ESTIMATION OF PRECISION IN FAKE NEWS DETECTION USING NOVEL BERT ALGORITHM AND COMPARISON WITH RANDOM FOREST.

Sudhakar Murugesan[1] and Kaliyamurthie K.P[1]

[1]Bharath Institute of Higher Education and Research

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Abstract

The purpose of this study is to improve prediction rate with a novel model of bidirectional encoder representations for transformers (BERT) compared with random forest algorithms. A dataset of size 1100 is used to compare Novel BERT's performance with Random Forests. With Random Forest, a framework for identifying fake news in electronic media networks is proposed. clinical calculates a sample size of 20 according to the framework. With regard to Precision rate, the Novel Bert algorithm beats the Random Forest algorithm by 8.33%. In comparison to the random forest algorithm, BERT achieves a rate of 0.002 that is significantly better than it. It is concluded that the novel BERT algorithm outperforms Random Forest in the prediction of fake news in this study.

INTRODUCTION

A large number of people are using the Internet as one of its most important inventions. They use the Internet for various purposes. They can access different social media platforms. Through these online platforms, anyone can post or spread news. This platform does not verify the users or their posts (Ahmed Et al., 2021). This results in some users spreading fake news. 'Fake news' can be used as propaganda to attack an individual, a society, an organization, or a political party (Manzoor et al., 2019). All this fake news is impossible for a human to detect. In order to identify fake news, algorithms must use machine learning. This paper aims to construct a machine learning model that can predict which Tweets are about real disasters and which ones are not. The dataset contains 10,000 tweets that have been manually classified.(al. & Al Ayub Ahmed Et al., 2021)

In order to optimize revenue, the application helps organizations predict which articles will be popular so that their targeted advertising campaigns can be optimized. (An overview of Random Forest Algorithm in Machine Learning, 2020) The Random Forest Algorithm is a technique of making a classification by using a bundle of decision trees. As well as avoiding overfitting, it is also considered to be an effective technique. It reduces overfitting and helps improve accuracy in decision trees. It can be applied to both classification and regression problems. Continuous and categorical data can both be used. Automatically fills in any missing values present in the data. As a rule-based approach is used, there is no need to normalize data. While random forest algorithms have many advantages, they also have some disadvantages. These algorithms require time and resources with high computational power as it builds numerous trees to combine their outputs. As many decision trees are used to determine the class, it also takes a lot of training time. Due to the number of decision trees, it is also difficult to interpret and fails to determine the significance of each variable. The definition of fake news generally refers to something that is verifiably false and intentionally so. Bias news does not fall under this definition. A biased report can be influenced by the individual's opinion, but fake news is fabricated intentionally. Their high level of social engagement is one of the most important factors behind the success of fake news stories. Facebook and Twitter give us access to other like-minded individuals. Whenever we read a sentence or a paragraph, our brains incorporate the information with the entire document and understand what the words mean. We teach a system to read and understand fake news with Machine Learning concepts (Shu and Liu 2019). The spread of false information and hoaxes online is on the rise as a result of the advancement of technology. Popular online platforms like social media and the Internet are popular sources of fake news. Various methods and tools have been used to detect fake news, including those that use artificial intelligence. Fake news, on the other hand, aims to fool readers into believing false information, which makes these articles difficult to comprehend. Machine learning cannot effectively detect fake news because the rate of producing digital news is high and runs at every second. (Carlson 2017). Due to the emergence of social networking sites, it has become possible to analyze the prevaIn developing countries like India, it is important to stop rumor-mongering and to focus on providing accurate, reputable news articles. (Jain et al., 2019)lence of fake news using new communication methods. This project aims to develop a method for detecting and removing false or misleading information from websites that users can access. By analyzing a few simple elements of the title and post, we can tell whether a post is fake or not. Authenticating news and articles appearing on social media sites such as WhatsApp groups, Facebook pages, Twitter, and other blogs and social networks is a question. Society is harmed when rumors are believed and are portrayed as news. The need of an hour is to stop the rumors especially in the developing countries like India, and focus on the correct, authenticated news articles.(Jain et al. 2019)

LITERATURE REVIEW

In this study, Hakak et al. identify the most significant characteristics that influence fake news classification. Ensemble models are used to achieve optimal accuracy in classifying fake news datasets. The ensemble classifier requires less training time. From the fake news datasets, the proposed model extracts significant features and then classifies the extracted features using a hybrid ensemble model consisting of Decision Tree, Random Forest and Extra Tree Classifier. A training accuracy of 99.8% and a testing accuracy of 44.15 percent were achieved on the Liar dataset. Training and testing accuracy were both 100% in the ISOT dataset. In its paper, Hossain et al. discuss the fact that feature engineering can be used to effectively address this issue: limiting the spread of fake news at the source, not after it has become a global problem. We manipulated text with extracted features, resulting in an effective level of fake news detection.

