An Improved Fake News Detection Model Using Hybrid Time Frequency-Inverse Document Frequency for Feature Extraction and AdaBoost Ensemble Model as a Classifier

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***Abstract*—Fake news information on the internet has recently emerged as one of the challenging concerns that can have an impact on society and individuals. Furthermore, the propagation of fake news on social media increases the risk of loss of trustworthiness and disseminates fake information across multiple online platforms. As a result, recognizing fake news on the internet plays an important role in society and among individuals. Knowing this, this study proposed an improved fake news detection model that uses the proposed Hybrid Time-Frequency-Inverse Document Frequency (TF-IDF) to extract features and the Adaptive boosting ensemble classifier, which is a combination of Iterative Dichotomiser 3 (ID-3), Random Forest (RF), and Nave Bayes (NB) classifiers. The characteristics are chosen using the Least Absolute Shrinkage and Selection Operator (LASSO), and the news is classified as fake or true using the Adaptive Boosting (AdaBoost) ensemble classifier. The obtained results show that TF-IDF with AdaBoost ensemble classifier has a higher classification accuracy of 98.98% than the existing N-Gram with TF-IDF and Bidirectional Encoder Representation from Transformer (BERT) and Word2Vec with Convolutional Neural Network-Bidirectional Long Short Term Memory (CNN-Bi LSTM) with 96.81% and 97.74%, respectively.**

***Keywords*—Adaptive Boosting (AdaBoost), fake news detection, hybrid time frequency-inverse document frequency, least absolute shrinkage and selection operator, social platforms**

I. Introduction

The usage of the internet and social media has reached its peak in recent days, this development has led to digitalization in communication of information technology. But, at the same time, it leads to the generation of fake news content [1, 2]. Due to the increased usage of social media as a platform for expressing opinions [3], the prevalence of fake news on these platforms can undermine accurate information and mislead readers. Social media acts as an important asset to publish any information at a low cost and in a faster time than newspapers and television [4]. But, the news presenter on social platforms may not be trustworthy on every occasion [5]. Fake news has a hidden motive that mutilates the individual or an organization. Moreover, fake news can create a protest or even leads to war among the nations [6, 7]. Generally, people tend to spread the news which is shared by their friends without any verification or proof. The fake news detection system helps users to identify and filter illusive information [8, 9]. The deceptive nature of fake news creates complications for people to identify the fake and real text (news) [10]. When large scaled news spreads in social media, manual validation becomes difficult.

Designing an automated fake news detection system creates an impact in the contemporary world. Fake news detection is a layered process that is comprised of the process of analyzing the contents to detect the truth present in the news [11–13]. Fake news is either in the format of text, image, video, etc. The combination of different types of data creates complexities in the process of detecting fake news. Fake news is comprised of noisy and unstructured data so pre-processing is an essential step to clean and make the data into a structured form which eases the detection process [14, 15]. The techniques based on deep learning have a great impact on the process of detecting fake news than the machine learning models. Additionally, deep learning methods can detect the features on their own without any dependencies [16, 17]. In recent days, the issues based on detecting fake news is extensively addressed by researchers, but a proper fake news detection system is still in some crises [18, 19]. So, a fake news detection system must be designed by incorporating an effective feature extraction phase that aids in the accurate detection of fake news which evolves around social media. To overcome the issues, this manuscript introduced a Hybrid Time-Frequency-Inverse Document Frequency (TF-IDF) for extracting the features and a Stacked Adaptive Boosting (AdaBoost) ensemble classifier to detect the untruth news effectively.

The major contributions of this research are listed as follows:

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(i) This research introduced an improved fake news detection model using hybrid TF-IDF for feature extraction and AdaBoost ensemble classifier to categorize the news as fake and true.
(ii) This research makes use of WELFake dataset to collect information about the news and the hybrid TF-IDF is used to extract the features which is a combination of Word2Vector with TF-IDF.
(iii) The results are evaluated to detect the effectiveness of the proposed classification model based on its performance with existing fake news detection methods.

The remaining part of this manuscript is organized in the following manner: Section II provides related works which are based on fake news detection models and Section III provides the proposed method of this research. Section IV provides results and analysis and finally, Section V presents the overall conclusion of this research.

II. RELATED WORKS

This section presents a review of some existing fake news detection methodologies which utilized the WELFake dataset.

Kumar *et al.* [20] introduced a fake news detection model known as OptNet that utilized a meta-heuristic algorithm to select the features and utilized a deep neural network to identify the news which was seemed to be fake and evolved in social platforms. At the initial stage, feature vectors for the initial stage were extracted using the Term Frequency Inverse Document Frequency (TF-IDF). The features extracted using TF-IDF were provided for Modified Grasshopper Optimization (MGO) that mines the optimal text features. The selected features are fed into Convolutional Neural Network (CNN) with varying layer sizes and obtain n-gram features from the textual data to detect fake news. The features selected by MGO probably minimized the categorization error with fewer features. However, the suggested approach faced complexities while evaluating the complex textual patterns.

