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Exploring News-Feed Credibility using Emerging Machine Learning and Deep Learning Models

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Abstract

In the recent past, the phenomenal growth, availability, and access of information on social media have made it perplexing to discern between real and fake information. The faster and easier dissemination of information through various means has accelerated the explosive growth of its falsehood. At the same time, the newsfeeds and their credibility in the social networks are in danger since the fake news is alarmingly disseminating very fast. Henceforth, the credibility of the newsfeeds or any information has become a real research challenge to cross-check the respective news or information. The cross verification can be performed concerning its source, the exact content, and the respective publisher to catalog it into fact or fake. Despite a few constraints, machine learning plays a crucial and significant role in classifying the respective news feeds. Various machine learning methodologies such as BLR (Bilinear logistic regression), NB (Naive Bayes), SVM (Support Vector Machine), and RF (Random Forest) have been reviewed and experimented with for detecting the fact and fake news feeds. After the experimentation, the limitations of the respective machine learning methods were explored and noted. Henceforth, a deep learning method called BERT is implemented and it is observed that BERT provides better efficiency than the machine learning algorithms. Furthermore, it is ascertained that the deep learning method provided the best accuracy of 99.79 % with the available dataset.

Keywords: Fake news detection, Predictive modeling, Clickbait, News verification, Automated deception detection.

1. Introduction

In recent times, furtherance in the media technology and dissemination of various news through diverse media have skyrocketed the spread of fake news very easily. Also, the consequences of such fake news dispersal have increased fast as well vigorously. It is the need of the hour to take appropriate measures to tackle and prevent it from happening [1]. These days, social media is been very effectively utilized to spread fake news at a faster pace to reach out to its viewers. Appropriate clarifications and understanding are very much imperative to better lead the future directions in identifying the bogus news. To have some sort of clarity, certain emerging paradigms can be very well employed to detect bogus news [2]. The different variety of fake news can be classified into Knowledge-based, Style-based, and Stance-based which can focus upon specific age groups, gender, culture, and political affiliations. The knowledge-based posts provide the readers/viewers with a scientific interpretation of a few uncertain issues and drive them to believe blindly the particular news is genuine [3]. Once the pseudo-journalists copy down the style of any authorized journalists and post the respective contents in the media is called style-based posts. Stance-based posts are the portrayal of any veracious statements which alter their original meaning and intention.

These days, media especially social media has become an enormous source of news for its viewers/readers. Everyone does not have sufficient time to fact-check or cross-verify whether the available news is genuine or not because everyone is caught up with their own lives. Basically, from the reader's point of view, its negligible effort, candid access, and swift spreading of information steer the readers to watch out and consume the posted news. It is very unfortunate that most of the viewers/readers are susceptible and perceive that all the posts that are been posted through online media are genuine [3]. Primarily, the rationale behind this consumption attitude is innate. Firstly, compared to conventional news media, social media is less expensive. Secondly, it is very much easier to share further with somebody, comment upon any topic, and debate with other readers as well. Detecting fake news or information becomes very significant and therefore attracts huge attention because of the deleterious impact on human beings and their community as well. To improvise the detection of bogus news, it is highly important to incorporate and utilize the user's social involvement as information and process it. Consequently, it demands a comprehensive comprehension between the social media user profiles and the fake news. Therefore, this paper examines, compares, and proposes an effective and efficient model to detect news feed credibility from Twitter posts [4, 5].

2. Literature Survey

A system to facilitate the human users to know who they are communicating with is focused upon. This has been intended by classifying the human users, the bots as well as the cyborg membership accounts [6] on Twitter social media. An assemblage of over 500000 Twitter accounts was utilized to perform a set of measurements. The discrepancies among the human users, bots, and cybrog accounts concerning Twitter posing behavior, the respective contents, and the user account properties were experimented with and observed. Consequently, a cataloging system that focuses on an entropy-

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based constituent, spam identification constituent, user account characteristic constituent, and a decision-maker has been proposed. A new-fangled convolutional neural network method [7] to amalgamate the product word composition methodology with the product review characteristics is proposed. A bagging technique is initiated to capture the neural network through two classifiers. The efficacy of this proposed approach is illustrated by experimenting with the real-life Amazon dataset. 62 million Twitter user profiles that were publicly available have been analyzed. A detailed analysis was performed to devise a strategy for detecting the automatically created fake profiles [8]. Based upon the devised strategy, highly reliable fake profiles have been detected that work behind pattern matching and update times analysis.

