees from IIT Kanpur, in 2004 and 2010, respectively. She is currently an Associate Professor of research and business analytics specialization with the Prin. L.N. Welingkar Institute of Management Development and Research, Bangalore. Before that she was with Christ University, Bangalore, for three years, and with IIT Roorkee, for six years, as an Assistant Professor. She has successfully guided four Ph.D. scholars. She is involved in industry consultancy and training assignments. Over all she is an enthusiast trying to explore and learn new avenues. She has more than 30 research publications in WOS and Scopus-Indexed peer-reviewed journals and many book chapters to her credit. Her research interests include applications of machine learning and text analytics to solve business problems, and recommender systems and time series analysis. She received many best paper awards for the paper presentation in various international conferences of repute. She is actively involved as a reviewer in many journals.

V. L. HELEN JOSEPHINE has a mix of academia and industry experience of more than 25 years. She is currently an Associate Professor of business analytics specialization with the School of Business and Management, Christ University, Bangalore. She is an approved Research Supervisor with Visveswaraya Technological University, Karnataka, and guiding Ph.D. student in computer science domain. She is a Research Academic Committee Member of Christ University. She developed and deployed various projects and machine learning projects, including health care, finance, banking, and education domain. She published six patents in the Indian patent office in the field of computer science, artificial intelligence, and the IoT domain. She presented research papers in various international and national conferences. She published more than 20 research papers in peer-reviewed international journals, which has been indexed in Web of Science and Scopus. Her research interests include artificial intelligence, machine learning, natural language processing, and image processing. She is a Board of Examiner and a Board of Study Member in various institution.

RASHMI SRINIVASAN received the degree in electronics and communication engineering from the KS Institute of Technology. She is currently pursuing the MBA degree in business analytics specialization with Christ University. She has two years of work experience in software service sector. Her interest in analytics has led her to develop a deep understanding of data-driven decision-making, and have honed her skills in this area through practical experience and academic training.

POORVI PRAKASH received the bachelor's degree (Hons.) in botany. She is currently pursuing the MBA degree in business analytics with Christ University. She was with Deloitte, under Risk and Advisory, as an Associate Solution Advisor, technology assurance. She is committed to using her skills and knowledge to make a meaningful impact on society, and aims to improve economic and healthcare outcomes through her work, contributing to society in a positive and impactful way.

ABEER D. ALGARNI received the B.Sc. degree (Hons.) in computer science from King Saud University, Riyadh, Saudi Arabia, in 2007, and the M.Sc. and Ph.D. degrees from the School of Engineering and Computer Sciences, Durham University, U.K., in 2010 and 2015, respectively. She has been an Assistant Professor with the College of Computer and Information Sciences, Princess Nourah Bent Abdulrahman University, since 2008. Her research interests include networking and communication systems, digital image processing, digital communications, and cyber security.

OM PRAKASH VERMA (Senior Member, IEEE) is currently an Assistant Professor with the Department of Instrumentation and Control Engineering, Dr. B. R. Ambedkar National Institute of Technology Jalandhar. He has supervised two Ph.D. students and also supervising two Ph.D. students. He is associated with six research projects: PI and Co-PI, funded by various funding agencies, such as ISRO, MeitY, and CSIR. He has credit for publishing more than 90 research publications, including international peer-reviewed SCI journals, patent applications, edited books, conferences, and chapters. He has recently authored a book titled *Butterfly Optimization Algorithm: Theory and Engineering Applications* (Springer) and edited eight renowned books of international conference proceedings published by Springer Nature. His research interests include machine/deep/quantum learning for machine/computer vision; unmanned system technology and navigation; applied soft computing and optimization techniques; nonlinear process design, integration, control optimization, and green energy biofuel. He is a member of IEEE Computational Intelligence Society, IEEE Control Systems Society, and Automatic Control and Dynamic Optimization Society (ACDOS), and a Lifetime Member of other internationally renowned societies: Instrument Society of India (ISOI) and STEM Research Society (STEM-RS). He is an Associate Editor of the *International Journal of Security and Privacy in Pervasive Computing* (IJSPPC) (SCIE and SCOPUS Indexed). He is an Editorial Review Board Member on Mechanical and Mechatronics Engineering, World Academy of Science, Engineering and Technology, USA.