Verma *et al.* [21] introduced a framework known as multi-modal Message Credibility (MCred) to detect fake news using the semantics of local and global languages. The MCred framework utilized Bidirectional Encoder Representations from Transformers (BERT) to establish relations among texts at the global level and Convolutional Neural Network (CNN) for local semantics. The introduced MCred model combined the semantics of global and the local language from BERT and CNN and process them into the dense network for the final prediction of news. But the introduced MCred model does not suits for larger input sizes due to high processing time.

Kausar *et al.* [22] introduced a hybrid fake news detection model which was a combination of N-gram with TF-IDF and LSTM-BERT. The N-gram with TF-IDF was utilized to extract the features based on contextual texts and the sequential features are extracted using LSTM/BERT model. After the extraction of contextual and sequential features, the feedforward neural network was comprised of two fully connected layers and a sigmoid function which was utilized to categorize the news as fake or true based on the contextual semantics. However, no improvisation was noticed when the data was trained and tested in the ratio of 75:25.

Ouassil *et al.* [23] have introduced a deep learning framework to detect fake news based on a combination of word embedding techniques and hybrid Convolutional Neural Network and Bidirectional Long Short Term Memory (CNN-BiLSTM). The CNN-BiLSTM was utilized in the process of training the architecture and creating feature maps as output. Additionally, the dimensions of the feature map were reduced using the pooling layer with significant information which helps to improvise the quality of detecting fake news. However, computational complexities occur due to the increased dimensionalities of embedded vectors.

Mallick *et al.* [24] introduced a cooperative deep learning-based fake news detection model which evaluates the trust level of the news and ranks the news based on its values. CNN was utilized in ranking news by using deep learning layers. The news with a low rank was prohibited to verify the validity whereas the news with a higher rank was considered as true news. The news with negative rates was sent back to train the system. The introduced model was helpful in a wide range of applications and media with enhanced trust levels. But the model has faced complexities in the high-speed news verification process.

Sciucca *et al.* [25] have introduced a deep learning-based Fake News Detection (FakeNED) to detect fake news from social networks. The FakeNED can extract the features from both the texts and images. Moreover, the BERT was utilized in the process of extracting features based on contextual texts, and the VGG-16 architecture was utilized to extract the features from the images. The extracted features were provided into a Fully connected layer to obtain the finalized output. But, the FakeNED model was not valid to categorize fake news from web pages.

Singhal and Kashef *et al.* [26] introduced Weighted Stacking Ensemble Model with Sampling (WSEM-S) to detect the fake reviews. The diverse sampling approaches were employed to overcome the data imbalance problem using Deception dataset. Moreover, the max-blending approach was used to enhance the classification accuracy of detecting fake news. The effective sampling utilized in this research helps to handle the problems related to data imbalance. However, WSEM-S does not suit the fake reviews of multilingual fraudulent.

Kaliyar *et al.* [27] have introduced BERT based deep learning approach by combining various parallel block into a single layer deep CNN of various kernel sizes and filters. The proposed approach has the capability to handle the ambiguity using the three parallel blocks of 1d-CNN with different size of kernels. The hybrid approach does not consider the view point of echo-chambers which acts as major tool in detecting the fake news in social community.

Essa *et al.* [28] have introduced a novel hybrid fake news detection system which was comprised with BERT and a Light Gradient Boosting Machine (LGBM). The LGBM model was built on the top of pre-trained BERT word embedding model. The suggested approach leverages the power of BERT and capture the linguistic pattern to optimize the feature space during the time of classifying the fake news. However, the suggested approach lacks the ability to extract information from the long contextual terms.

The overall outcomes of the existing approaches show that the existing methods faced problems in detecting the fake news due to inappropriate selection of features and the inappropriate feature selection results in poor detection accuracy. So, this research introduced a hybrid feature selection approach to overcome the issues in existing methods and aids in better detection accuracy.

III. Detecting the Fake News Using Hybrid TF-IDF and AdaBoost Ensemble Classifier

This research introduced an adversarial approach to detect fake news using the introduced hybrid TF-IDF as a feature extractor and AdaBoost ensemble classifier to detect the news as true or fake. Moreover, the methodology of the fake news detection framework is comprised of six stages such as the acquisition of data, pre-processing, extraction of features, normalization, feature selection, and classification. The overall process involved in detecting fake news is diagrammatically represented in Fig. 1 as follows:

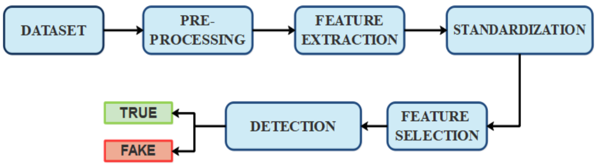

Fig. 1. Block diagram of the process involved in detecting the fake news.