The real issue of social media fake news identification is very much relevant as well as challenging. To further expedite the research on this very particular issue, a detailed survey has been conducted. A comprehensive study of fake news detection and classification [9] based on social theories, psychology, evaluation metrics, and algorithms from a data mining point of view has been presented. An algorithmic solution for over-amplification of fake information [10] is presented based on three techniques such as content-based, source-based as well as diffusion-based. Awareness regarding the issues, challenges as well as business possibilities were raised in the conclusion. The exhibition of click baits analyzes the existence of fake news because of the communication advancement [11] is analyzed. The primary intention is to find a solution for the respective users that detects and filters the websites that have fake as well as misleading information with the aid of selected features. The empirical results show an accuracy of 99.4 % using the logistic classifier. A bottom-up approach that evaluates the credibility and consistency of the contents [12] in a node has been proposed. The suggested approach uses relative, manual as well as mutual evaluation models to evaluate the credibility. The significance of this proposed system is that every node will be evaluated by other nodes for the consistency of the node contents. A content analysis application along with a network visualization [13] is presented which serves as an effective web crawler. The developed system is capable of performing empirical research in web analysis, and text comparison based on the user's learning.

A fake news identification method based on two-way Long Short-Term Memory (LSTM)-recurrent neural network [14] has been presented. To estimate the performance of the developed model, publicly available two unstructured news articles were utilized. And, it is observed that the developed technique is supreme to the other models such as convolutional neural networks, recurrent neural networks as well as one-way Long Short-Term Memory. Automatic cataloging of news articles [15] was proposed using machine learning ensemble methodology. Different textual characteristics have been explored to discriminate between fake and fact contents. A combination of various feature sets is trained through ensemble methods where superior efficacy is achieved. Empirical research on the unaware effects of wrong information is explored and also the impact of fake information that changes human behavior [16] is presented. The behavioral impact of 233 undergraduate students was investigated related to fake news. It is noticed that the evidence obtained shows that misinformation can secretly alter ones' behavior. And also, it raises alarms that the currently existing approaches are inadequate to safeguard the users from fake news. A system that characterizes and examines the fake news threat identification [17] is presented. A detailed study and analysis of various intelligent computing techniques that identify fake news is projected in the context of big data. It is observed that the most utilized methods were LSTM, Naive Bayes algorithms.

A morphological investigation [18] on two datasets that contain 28870 news items has been dealt with here in this work. Consequently, the obtained results were validated along with a third dataset that contains 402 news items. The investigation of the respective datasets was conducted through lemmatization and POS labeling. After the investigative examination, it is found that statistically substantial discrepancies are primarily in the verbs word classes as well as nouns word classes. A construed text cataloger named TC-CNN [19] has been proposed to identify fake news and emotion cataloging. The primary focus is to classify the emotions where it depends upon two classifiers as well a one hate identifier. Based on these, a case study has been performed in comparison with the mainstream media and alt-right media. A detailed study, as well as an extensive analysis of new items [20] in the latest literature that identifies fake news items on social media, is presented. A newfangled hybrid deep learning technique [21] has been proposed to catalog fake news based on combining CNN and RNN. Two fake news data items namely ISO and FA-KES were deployed to validate the fake news items. It is observed that the validation is better than the non-hybrid baseline techniques.

