IJCRSSSL International Journal of Current Researches in Sciences, Social Sciences and Languages
International Journal of Current Researches in Sciences, Social Sciences and Languages
Volume: 04 | Issue: 02 | 2024 | Open Access | Impact Factor: 5.735

Enhanced Fake News Detection Model using Hybridization of word2vec and BERT Embedding's

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Abstract: The growth of fake news on the web offers important societal concerns, including the dissemination of misinformation and the erosion of trust in media sources. This paper offers an innovative false news detection model that leverages a hybrid of Word2Vec and BERT embeddings to handle these difficulties. By integrating the characteristics of both embeddings, the model intends to capture nuanced contextual information and semantic links in textual content, hence boosting detection accuracy. The research technique involves data collecting, preprocessing, and feature extraction using Word2Vec and BERT embeddings, model training, and evaluation. Results highlight the efficacy of the proposed model in identifying both fake and authentic news articles, attaining an accuracy rate of around 99%. Visualizations offer insights into the model's performance across many measures. This study contributes to the evolution of false news identification approaches and creates a basis for future research in this crucial area.

INTRODUCTION

BACKGROUND OF THE STUDY

The growth of fake news on social network platforms and online news channels has become a big concern in the digital age Shu et al., (2017) fake news, which refers to intentionally fabricated or manipulated information designed to mislead readers, can have detrimental consequences on individuals, communities, and society as a whole (Zhou & Zafarani, 2020) the spread of misinformation can undermine public trust, fuel social divisions, and even impact political processes and decision-making (Bondielli & Marcelloni, 2019) as a result, the creation of effective false news detection algorithms has become a major subject of research in Natural Language Processing, also known as NLP, and Machine Learning (ML).

Traditional approaches to false news detection have primarily focused on analyzing the textual content of news articles, relying on linguistic features, writing styles, or sentiment analysis (Alonso et al., 2021; Perez-Rosas et al., 2017) however, these content-based methods often fail to capture the nuanced contextual information and semantic relationships present in language, leading to limitations in their accuracy and robustness Singhal et al., (2019) moreover, as fake news creators become more sophisticated, they may employ techniques to mimic the language patterns of legitimate news sources, further complicating content-based detection (Zhou et al., 2019).

In the past few years, the introduction of deep learning and natural language representation techniques, such as word embedding's, has opened new avenues for enhancing fake news detection Ruchansky et al., (2017) word embedding's are rich vector reconstructions of phrases reflecting their lexical and syntactical links inside a continual vector space (Mikolov et al., 2013). These embedding's have shown to be successful in several NLP applications, including sentiment evaluation, text categorization, and automated translation. (Goldberg, 2017).

An influential model for word embedding is Word2Vec, first presented by (Mikolov et al., 2013). This model uses neural networks to generate word representations from extensive text collections. Word2Vec uses the contextual information of the present phrase or neighbouring words to make predictions (skip-gram or continuous bag-of-words, CBOW), or allowing it to grasp the contextual information of words. Through these acquired embedding's, NLP models can enhance their understanding of semantic connections between words and capture their contextual meanings more effectively (Rong, 2017)
While Word2Vec has been successfully applied in various NLP tasks, it has limitations in capturing long-range dependencies and accounting for polysemy, where a word can have multiple meanings depending on the context (Devlin et al., 2019). More sophisticated language algorithms, like the Bidirectional Encoder Representation from Transformers (BERT), were created to overcome these restrictions (Vaswani et al., 2017). According to Devlin et al. (2019), BERT is a transformer-based language paradigm that uses self-awareness techniques to gather relevant data about a word in both its left and right directions. BERT may acquire sophisticated language representation through initial training using vast textual databases, which can then be optimized for a variety of subsequent tasks, such as categorization of texts, inquiry responding, or natural language inference (Qiu et al., 2022).

REVIEW OF RELATED LITERATURE

Researchers have created a multitude of deep learning-based methods for identifying false information. For example, Shalini et al., (2023) research presented a deep learning and machine learning based fraudulent account identification system for social media. Several machines learning methods, including as SVM, RF, NB, and RNN, have been used to tackle the major problem of identifying fraudulent identity accounts on social media. With an accuracy percentage of 96.10%, RNN with Sigmoid performs the best out of all of these methods. It is important to remember that the system's performance varies according on the dataset and classification method used. Comparing the experimental findings to state-of-the-art approaches found in relevant literature, it is clear that the suggested strategy produces good results. Data from social media web domains related to twitter was gathered for this study, which was especially concerned with identifying phoney profiles.
In order to find and evaluate papers, (Fernandes and Universidade 2023) suggested an exploratory research strategy that made use of a methodology and a research procedure. As a consequence, algorithms with rates of precision of 99.9%, 99.8%, and 99.8% were developed, including the Stacked Technique, Bidirectionally Receiver Artificial Neural Network (BiRNN), and a cognitive network (CNN). Though these rates of precision are excellent, it's crucial to remember that the majority of the study was done using controlled datasets from places like Kaggle or without access to real-time updates from social networks. As a result, very little research has been done in social network settings, where information sharing is most common in today's world. Platforms that were found to have regularly utilised datasets included Kaggle, Weibo, FNC-1, covid-19 false News, and Twitter.
Segura and Alonso, (2022) proposed Multimodal Fake News Detection, Utilising all single-modal along with multidimensional techniques, researchers carry out a detailed categorization of disinformation on the Fakeddit dataset. In light of their experiments,
It has been found that the combination of text and image data using a Convolutional Neural (CNN) architecture in a multimodal approach leads to the highest accuracy of 87%. Specifically, certain categories of fake news. On the other hand, when considering unimodal approaches utilizing only text data, the best model is Bidirectional Encoder Representations from Transformers (BERT), which achieves an accuracy of 78%. It is evident that incorporating both text and image data significantly enhances fake news detection performance.
A collaborative artificial intelligence system utilising VGG 16 CNN was used by Mallick et al., (2023), who assessed the model's performance using a range of metrics, including reliability, recollection, and the F-measures. Based on experimental results, the proposed model demonstrated an amazing 98% prediction accuracy. The results indicate that, for the provided news categories, the recommended model