A. Data Acquisition

This research utilized WELFake dataset [29] to acquire the data for detecting fake news which consists of 72,134 articles in which 35,028 news is real and 37,106 news is fake. The WELFake dataset is a combined form of four famous datasets such as McIntyre, Kaggle, Buzz feed Political, and Reuters. These combinations of datasets help to prohibit the classifier overfitting and offer a qualified text to train the detection model. Moreover, the dataset includes four columns as Serial number (which begins from zero), the text of news content, title (i.e., text about the heading of news and label (i.e., true as 1 and fake as 0). There are around 78,098 entries of data present in the CSV file where only 72,134 entries are accessible per frame of data.

B. Data Pre-processing

After the stage of data acquisition, the raw data from the data set should be pre-processed to remove unwanted noise and irrelevant information. Data pre-processing is also referred to as a data mining process that can convert unstructured data into structured one. Data pre-processing involves various stages such as converting the normal textual data to lowercase, stop word removal, stemming, and tokenization. This section provides a brief description of the process that takes place in the stage of pre-processing. The flow chart for the pre-processing phase is presented in Fig. 2 as follows:

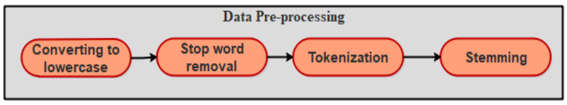

Fig. 2. Stages involved in the phase of data pre-processing.

1) Stop word removal

The stop words present in the news articles are unimportant but they are utilized to combine the expressions and connect the sentences. These stop words usually exist in news articles which doesn't carry any useful information. There are around 500 stop words present in the English language that is comprised of conjunctions, pronoun, and pre-positions. Some examples of stop words are a, an, where, and, above, below, etc. These stop-word deletions probably minimize the time of detecting fake news.

2) Tokenization

Tokenization is defined as the process involved in dividing text data into small segments known as tokens. Moreover, tokenization is performed to remove the punctuations from the textual data and the specified terms present in the sentence. In other words, it is defined as the process involved in converting the whole news article into a token of small words. Finally, the words with minimum characters are detached by utilizing N-char filters.

3) Stemming

The ultimate goal of stemming is to achieve the basic form of words which is comprised of similar contextual meanings with different words. At the time of the stemming process, different grammatical words such as nouns, adjectives, verbs, etc. are transformed into their original form. For instance, the words such as cultivated, and cultivating are shortened to cultivate (i.e., original form). In such a way, the words are reduced to their fundamental form.

Thus, the aforementioned steps are involved in the stage of pre-processing where the raw data is transformed into a structured one.

C. Feature Extraction

After obtaining the structured data through pre-processing, the features are extracted by using the stage of feature extraction. Feature extraction is defined as the process of converting the raw data into numerical features without any change in the original dataset. In this research, the hybrid Time Frequency- Inverse Document Frequency (TF-IDF) method is introduced to extract the essential features from the pre-processed output. The hybridization is made by combining the word embedding technique with TF-IDF and the Word2Vec method is utilized to learn about word embedding.

1) TF-IDF

Generally, TF-IDF [30] is a weighting method that is utilized to allow weights to each term present in the news article which reflects saliency in the document. The weight of the text in the news article is defined as a summed value of the individual weights in the post and it is evaluated using the Eq. (1) as follows:

$$TF - IDF = t_{f_{ij}} \times log_2 \frac{N}{df_j} \quad (1)$$

where the frequency of the term is represented as $t_{f_{ij}}$ which is present in the news article D_i. The total count of documents is denoted as N and the number of terms contained in the set is denoted as T_j. The value of TF-IDF is comprised of two parts such as TF and IDF, TF is responsible to allot weights to the text present in the news articles and IDF compensates for some frequently repeated stop words in the news article. So, the TF component present in the TF-IDF utilized the entire text collection present in the news articles whereas the IDF considers the text as the individual article. The TF-IDF algorithm is summarized in the following way which is presented in Eqs. (2)–(6) as follows:

$$W(s) = \frac{\sum_{i=0}^{\#Words\ in\ post} W(w_i)}{nf(s)} \quad (2)$$

$$W(w_i) = tf(w_i) \times log_2(idf(w_i)) \quad (3)$$

$$tf(w_i) = \frac{Repitition\ of\ text\ in\ news\ articles}{Total\ number\ of\ words\ in\ news\ articles} \quad (4)$$

$$idf(w_i) = \frac{news\ article}{Repitition\ of\ word\ in\ news\ article} \quad (5)$$

$$nf(s) = max[Min.threshold, words\ in\ the\ news\ article] \quad (6)$$

where the weight allotted to the text present in the news article is denoted as W, the word present in the i th iteration is denoted as w_i and the news article is denoted as s. TF-IDF prohibits the occurrence of redundant words and verifies the presence of similarities to select the articles.