An efficient method that investigates the capable methodology to detect clickbait [22] as a form of subterfuge automatically has been proposed. A comprehensive survey that recognizes both the textual as well as the non-textual clickbait activity has been performed. Based on the survey that is done, a useful and effective hybrid approach that identifies click-baiting has been suggested. Appertaining to the amalgamation of three different characteristics such as the article text, user feedback, and the user origin fostering it [23], a method that automatically predicts the fake news is proposed. The empirical analysis of real-world datasets shows that the purposed system accomplishes a higher accuracy when compared with the available existing methods. It also obtains the meaningful latent depiction of users as well as articles. An end-to-end system that derives the event-invariant features and benefits the bogus news detection on new happenings is proposed. The respective proposed framework termed Event Adversarial Neural Network (EANN) [24] has three primary components as multi-modal feature extractor, bogus news detector, and the event discriminator. With the help of multimedia datasets from Weibo and Twitter, comprehensive experiments were conducted. Based on the empirical results, the designed method outperforms all other existing methods. Also, it is observed that the EANN method learned the transferable feature representations effectively. A fake news detection system that utilizes and maneuvers both the news as well as the user commentary based on sentence comment co-attention subnetwork [25] has been developed. The developed system grabs the top-k check useful sentences and user exegesis for an effective fake news identification. For the demonstration purpose, comprehensive experiments were carried out and it is noted that the developed system outperforms seven other fake news identification systems by 5.33 percent in F1- score and 30.7 percent in precision. A novel gated graph neural network named as Fake-Detector [26] has been introduced to investigate the principles, methods, and various algorithms to detect fake news and its creators by evaluating the respective performance. To learn the news articles representations, creators, and subjects, a deep diffusive neural network has been built.

3. Proposed Methodology

The overall architecture of the proposed methodology that explores the credibility of newsfeeds using machine learning as well as deep learning is shown in figure 1. Once the news is fed into the developed system, the respective data is pre-processed which transforms the raw data into a structured format. From the pre-processed data, the respective features are extracted. Then the extracted features are fed into the machine learning as well as the deep learning models to get trained up and classify the newsfeeds. The classification will suggest whether the newsfeed is a fact or fake and subsequently the respective efficiency is obtained.

3.1. Dataset

The dataset utilized in this research effort is obtained from Kaggle with the following weblink https://www.kaggle.com/clmentbisaillon/fake-and-real-news-dataset#True.csv. The respective dataset contains varieties of True news articles and Fake news articles.

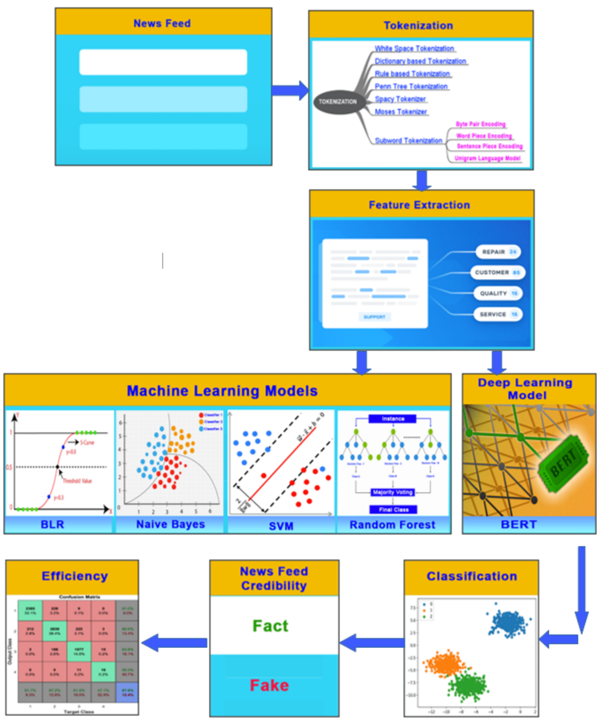

Fig. 1. System Architecture.

3.2 Data Pre-processing

Data pre-processing is a data mining technique that transforms the raw data into a structured or understandable format. In reality, the real-world data will be incomplete and vague. The data obtained could have lacking attribute values, noisy and inconsistent. In the process of tokenizing, any kind of textual data, the initial step is to segregate the body text of the article into tokens to obtain corpora. By obtaining the respective corpus, the characteristics of the respective words can be obtained. Every single article is tokenized utilizing the NLTK package. Steps carried out through the NLTK package for tokenizing the articles are given below.