A deep learning model was then developed and tested. Using this study, it was successfully shown that the original features had an impact on deep learning models that were unknown.

By analyzing the accuracy of a report and predicting its authenticity, we propose a model for detecting fake news (Agarwal & Dixit, 2020). By extracting features from the textual information and constructing credibility scores, this model builds an ensemble network that can simultaneously learn the depictions of news reports, authors, and titles. A variety of machine learning algorithms are used for higher accuracy, including SVM, CNN, LSTM, KNN, and Naive Bayes, and the LSTM algorithm shows the best accuracy at 97%. Using precision, recall, and the F1-Score, we evaluated the performance and effectiveness of classifiers. Different algorithms were used to show the effectiveness of the performance. Kaliyar et al., 2019), In this work, the author proposes an ensemble machine learning framework based on a tree-based gradient boosting technique, which combines content characteristics and contextual features for the detection of fake news. Recently, gradient descent algorithms have been derived as adaptive boosting methods for classification problems. A single objective function is optimized using this formulation, which shows why specific elements and parameters are used in the methods. We apply various machine learning models for classification based on a multi-class dataset (FNC). Comparing the ensemble framework to existing benchmark results, experimental results demonstrate its effectiveness. For multi-class classification of fake news with four classes, we achieved an accuracy of 86% by using Gradient Boosting algorithm (an ensemble machine learning framework). (Elyassami et al., 2022) classifies news as fake or real by using machine learning models. A total of five classifiers were developed using Random Forest, Support Vector Machine, Gradient Boosting, Logistic Regression, and Naive Bayes. Open-source datasets extracted from online sources covering a variety of domains were used to train the models. Using text lemmatization, vectorization, and tokenization, valuable information was extracted from news text, increasing generalization and accuracy of fake news classification models. An investigation of how voting strategy impacts ensemble learning models was conducted. The four performance measures used to evaluate the five classifiers were accuracy, F1-score, recall, and precision. We are encouraged by the results. It is possible to use these ensembles against fake news spreading since they outperform other classifiers when trained with random forest algorithms and gradient boosting algorithms. In this paper, (Masciari et al). present their complete framework for detecting fake news and describe their machine-learning-based solution. Using two well-known and widely used real-world datasets, we demonstrate that our settings are superior to state-of-the-art algorithms and are capable of detecting fake news with high accuracy even in the absence of complete content information.

MATERIALS & METHODS

In this paper, the system is presented in four parts. In the first part, the datasets are identified, the second step novel ensembling technique is identified, third step training the model with three various ensembling classifiers and fourth step is to evaluate the models to choose the better classifier model for fake news prediction. As part of this experiment, Machine Learning uses Python and Sci-kit libraries, which are easy to use. For ML algorithms, Sci-Kit Learn is the best source, with algorithms for nearly every type readily available in Python, for easy and quick evaluation of ML algorithms. The dataset is collected from kaggle open source repository , LIAR: a benchmark dataset for fake news detection. (Giglietto et al. 2019). Configuration Google Colab with free GPU The GPU became exhausted after two iterations, but we created a checkpoint to save the model. Using the Google GPU cloud infrastructure, models can be trained and deployed more quickly. Our coding environment is Keras or Tensorflow. Depending on requirements, we can work with that TF version and utilities, such as the core, and the functional APIs. The training set of fake news also contains 800 rows. The number of real news and fake news is the same. Therefore, it won't be an imbalanced classification problem. Currently, 5621 subtexts have been extracted from 1280 texts. From 320 texts, 1305 subtexts have been extracted for validation. From 400 texts, 1568 subtexts have been extracted for testing.. Twitter users discussed the eruption of Taal Volcano in Batangas, Philippines, Coronavirus, the Bushfires in Australia, and the downing of flight PS752 in Iran. There is text in this dataset that may be considered profane, vulgar, or offensive. To complement the existing data on this topic with newly collected and manually classified tweets, this project was undertaken. Disasters on social media, which was used in Real or Not?, was the original source. Kaggle competition on natural language processing and disaster tweets. Figure 1 represents the class distribution of the dataset collected and it shows the both classes are equally distributed as it is a balanced class.