2) Word2Vec

The Word2Vec is one of the vastly utilized techniques which is utilized in the process of word embedding. The mathematical operation is performed in the text corpus to position similar words in the same vector. The Word2Vec model [31] is comprised of two techniques such as skip gram method and Continuous Bag of Words (CBOW). Among these two methods, the skip gram model is used in the process of predicting the words in the news articles based on their context and the CBOW model is utilized in the process of predicting the term based on the context.

3) Hybrid of Word2Vec with TF-IDF

This research utilized the word embedding technique (i.e., Word2Vec) with TF-IDF to extract effective features which probably enhances the performance of detecting fake news. The features from TF-IDF with Word2Vec proved their efficacy in extracting the features from the news articles and improvise the detection performance. At the initial stage, the TF-IDF is applied to the WELFake dataset to provide the text syntactically and the weighted vectors are included in every individual word in the news article. The hybrid TF-IDF used in this research convert the raw strings into vector every individual word and the Word2vec generates a vectorized packet presentation. After this stage, semantic features are captured by multiplying the word embedding Word2Vec with the weight of the text obtained from TF-IDF. The inappropriate features are removed and an array of terms along with TF-IDF values with the list of feature vectors are returned during the stage of feature extraction using the hybrid approach. During the stage of feature extraction using hybrid TF-IDF, the vectors of each stage are acquired from the phase of categorization, and the matrix multiplication in the proposed hybrid method is performed by using Eq. (7) as follows:

$$F_{ij} = \sum_{k=1}^{P} a_{ik} b_{kj} \quad (7)$$

where P denoted the total count of tokens present in the news article and the matrices in TF-IDF and the semantic words are denoted as a and b respectively. The final multiplication process is denoted as F . Thus, the combination of syntactic and semantic words are complement one another and this fusion helps to enhance the detection accuracy of the model by extracting the relevant features.

D. Standardization

After the stage of extracting the features, the feature scaling is performed to evaluate the distance among the features which is present in a biased and unscaled state. In this research, the standardization technique is utilized in the process of scaling the features. Standardization is also known as Z-score normalization which transforms the features by deducting from the mean and dividing with standard deviation. The standardization is performed using Eq. (8) presented as follows:

$$Standardization = \frac{X - mean}{standard\ deviation} \quad (8)$$

However, standardization does not affect the shape of the distribution of data when the value of the mean and standard deviation gets varied.

E. Feature Selection

The scaled features obtained from the standardization are processed into the stage of feature selection where the necessary features are selected. Here, the Least Absolute Shrinkage and Selection Operator (LASSO) [32] is utilized in the process of feature selection. This method targets removing the unimportant features and minimizes the fluctuations by simplifying the features. LASSO is comprised of least square regression values with L-1 regularization function and it is estimated based on the following Eq. (9).

$$\beta^{lasso} = arg_{\beta}\ min\left\{\frac{1}{2}\sum_{i=1}^{N}\left(y_i - \beta_0 - \sum_{j=1}^{P} x_{ij}\beta_j\right)^2 + \lambda \sum_{j=1}^{P}\left|\beta_j\right|\right\} \quad (9)$$

That can be expressed as $\beta^{lasso} = arg_{\beta} \min \sum_{i=1}^{N} \left(y_i - \beta_0 - \sum_{j=1}^{P} x_{ij}\beta_j\right)^2$, subjected to $\sum_{j=1}^{P} |\beta_j| \le t$.

Where y is the determined response which minimizes the variance y and t is the parameter concerning time. LASSO converts every individual co-efficient value into a constant value λ. The Lasso regularization has the ability to assign some co-efficient values to zero which means LASSO can be used as a variable selector. Whenever the values of co-efficient features are zero, the features from the data is removed and helps to select the relevant features. Moreover, LASSO is described in a context with minimal square values and it can improve the quality of the feature selection process by providing interpretability to the model. The variance among the features is minimized by shrinking the co-efficient values to zero. The LASSO upgrades the interpretability and the exactness of the model by solidifying the characteristics based on edge relapse and selection of subset. Thus, LASSO picks the features by contracting a portion of all co-efficient to zero and creates effective communication in the selection of features with optimistic characteristics.

F. Detection of Fake News

The features selected using LASSO are processed to the stage of detection where the news article is detected as fake or true. In this research, the AdaBoost ensemble classifier is utilized in the process of detecting fake news. Before the process of classification, the data split takes place where the data is splitted in the ratio of 80:20, in which 80% of the data is used for training and 20% of the data is used for testing. The k-fold method was used to split the data in 80:20 ratios which aids in better classification results. Ensembling is performed between the classifiers such as Iterative Dichotomiser 3 (ID-3), Random Forest (RF) and Naïve Bayes (NB). This section provides a detailed description of each aforementioned classifier which is utilized in this research.