NLTK package for tokenizing articles

Step 1: Import the dataset.
Step 2: Import the English stop words and add update the stop words to it.
Step 3: Separate each article into tokens (removes whitespaces).
Step 4: Convert all words to lowercase.
Step 5: Remove the punctuation and stop words.
Step 6: Remove the numbers.
Step 7: Convert to lemmatized words (root form)
Step 8: Create the n-grams.
Step 9: Stop.

3.3 TF-IDF (Term Frequency – Inverse Document Frequency)

Term Frequency-Inverse Document Frequency (TF-IDF) is a well-known method for grading the data/words in a machine learning mechanism, especially with textual data. Usually, such kind of scoring is prominent in detecting email scams. Term Frequency (TF) is defined as an operation to measure the frequency of occurrence of a particular word in a document. The simplest way of calculating the frequency of occurrences is to count the time that particular word has appeared in the respective document. But, in order not to obtain any biased results, the obtained frequency values have to be normalized. The normalization process can be done by

$$TF(\text{'aju'}) = (\text{No. of Times term 'aju' appeared in Document}) / (\text{Length of the Document}) \quad (1)$$

Inverse Data Frequency (IDF) is defined as a process to measure how the occurred word is termed as rare or common in the document which is called as Corpus.

$$IDF(\text{'aju'}) = \log e\ (\text{No. of documents in Corpus} / \text{No. of documents with term 'aju' in it}) \quad (2)$$

If the value of IDF is closer to 0, then the particular word is more common and is also considered less important. To differentiate the relevant and non-relevant words, an IDF factor has to be incorporated by weighing down the frequent words and scale up the uncommon words. Subsequently, the TF-IDF is calculated by performing the product of TF and IDF.

$$TF\text{-}IDF(\text{'aju'}) = TF(\text{'aju'}) * IDF(\text{'aju'}) \quad (3)$$

When a particular word is having a high TF value, then that respective word is considered highly pertinent and subsequently given a higher value and a low frequency of occurrence. In this scenario, since the log value is larger than 1, the IDF value will also be greater than 1. Despite this, if the word is more common, then the TF-IDF value will be nearer to 0. To calculate the TF-IDF score, Tfidfvectorizer is utilized.

In the implementation process that is carried out, the overall data is split into a training dataset as well as a testing dataset. Only the words that are greater than 10% of the documents are considered for processing to reduce the number of characteristics to manage the matrix. Also, it overrides the pre-processor where only the words that are created through the tokenizing process are considered and utilized as features. Now, the resultant matrix will be a Document-Term matrix where one will be the training dataset and another one will be the testing dataset. In the experiment, 215 words are obtained as characteristics with 37,368 articles in the training set and 9,343 articles in the testing set. These extracted features are applied and processed with different machine learning and deep learning models for classification.

3.4 Support Vector Machine

Primarily, a Support Vector Machine (SVM) is a supervised learning algorithm that is utilized for classifying objects. In addition to this, it is also suitable for regression. The main functionality of SVM is to distinguish various classes by separating them into different classes through a decision boundary. The significant part of processing an SVM algorithm is the determination of its decision boundary to segregate the respective objects. Every data point is charted in an n-dimensional space for generating the decision boundary. In the 2D space, n is the number of characteristics used for classification. As an illustration, if length and width are used for classification, the respective observations are charted in a 2D space with a boundary line for its disparity. If three features are used, the decision boundary will be a plane in a 3D space. And if more than three features are used for classification, the decision boundary will be a hyperplane which would be pretty difficult to visualize.