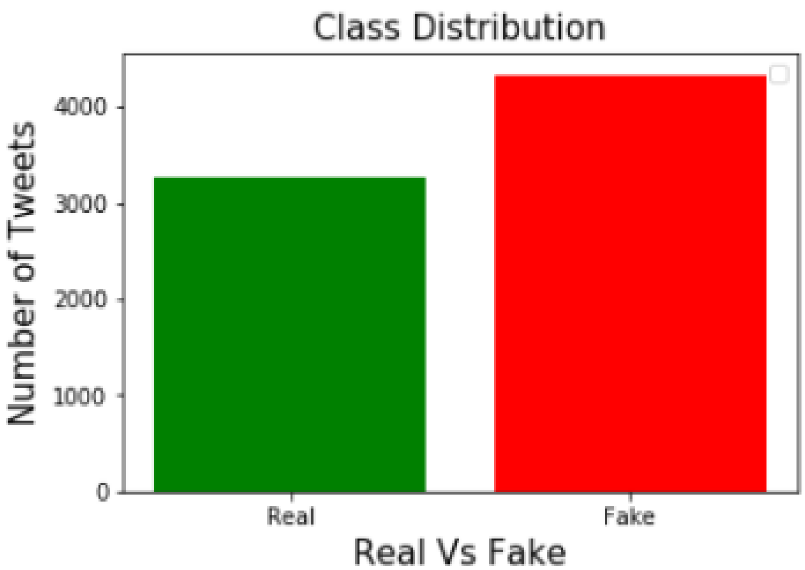
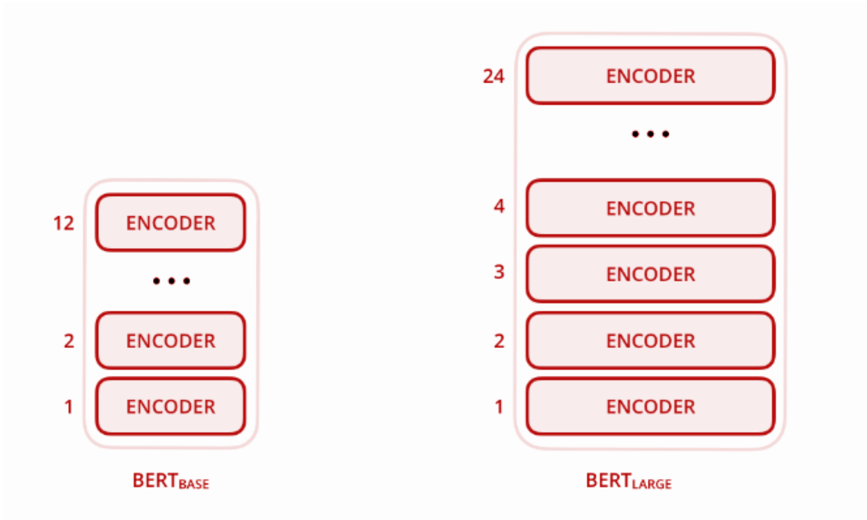


Fig 1: Class Distribution of the dataset.

BERT

- BERT is a deep learning model that has given state-of-the-art results on a wide variety of natural language processing tasks. It stands for Bidirectional Encoder Representations for Transformers. It has been pre-trained on Wikipedia and BooksCorpus and requires (only) task-specific fine-tuning.
- BERT is basically a bunch of Transformer encoders stacked together (not the whole Transformer architecture but just the encoder). The concept of bidirectionality is the key differentiator between BERT and its predecessor, OpenAI GPT. BERT is bidirectional because its self-attention layer performs self-attention on both directions.
- BERT is pre-trained on a large corpus of unlabelled text including the entire Wikipedia(that's 2,500 million words!) and Book Corpus (800 million words). This pretraining step is really important for BERT's success. This is because as we train a model on a large text corpus, our model starts to pick up the deeper and intimate understandings of how the language works.
- BERT is a deeply bidirectional model. Bidirectional means that BERT learns information from both the left and the right side of a token's context during the training phase.This bidirectional understanding is crucial to take NLP models to the next level.
- Finally the biggest advantage of BERT is it brought about the ImageNet movement with it and the most impressive aspect of BERT is that we can fine-tune it by adding just a couple of additional output layers to create state-of-the-art models for a variety of NLP tasks.