1) ID-3 classifier

The ID-3 algorithm is a kind of decision tree algorithm which is recursive by its form and the significant function of ID-3 algorithm is referred to as information gain. Information gain is utilized in the process of obtaining the optimum set for the detection model. Moreover, ID-3 selects the attributes which is very much utilized in the process of categorizing the data. The instance of data is assumed as D and D requires the expected outcome to classify the news articles as fake and true which is presented in Eq. (10) as follows:

$$E(D) = -\sum_{i=1}^{n} \frac{|C_{i,}D|}{|D|} log_2 \frac{|C_{i,}D|}{|D|} \quad (10)$$

where $\frac{|C_{i,}D|}{|D|}$ denotes the possibility where arbitrary instance D belongs to a class C_i, the information related to binary encoding is denoted as log_2 and the entropy value is denoted as $E(D)$. When the attributes present in the data D is comprised of distinct values $\{a_{1,}a_{2,} \dots, a_{vj,}\}$, then the subset D_j it corresponds to a_j of A. The entropy value for A is evaluated using the Eq. (11) as follows:

$$E_A(D) = -\sum_{J=1}^{V} \frac{|A_{jv}|}{|A_j|} \times E(A_{jv}) \quad (11)$$

where the probable information required to partition the data is denoted as $E(A_{jv})$ and the information gain of the attribute is evaluated using the Eq. (12) as follows:

$$Gain\ (A) = E(D) - E_A(D) \quad (12)$$

The attribute with the highest gain is utilized to support the decision node which is present in the decision tree, thus the ID-3 selects the attributes with maximum information gain.

2) Random Forest (RF) classifier

RF is a type of supervised learning algorithm that is effective for the process of classification and regression. In this research, the RF is used to classify the news as fake or true. Moreover, a random forest is comprised of decision trees on the sample of data then the detection takes place by voting technique to select the best solution. The RF classifier can address the problems regarding overfitting and helps to enhance detection accuracy. The process involved in training the data in RF is mathematically expressed in Eq. (13) as follows:

$$D = \left\{(f_{I,}C_i)_{i=1}^{N} \middle| f_i \in R^F,\ C \in \{1,2, \dots, c\}\right\} \quad (13)$$

where the number of samples utilized in training is denoted as N, the features are denoted as f_i and the count of samples which is utilized in training is denoted as C_i. Every decision tree present in the RF classifier is comprised of a bag of samples $(\mathrm{i.e.}, \mathrm{D_1}, \mathrm{D_{2,}} \dots, \mathrm{D_P})$ and the detection accuracy is evaluated using Eq. (14) as follows:

$$\hat{C} = majority\ \{\hat{C}^d\}_1^d \quad (14)$$

where the prediction class is denoted as $\hat{C}^d$.

3) Naïve Bayes classifier

Naïve Bayes algorithm is utilized in the process of classification which is constructed based on Bayesian theorem where the assumption is made for all predictors which are independent of one another. In other words, the presence of a feature in a class should be independent of other features in the same class. The classification based on Bayesian theorem detects the possibilities with observed features and the quantitative representation of Naïve Bayes theorem is expressed in Eq. (15) as follows:

$$P(L|Features) = {}^{P(L)P(Features|L)}\!\big/_{P(Features)} \quad (15)$$

where $P(L|Features)$ is the probability of the posterior class, $P(L)$ is the prior class and $P(Features)$ is the predictor of the prior probability value.

The outcomes obtained from three classifiers are fed into the ensemble model and the results are obtained as true or fake.

1) Ensembling

Ensembling methods are well-known in machine learning and recognition of patterns, and the ensemble approaches combine the output of the weaker algorithms to improve the model's accuracy and classification efficiency. Ensemble methods are broadly classified into two types: dependent frame and independent frame. In the dependent framework, the output of the individual inducer influences the next process, and the independent inducer is built independently of the other inducers. Because it integrates the classification algorithms that are used to perform successfully, as the ensemble model has higher classification accuracy. The prediction efficiency of individual classifiers is evaluated and combined using the adaptive boosting methodology in this method. Because the parameters are not jointly optimized, the AdaBoosting technique is less prone to overfitting. Due to the effectiveness of AdaBoosting technique, this research used AdaBoost as a tool to ensemble the results of those weaker models and aid in better performance.

2) Adaptive boosting

The adaptive boosting technique was developed to perform binary classification. The AdaBoost algorithm use the boosting concept which helps to produce a robust classifier from weaker classifiers. AdaBoost can increase the overall effectiveness of ML classifiers by integrating bad classifiers and extracting the prediction value to create a superior classifier known as an ensemble classifier. The AdaBoost classifier minimize the problems related to overfitting and aids in better results. It considered the better values of every individual classifier and select the better values based on voting approach. In the final stage of voting, the various classifiers are mixed with the training set to yield weight. The AdaBoost technique considers two techniques such as training the subset with a weak classifier and a random subset for training the entire group and assigning a weight factor to the subset.