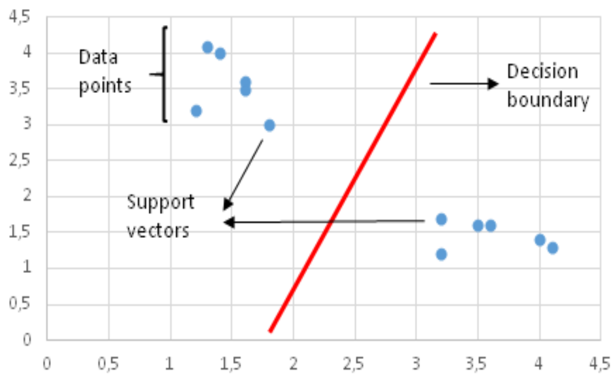

Fig. 2. Decision border in 2D space with a line

Primarily, the space to the support vectors is minimized while drawing a boundary line. The support vector will be greatly perceptive to noise and thus will not infer properly if the decision border is very close to the vectors. There may be misclassification even if there is a very small deviation in the independent variables. The data points obtained are not linearly separable always. In a higher-dimensional space, SVM utilizes the kernel function to measure the closeness of the respective data points to build them linearly severable. Kernel functions are used to measure the similarity of the data points. The input to the SVM classifier is the original feature set and its output is the degree of similarity in a feature space. The SVM is very well effective when multiple dimensions are surpassing the distribution of samples. To make it memory efficient, a subset of training points is utilized instead of using all data points. It can be observed that the time is increased for training the large dataset that adversely affects the classification performance.

3.5 Naive Bayes

Naive Bayes classifier is a supervised learning algorism utilized for classifying objects. It works based upon a few assumptions in the first place. It supposes that the features obtained are independent of each other so that there exists no correlation among the obtained characteristics. Practically it is not true in the real-life scenario. The ingenious supposition of the features being non-correlated is the primary reason for this classifier being called naive.
Essentially, the instinct behind the naive Bayes algorithm is the Bayes theorem.

$$p(A|B) = \frac{p(A)\cdot p(B|A)}{p(B)} \; (Bayes'Theorem) \quad (4)$$

where,
p(a|b) is the posterior probability of class (a, target) given predictor (b, attributes).
p(b|a) is the likelihood. It is the probability of the predictor given class.
p(a): is the prior likelihood of predictor.
p(b): is the prior likelihood of class.
Naive bayes classifier calculates the probability of a class given a set of feature values (i.e. p(yi | x1, x2 , … , xn)).

The supposition that all the extracted characteristics are autonomous establish this algorithm very quickly as compared to other algorithms. Sometimes, swiftness is preferred and considered over higher precision. Contrary to this, the same supposition makes this algorithm less accurate when compared to other existing algorithms. And naturally, the swiftness of this algorithm comes at a price.

3.6 Logistic Regression

A supervised learning algorithm that is widely utilized for binary cataloging is called logistic regression. Albeit the word regression belies with classification, the primary word that has to be focused upon is logistic. Logistic refers to a logistic function that principally performs classification in this respective algorithm. As it is known, the logistic regression algorithm is a simple yet very effective cataloging method used for binary classification. Aad click detection, classifying fake websites and spam email identification are a few examples of logistic regression being a provider of influential solutions. The very foundation of logistic regression is its logistic function which is the sigmoid function. This sigmoid function accepts any real number and further normalizes the respective number betwixt 0 and 1. The sigmoid function is represented as

$$Sigmoid\ Function: y = \frac{1}{1+e^{-x}} \quad (5)$$

The logistic regression classification method takes a linear equation as its input and utilizes a logistic function and accomplishes a binary classification based on the logarithm of the odd ratio. In this cataloging method, if the likelihood is greater than 50%, then the divination is positive which is termed 1. And, if it is less than 50% then the prediction is negative which is termed 0. Since the prediction in this classification is problem-dependent, a threshold value between positive and negative classes is utilized. Based on the problem, the threshold value can be adjusted for precise classification.

3.7 Random Forest

Random forest is a user-friendly machine learning algorithm that produces great classification results. A random forest is an ensemble of several classification trees. The ensemble of decision trees called a forest is built through training using the bagging technique. In the bagging method, the classification trees use parallel estimators. This algorithm can be used for classification as well as regression. When the classification result is based on the majority votes received from each decision tree, then it can be used as a classification solution. At the same time, the divination of a leaf node will be the average value of the target value with that particular leaf for regression. The accuracy of a random forest is significantly higher when compared to a single decision tree. Also, it minimizes the threat of overfitting. The important factor of random forest is the time of execution does not become a gridlock since it executes in parallel.