ARCHITECTURE OF BERT



BERT is a multi-layer bidirectional Transformer encoder. He has implemented a BERT base – 12 layers (transformer blocks) which has 12 attention heads, and 110 million parameters. Figure 2 represents BERT architecture ,figure 3 shows input embedding is a combination of 3 embeddings: token embedding, segment embedding and the position embedding.

Figure 2: BERT Architecture

Preprocessing Text for BERT

The input representation used by BERT is able to represent a single text sentence as well as a pair of sentences in a single sequence of tokens.

The first token of every input sequence is the special classification token – [CLS]. This token is used in classification tasks as an aggregate of the entire sequence representation. It is ignored in non-classification tasks.

For single text sentence tasks, this [CLS] token is followed by the WordPiece tokens and the separator token – [SEP].

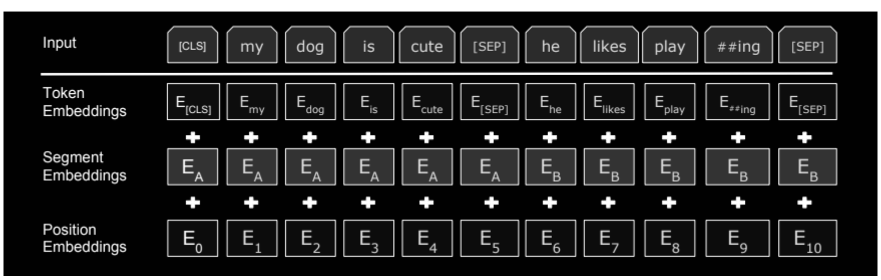


Figure 3 : input embedding is a combination of 3 embeddings

BERT developers have set a specific set of rules to represent languages before feeding into the model.

- Position Embeddings: BERT learns and uses positional embeddings to express the position of words in a sentence. These are added to overcome the limitation of Transformer which, unlike an RNN, is not able to capture "sequence" or "order" information

- Segment Embeddings: BERT can also take sentence pairs as inputs for tasks. Therefore it learns a unique embedding for the first and the second sentences to help the model distinguish between them. In the above example, all the tokens marked as EA belong to sentence A
- Token Embeddings: These are the embeddings learned for the specific token from the WordPiece token vocabulary For a given token, its input representation is constructed by summing the corresponding token, segment, and position embeddings.

Tokenization: BERT uses WordPiece tokenization. The vocabulary is initialized with all the individual characters in the language, and then the most frequent/likely combinations of the existing words in the vocabulary are iteratively added.

ALGORITHM.

Step 1: Data Cleaning

1. ”stop words” usually refers to the most common words in a language. for example ’a’, ’the’ etc. These words are essential parts of any language but do not add anything significant to the meaning of a word.
2. punctuation marks are marks such as a full stop, comma, or question mark, used in writing to separate sentences and their elements and to clarify meaning.
3. convert all the messages in lowercase so that words.
4. convert the words to its lemma form.
5. embedded special characters, ”URLs” and finally digits are removed from the tweets

Step 2: apply this vocab on our train and test datasets.

Step 3 : Apply N-gram analysis.

Step 4: Word embedding methods are applied to learn a real-valued vector representation for a predefined fixed sized vocabulary from a corpus of text.

Step 5: Embedding layer is applied to the neural network with a Backpropagation algorithm.

Step 6: Word2Vec is applied for efficiently learn a standalone word embedding from a text corpus.

Step 7: Continuous Bag-of-Words, or CBOW mode is applied to learns the embedding by predicting the current word based on its context.

Step 8: Continuous Skip-Gram Model is applied for learning by predicting the surrounding words for a given current word.

Step 9: The Global Vectors for Word Representation (GloVe) algorithm is applied for a classical vector space model representation of words using matrix factorization techniques that helps in calculating analogies.

Step 10: Apply CNN with word Embeddings.

1. mapping of words to integers has been prepared, encode the tweets in the training dataset and ensure that all documents have the same length
2. find the longest review using the max() function on the training dataset and take its length and truncate tweets to the smallest size or zero-pad.
3. define neural network model, The model with embedding layer as the first hidden layer and specify the size of the real-valued vector space, and the maximum length of input documents.
4. The maximum document length was calculated.

Step 11: Develop a multi-channel convolutional neural network for the Tweet analysis prediction problem.

1. CNN configuration with 32 filters, kernel size of 8 with a rectified linear (relu) activation function.
2. The back-end with standard Multilayer Perceptron layers to interpret the CNN features.
3. The output layer with sigmoid activation function to output a value between 0 and 1 for the negative and positive sentiment in the review

4. Fit the network on the training data having the parameters of stochastic gradient descent optimizer and training epochs as 100, to obtain the metrics accuracy and loss.