The classifier with 50% accuracy provides zero weight and the classifier with accuracy less than 50% exhibits negative weight for the classifier.

$$H(X) = SIGN(\sum_{t=1}^{t} \alpha t \; ht\;(x)) \tag{16}$$

where the output of the classifier for input x is represented as $ht\;(x)$ and the weight assigned to the classifier is denoted as αt.

The value of αt can be computed using the formula mentioned in Eq. (17) as follows:

$$\alpha t = 0.5\; \times ln(\frac{1-E}{E}) \tag{17}$$

where the error rate produced is denoted as E.

IV. Results and Analysis

This section provides the results obtained from the proposed Fake news detection model using hybrid TF-IDF as a feature extractor and the AdaBoost ensemble classifier. Moreover, the efficiency proposed fake news detection model is evaluated with existing fake news detection models which were discussed in the related works of this paper. The performance is evaluated using accuracy, specificity, recall, and F1-score. The mathematical expressions to evaluate the fore mentioned performance metrics are represented as follows in Eqs. (18)–(21) respectively. The proposed fake news detection model is simulated in the python software and implemented on a system with specifications such as an i5 processor at 3.40 GHz with 8 GB Random access memory.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \tag{18}$$

$$Specificity = \frac{TN}{TN+FP} \times 100 \tag{19}$$

$$Recall = \frac{TP}{TP+FN} \times 100 \tag{20}$$

$$F - Measure = 2 \times \frac{Precision \times Recall}{Precision + Recall} \times 100 \tag{21}$$

where, TP = True Positive, TN = True Negative, FP = False Positive and FN = False Negative

A. Performance Analysis

In this sub-section, the performance of the proposed AdaBoost ensemble classifier is evaluated with the existing classification models such as ID3, RF, Naïve Bayes and AdaBoost. Here, the performance is evaluated based on the efficiency of the classifiers, feature selection approach and feature extraction approach. Moreover, the performance of the classifiers is evaluated based on the presence and absence of feature selection. Tables I and II show the performance of the classifiers with and without feature selection, respectively.

TABLE I. Performance of the Classifier without Feature Selection

Classifier	Accuracy (%)	Specificity (%)	Recall (%)	F1-score (%)
ID3	94.61	95.00	95.00	95.00
RF	89.65	80.00	90.00	85.00
AdaBoost	89.71	80.00	90.00	85.00
Naive Bayes	83.46	82.00	83.00	82.00
AdaBoost ensemble classifier	98.85	98.49	98.63	98.81

TABLE II. Performance of the Classifier with Feature Selection

Classifier	Accuracy (%)	Specificity (%)	Recall (%)	F1-score (%)
ID3	96.32	96.00	96.00	96.00
RF	89.71	80.00	90.00	85.00
AdaBoost	96.32	96.00	96.00	96.00
Naive Bayes	93.87	94.00	94.00	94.00
AdaBoost ensemble classifier	98.98	98.61	99.00	99.00

Based on the results obtained from Tables I and II, the proposed AdaBoost ensemble classifier performs well in overall metrics. Moreover, the proposed classifier model can perform better in both the scenarios in presence and absence of feature selection. The LASSO is utilized as the feature selector which targets removing the unimportant features and minimizes the fluctuations by simplifying the features which aid in better classification performance. Moreover, AdaBoost can increase the overall effectiveness of ML classifiers by integrating the efficiency of bad classifiers and providing better results. For instance, with the presence of LASSO (feature selector), the proposed classification model achieved better detection accuracy of 98.98% which is comparatively higher than the existing ML classifiers such as ID3, RF, Naïve Bayes and AdaBoost ensemble classifier.

Secondly, the performance of various feature selection models is evaluated based on the metrics such as accuracy, sensitivity, recall, and F1-score. The performance of LASSO is compared with the existing techniques such as chi-Square, Recursive Feature Elimination, and linear regression. Table III presented below shows the outcome of the result based on the efficiency in the extraction of features.

The results from Table III show that the LASSO regression method utilized in this research offers better results than the existing feature selection methods. For instance, accuracy is considered a parameter to evaluate the efficacy of the feature extraction model. The LASSO regression has achieved an accuracy of 98.98% which is comparatively higher than Chi-Square, Recursive Feature Elimination and Linear regression. Since, LASSO is described in a context with minimal square values and it can improve the quality of the feature selection process by providing interpretability to the model. The graphical representation of the performance of various feature selection approaches is shown in Fig. 3.