Once the feature set is obtained, it is sent to create the bootstrap samples. To avoid uncorrelated decision trees, random forest achieves bootstrapping and randomness in the feature set. Once the samples are selected randomly from the training data set, it is called bootstrapping. Such samples are known as bootstrap samples. The bootstrap samples are fed to the random forest for decision-making. The decision tree trains up to every bootstrap sample thereby creating feature randomness. The number of characteristics utilized for every single tree is controlled by the maximum features parameter. The outcome of the random forest will be an average classification model. This random forest classification model is an extreme precision model for most classification problems that do not require a normalization process. In contrast to this, the model would not be a better choice for multi-dimensional datasets.

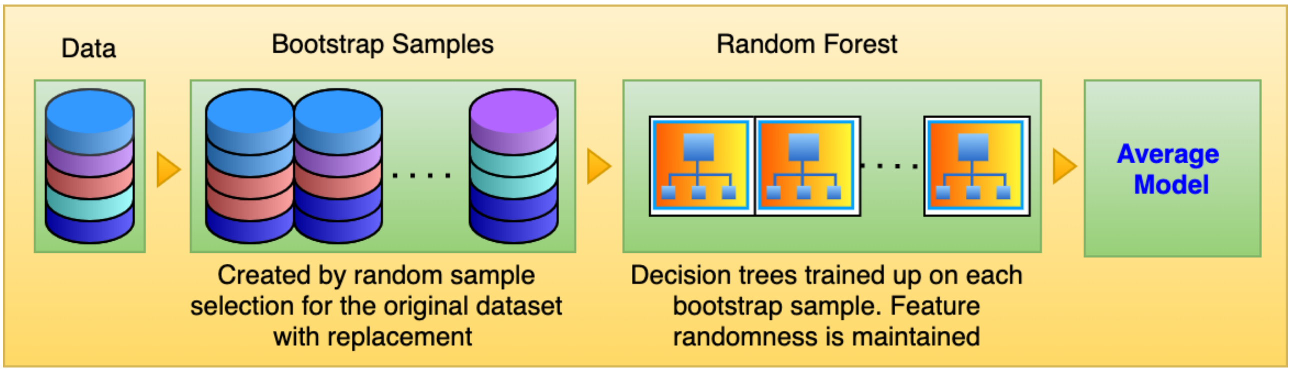

Fig. 3. Random Forest Classification Process.

3.8 BERT (Bidirectional Encoder Representations from Transformers)

Fundamentally, BERT is designed to pre-train the deep bi-direction models from the non-tagged text by conjointly training all layers through Masked Language Modeling (MLM) in terms of both left and right context. Consequently, the pre-trained model can be refined to generate a cutting-edge model for a broad range of tasks just by considering one extra output layer. The broad range of tasks includes question answering and language illation without significant task-specific architecture alterations. The main process that is involved with BERT is pre-training and fine-tuning. During the process of pre-training, the respective model is trained up with the unlabeled data over various other pre-training tasks. Concerning fine-tuning, the said model is primarily initialized with the defined pre-trained parameters, and subsequently, all parameters are also fine-tuned with the labeled data. The primary goal of BERT is to create a language model for classification.