Step 12: Make predictions on test data.

Step 13: Evaluate and compare the model.

RESULTS:

In the performance evaluation of BERT algorithm and Random forest classifiers on disaster tweets dataset are discussed. It is evident from the figure 4 that the BERT classifier outperforms the Random forest classifiers with accuracy rate 99.04%. Figure 4 represents the ROC curve with AUC of 99% obtained by the proposed algorithm.

A

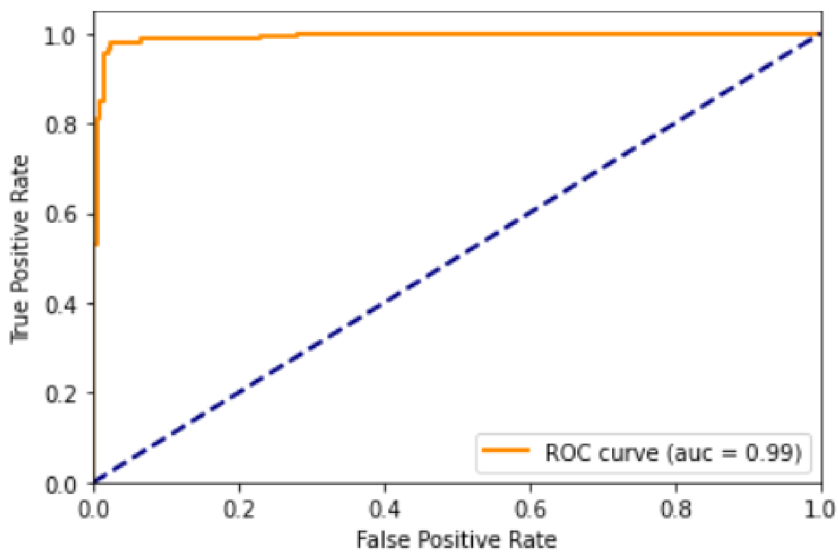


Figure 4: ROC curve shows AUC of 99% obtained using proposed BERT algorithm.

The Training loss and validation loss obtained by the proposed BERT algorithm in each epoch are represented in figure 5. It proves that the curve starts from 25% and gradually decreases and reaches below 0.05 in 30 epochs.

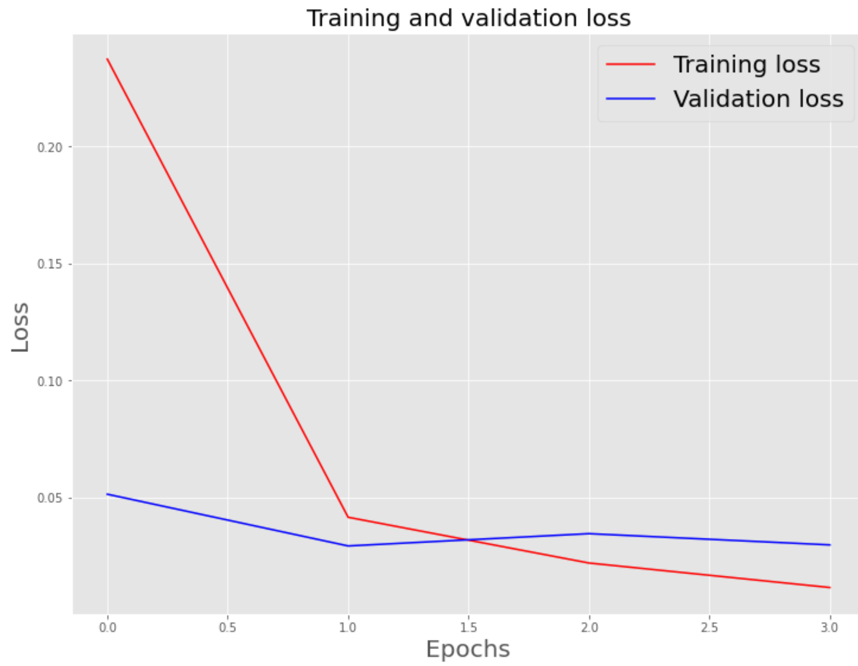


Figure 5 : Training and validation loss of the proposed BERT algorithm for 30 epochs

The Training accuracy and validation accuracy obtained by the proposed BERT algorithm in each epoch are represented in figure6. It proves that the cure starts from 85% and gradually increases and reaches 99% in 30 epochs. Also the Proposed BERT algorithm obtains the precision rate of 98% .