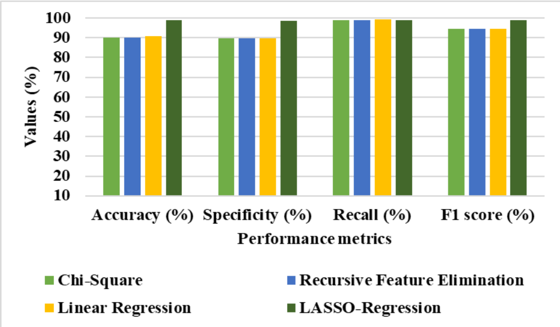

Fig. 3. Graphical representation for evaluating the performance of feature selection.

At last, the efficacy of the feature extraction model is evaluated with the existing feature extraction models such as Word2Vec and TF-IDF. Table IV shows the performance of the existing feature extraction models with the proposed hybrid TF-IDF.

TABLE III. DIFFERENT FEATURE SELECTION APPROACHES FOR PROPOSED MODEL

Feature selection	Accuracy (%)	Specificity (%)	Recall (%)	F1-score (%)
Chi-Square	90.17	89.63	99.07	94.36
Recursive Feature Elimination	90.17	89.63	99.07	94.36
Linear Regression	90.81	89.70	99.40	94.54
LASSO-Regression	98.98	98.61	99.00	99.00

TABLE IV. DIFFERENT APPROACHES UTILIZED IN THE PROCESS OF FEATURE EXTRACTION

Feature Extraction	Accuracy (%)	Specificity (%)	Recall (%)	F1-score (%)
Word2Vector	89.77	88.09	91.07	91.36
TFIDF	97.63	96.00	97.00	97.00
Hybrid-TFIDF	98.98	98.61	99.00	99.00

The results from Table IV show that the proposed hybrid TF-IDF has achieved better results in overall metrics. For instance, the accuracy of the proposed feature extraction model is 98.98% which is comparatively higher than the existing Word2Vec and TF-IDF with 89.77% and 97.63%, respectively. The better result of the proposed hybrid TF-IDF is due to the inclusion of weighted vectors for every individual context in the news article and Word2Vec multiplies the semantic features of the text obtained from TF-IDF. Fig. 4 shows the graphical representation of the performance of various feature extraction models.

Moreover, the proposed hybrid TF-IDF with AdaBoost ensemble classifier is evaluated with different K-fold values such as 2, 3, 5, 8, and 10. Table V depicted below presents the results obtained while evaluating the proposed approach with different K-fold values for WEL-FAKE dataset.

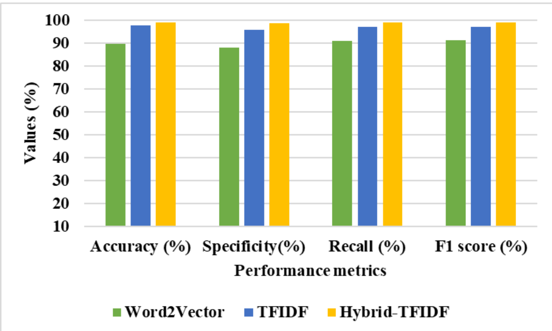

Fig. 4. Graphical representation for evaluating the performance based on feature extraction.

The results from the Table V shows that the proposed approach achives better results when the K-fold value is assigned as 5. When the K-fold value is assigned as 5, the data is splitted in the ratio of 80:20. The 80% of the data is used for training and the 20% of the data os used for testing.

The splittig of data in 80:20 ratio aids in better results when compared with other K-fold values. The Fig. 5 presents the graphical representation for evaluation of proposed approach with different K-fold values.

TABLE V. EVALUATION OF PROPOSED METHOD FOR DIFFERENT K-FOLD VALUES

K-values	Accuracy (%)	Specificity (%)	Recall (%)	F1-score (%)
2	94.49	92.47	94.52	95.30
3	95.72	95.35	95.86	94.55
5	**98.98**	**98.61**	**99.00**	**99.00**
8	96.14	97.49	96.18	96.32
10	96.17	96.52	94.73	98.73

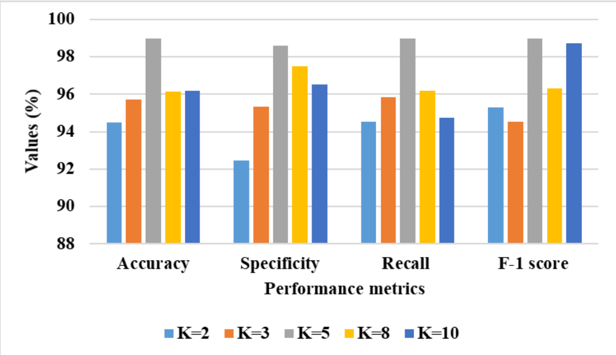

Fig. 5. Evaluation of proposed approach for different K-values.