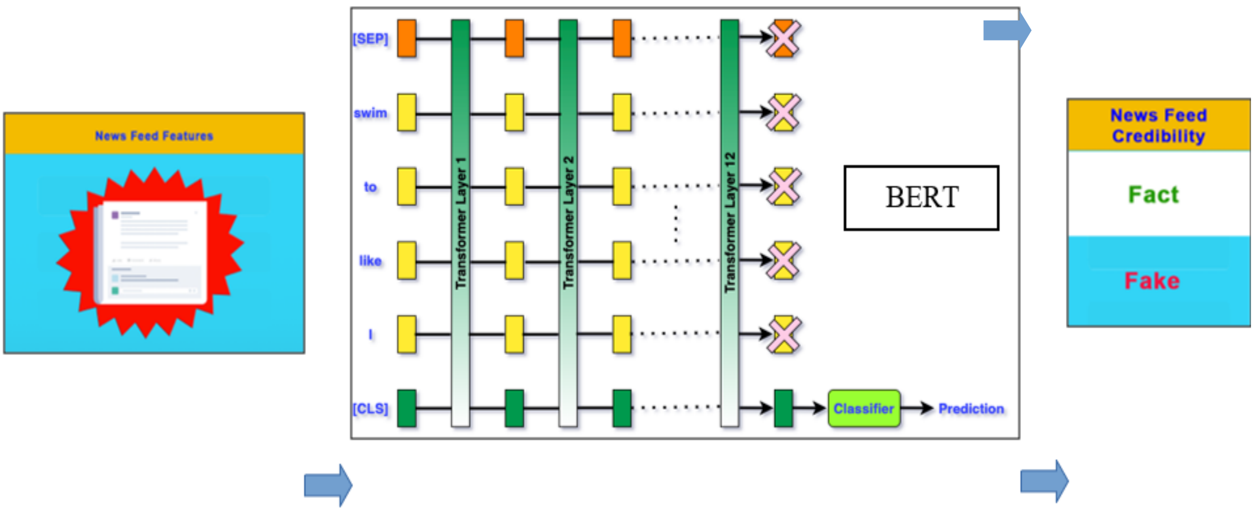

Fig. 4. Bidirectional Encoder Representations from Transformers (BERT).

4. Result Analysis: Performance Measures

It is understood that Random Forest accomplishes the best and has the maximum precision with the least number of false negatives. Also, it is observed that the Support Vector Machine, as well as the Binomial Logistic Regression, has similar precision and false negatives. Furthermore, both their precision, recall, and F1-Scores are found to be identical. Also, it is noted that Naive Bayes performs the worst comparatively. The cause of its worst performance might be a large number of dependent words were not identified because of the non-usage of bi-grams and tri-grams. BERT

(Bidirectional Encoder Representations from Transformers) Neural Network is a methodology that uses pre-trained deep learning models. This model extracts features from the text data and fine-tunes the present model to generate the divinations from the textual data. The utmost length of an article in the BERT model is 512 tokens. It is observed that the memory was running out when the number of tokens was increased. Due to this memory issue, the batch size was significantly reduced. Finally, 64 tokens per article are considered and executed with this number of tokens to achieve an efficiency of 99.79%.

Table 1. Efficiency Comparison of Machine Learning / Deep Learning Models.

Sl. No	Machine Learning / Deep Learning Models	Accuracy	AUC	Mean Squared Error
1	Naive Bayes	86.10%	0.93	0.37
2	Binomial Logistic Regression	89.41%	0.96	0.33
3	Support Vector Machine	89.42%	0.89	0.33
4	Random Forest	92.84%	0.98	0.27
5	BERT (Bidirectional Encoder Representations from Transformers)	99.79%	0.99	0.045

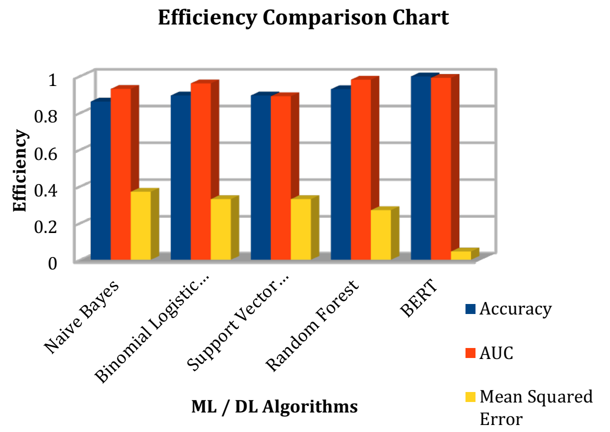

Fig. 5. Efficiency Comparison of Machine Learning and Deep Learning Models.