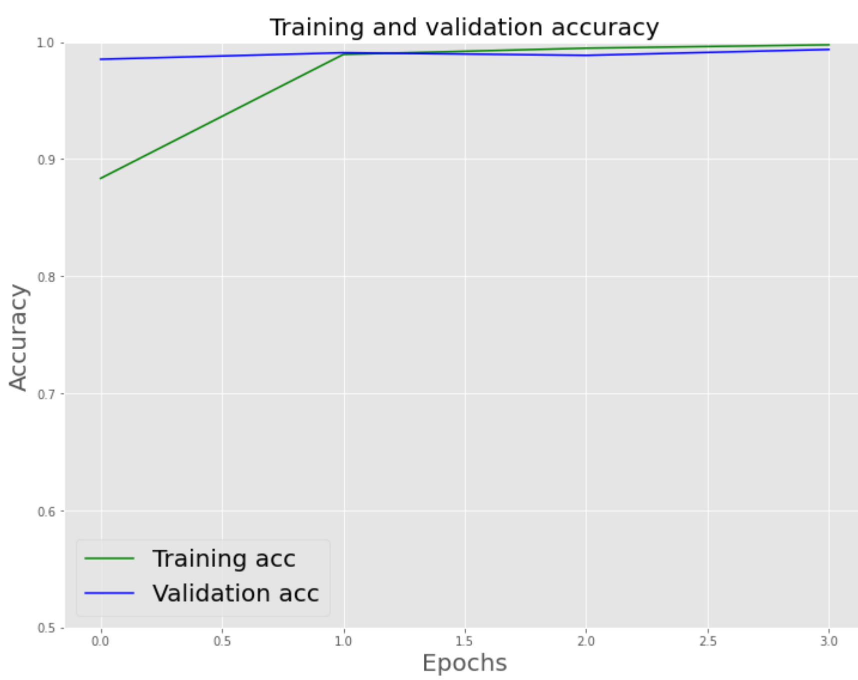


Figure 5 : Training and validation Accuracy obtained by BERT algorithm for 30 epochs

DISCUSSION

Text features are extracted from the text to simplify the classification of text data. Through the process of feature extraction, we reduce the dimensionality of the text, and thus eliminate irrelevant features from text data. As a result, classifiers become more accurate and the reduction of noise is improved. Statistically, the difference between these two methods (Nagashri and Sangeetha 2021) is not statistically significant. Term frequency–inverse document frequency (TFIDF) as well as count vector techniques is used separately for text preprocessing.Six Machine learning algorithms namely passive-aggressive classifier (PAC), naive Bayes (NB), random forest (RF), logistic regression (LR), support vector machine (SVM), and stochastic gradient descent (SGD) are thought about utilizing assessment measurements like precision, accuracy, recall, and F1 score, The outcomes have shown that the TFIDF is a superior text preprocessing method. PAC and SVM calculations show the best presentation for the considered dataset. (Choudhary et al. 2021)manages an audit of existing Machine Learning algorithms Naïve Bayes, Convolutional Neural Network, LSTM, Neural Network, Support Vector Machine proposed for recognizing and decreasing phony news from various online media stages like Facebook, whatsapp, twitter, and so forth This survey gives a far reaching point of interest including information mining viewpoint, assessment measurements, and agent datasheets. (Smitha and Bharath 2020)paper represents model and system to distinguish counterfeit news from news story with the help of Machine learning and Natural language preparing.Seven distinctive Machine learning Classification algorithms are prepared to group news as phony or genuine and are analyzed thinking about precision, F1 Score, review, accuracy and best one is chosen to fabricate a model to arrange news as phony or genuine. (Jiang et al. 2021)proposed our novel stacking model which accomplished testing accuracy of 99.94% and 96.05 % individually on the ISOT dataset and KDnugget dataset. Assessed the exhibition of five Machine Learning models and three deep learning models on two phony and genuine news datasets of various sizes with hold out cross validation. Different classifiers are used for identifying the fake news ,and the approach is executed on two datasets of phony and genuine news. In the wake of playing out the examination, it is seen that Passive-Aggressive Classifier gives the best outcome(Gupta and Meel 2021).

CONCLUSION:

In this paper it is demonstrated that the proposed BERT algorithm performs better with highest accuracy in prediction of fake news. This work has extraordinary potential and can be effective in holding , improving and identifying the fake news, hence it tends to be carried out in social networking sites like twitter, facebook etc..

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