B. *Comparative Analysis*

In this section, the performance of the proposed Hybrid TF-IDF with AdaBoost is evaluated with existing fake news detection techniques which utilized a similar dataset (i.e., WELFake dataset). The existing methods include N-Gram with TF-IDF and BERT [22] and Word2Vec with CNN-Bi LSTM [23]. The performance is evaluated by means of accuracy, sensitivity, recall, and F1-score and Table VI shown below presents the comparative results based on the classification efficiency.

The results obtained from Table VI show that the suggested classifier has achieved better classification results than N-Gram with TF-IDF and BERT and Word2Vec with CNN-Bi LSTM in overall metrics. Among three classification methods, the proposed Hybrid TF-IDF with AdaBoost has achieved a better classification accuracy of 98.98% whereas N-Gram with TF-IDF and BERT, and Word2Vec with CNN-Bi LSTM have achieved 96.8% and 97.74% respectively. The existing approaches such as N-Gram with TF-IDF and BERT faced issues due to its slow training rate and a greater number of weighted factors need to be updated, this results in poor detection performance. Moreover, the Word2Vec with CNN-Bi LSTM require a greater number of labeled data to train the model. Additionally, the class imbalance occurs during the stage of detecting the fake news. The proposed hybrid TF-IDF approach overcome those existing issues helps to obtain better results by extracting the weighted vectors of each context in a news article and the Word2Vec multiplies the semantic features of the text obtained from hybrid TF-IDF. Moreover, AdaBoost can increase the overall effectiveness of ML classifiers by integrating the efficiency of bad classifiers and providing better results.

TABLE VI. COMPARATIVE RESULTS BASED ON THE PERFORMANCE OF THE CLASSIFIERS

Classification methods	Accuracy (%)	Specificity (%)	Recall (%)	F1-score (%)
N-Gram with TF-IDF and BERT [22]	96.80	-	97.12	96.27
Word2Vec with CNN-Bi LSTM [23]	97.74	98.16	97.35	97.75
Hybrid TF-IDF with AdaBoost	**98.98**	**98.61**	**99.00**	**99.00**

V. DISCUSSION

This research introduced an effective approach using hybrid TF-IDF and AdaBoost ensemble classifier to detect the fake news. The performance of the proposed approach is validated using the WEL-FAKE dataset. The performance of the AdaBoost ensemble classifier is evaluated based on presence and absence of feature selection. The AdaBoost ensemble classifier achieved classification accuracy of 98.85% without feature selection and 98.98% with feature selection. These obtained results of the proposed classifier is comparatively higher than the existing classification approaches. The ensembling approach employed in the research extracts the better result from every individual classifier and selects the best value using the voting approach. Moreover, the performance of the proposed hybrid TF-IDF with AdaBoost classifier is evaluated with existing approaches such as N-Gram with TF-IDF and BERT [22] and Word2Vec with CNN-Bi LSTM [23]. The overall accuracy of the proposed approach is 98.98% which is comparatively higher than the existing N-Gram with TF-IDF and BERT, Word2Vec with CNN-Bi LSTM with accuracy of 96.8% and 97.74% respectively. Thus, the proposed approach achieved better results in overall metrics when compared with the existing ones. However, the proposed fake news detection model is not built to detect the fake news based on real time applications. Moreover, the spammers spread the same fake news in different languages which causes multilingual fraudulent. By considering this, the proposed model can be trained to detect the fake news from varying languages.

VI. CONCLUSION

Fake news refers to false or misleading information which results in serious issues to the individuals, societies and the organizations. Since the raise of fake news leads to spread of fake information in the social media and the literally affects the mind state of people which affects the economic growth of individual and the nation. So, this research introduced an improved fake news detection system using the proposed Hybrid TF-IDF and the AdaBoost ensemble classifier. Initially, the data is obtained from WEL-FAKE dataset and the pre-processing is performed to remove the stop words and tokenize the words. After this, the hybrid TF-IDF with Word2Vec is used in the process of feature extraction and the LASSO is used as feature selector which selects the relevant features. Finally, the classification is performed using the proposed AdaBoost ensemble classifier which effectively classify the news as fake and true based on its nature. The comparative results show that the proposed Hybrid TF-IDF with AdaBoost achieved a better classification accuracy of 98.98% which is comparatively higher than N-Gram with TF-IDF (96.8%) and BERT and Word2Vec with CNN-Bi LSTM (97.74%). The better result of the proposed approach is due to extraction of the weighted vectors of each context in a news article and the Word2Vec multiplies the semantic features of the text obtained from hybrid TF-IDF. Moreover, AdaBoost can increase the overall effectiveness of ML classifiers by integrating the efficiency of bad classifiers and providing better results. In the future, the ensemble approach can be implemented with deep learning classification techniques to enhance the overall performance of the detection model.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

L.H., conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, visualization; K. S. Kavitha, supervision and project administration. All authors had approved the final version.

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