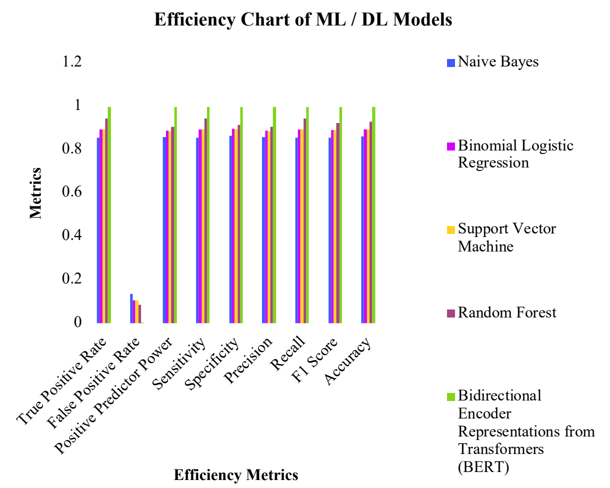

Fig. 6. Efficiency of different Machine Learning / Deep Learning Models.

To have a reasonable assessment, a comparative analysis of various fake news detection methodologies has been tabulated in Table 2. The publicly available LIAR dataset was utilized to experiment with all the methods on fake news. It is observed that with the LIAR dataset, the Blending (BLD) Ensemble method has the least accuracy of 63%, and the Random Forest – LIWC (Linguistic Inquiry and Word Count) has an accuracy of 99%. Also, it is observed and noted in Table 1 that with the help of the proposed methodology, along with BERT (Bi-directional Encoder Representations from Transformers), the maximum accuracy of 99.79 is achieved as shown in figure 7.

Table 2. Comparison of Various Fake News Articles to their Accuracy

Sl. No	Year	Methodology	Accuracy (%)
1	2016	NLP [29]	76
2	2017	Naïve Bayes [30]	74.
3	2018	CNN [31]	86.65
4	2019	Naïve Bayes, SVM, NLP [32]	93.50
5	2020	Logistic Regression – LIWC [32]	97
6	2020	Random Forest – LIWC [32]	99
7	2021	Conv1d [33]	97
8	2021	Blending (BLD) Ensemble [34]	63
9	2021	Fake Detect [35]	89.9

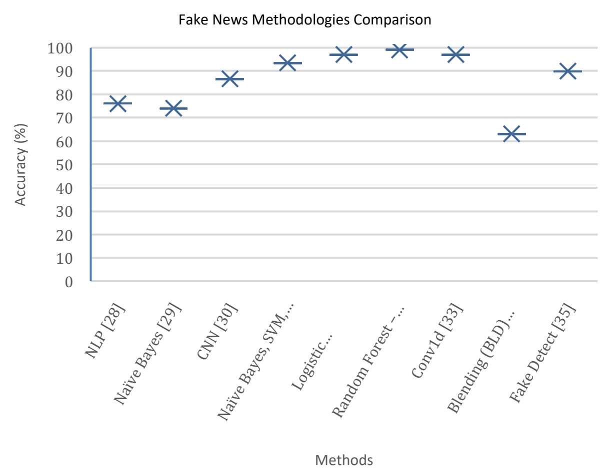

Fig. 7. Comparison of various fake news articles to their accuracy.

5. Conclusion

Exhaustive experimentation and analysis on different machine learning methods like BLR, NB, SVM, and RF and the deep learning method, BERT for detecting the fake news as well as the fabricated news are performed. It is very well observed that the Bidirectional Encoder Representation from Transformers (BERT) outplayed and performed best**.** This respective model provided an overall efficiency of 99.97 % and the area under the ROC curve is 99. Since the BERT model provides the maximum efficiency, it is considered the best and utilized for further classifying to know whether the input needs are genuine or not. One of the advantages of BERT is that it has a comprehensive vocabulary module as well as an efficient deep network of layers so that it does not require any text preprocessing. Even though the model is considered to be the best, it is computationally expensive compared to the other machine learning models.

To improvise upon the developed system, the following things can be inculcated along with the model building in the future. The larger dataset spans a longer time, determination of news headlines, the number of tokens increases for every single new article and incorporating the sentiment analysis for performing the right prediction.

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