outperforms the News Category (NB) approach by approximately twelve percent with regard to a mean precision value. It also shows an improvement in average accuracy values of around 10% when compared to the SVM model. Furthermore, with respect to average accuracy values for the specified news categories, the suggested model performs around 14% better than the NB model and approximately 8% better than the SVM model. In the specified categories, it is evident that the proposed model exhibits an approximate 8% improvement compared to the SVM model and a remarkable 15% improvement compared to the NB model in terms of average AUC values. The outcomes provide clear evidence that suggested model excels in accurately classifying fake news across various domains of news articles.

Fernandes and Universidade, (2023) examined the machine learning algorithms and datasets employed in training to detect fake news reported in the literature. This research follows an exploratory approach with a qualitative methodology, utilizing research to identify relevant studies for analysis. The findings reveal the utilization of three algorithms: Stacking Method, Bidirectional Recurrent Neural Network (BiRNN), and Convolutional Neural Network (CNN), which yielded accuracy rates of 99.9%, 99.8%, and 99.8% respectively. It is important to note that while accuracy rates are impressive, the majority of the studies utilized datasets from controlled environments like Kaggle or lacked real-time updated information from social networks.

Saha and Kobti, (2023) introduced a framework, which is a fusion of DeBERT a model and the ConvNeXT model, and both of these are state-of-the-art in their field as they overcome the obstacles of the previous benchmark models. The model underwent training and testing using various benchmark datasets including Fakeddit Dataset with an accuracy rate of 0.912, FakeNews with 0.913, Politifact Dataset with 0.913, and Gossipcop with 0.902 accuracy respectively.

Guo et al. (2023) proposed a two-branch multimodal fake news detection model based on self-attention mechanisms and multimodal bilinear pooling to handle the problem of merging text and image features for fake news detection. The extraction of features and generation of more valuable data is achieved by utilizing two networks and pre training. For feature fusion, an inter-modal information fusion module based on multi-modal bilinear pooling is employ to join the distinctions among text and image modalities. Additionally, an intra-modal information enhancement module that relies on the self-attention is utilized to highlight significant details within each modality.

However, the effectiveness of the feature extraction module and fusion module is validated through extensive experimentation on two multi-modal datasets. Our model surpasses the benchmark model in terms of detection accuracy, which can be attributed to studies solely focusing on fake news content while neglecting social subjects. However, it is important to consider that fake news is generated by social subjects, hence analyzing the characteristics of these aids in accurate detection. Additionally, within the same post, multiple images may be attached, each conveying information from different perspectives to users. The achieved accuracy is 0.868.

DATA COLLECTION

The data set contains publications labeled to indicate true or fake news. This process entailed acquiring real articles by scraping data from Reuters.com, a trustworthy media source. In contrast, the unverified news pieces took their information from various unreliable domains recognized by Politifact, a well-known fact-checking organization.

The collection includes a wide range of articles on a variety of themes, with a special focus on governmental and world news. The dataset is divided into two CSV files, "True.csv" and "Fake.csv," with the "True.csv" file including over 12,600 publications sourced from Reuters.com and the "Fake.csv" file containing an equal number of publications from other fake news sites. Each entry in the dataset contains important information such as the publication's title, words, publication category, and when it was published. To ensure alignment with the fake news data available on Kaggle.com, meticulous attention was paid to sourcing articles primarily from the years 2016 to 2017. Despite undergoing cleaning and pre processing, the original fake news articles retained their punctuation and errors within the text. The

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table below shows an arrangement for sections, as well as the total count of publications inside every single one.

Category	Number of Articles
Real News	21,417
Fake News	23,481

Table 1: Data Set

DATA PREPROCESSING

Data preparation is a key process in readying the data set for model training and evaluation. This procedure comprises extraction, converting, and arranging the original information to ensure it is compatible with the machine learning algorithms applied for detecting fake news.

The specific preprocessing steps applied to the ISOT Fake News Dataset are outlined below:

- **Text Cleaning:** Eliminate any extraneous characters, including special symbols, quotation signs, as well as numbers, and text information. The procedure eliminates noise and standardizes the text format across articles.
- **Tokenization:** Divide the text in different signs, typically words or sub words, to permit additional analysis. Tokenization generates an organized structure of any written information, which is necessary in feature extraction.
- **Lower-casing:** Transform every written information to lower-case to guarantee consistency in word representations. It stops a model from considering phrases that have various capitalizations like independent entities.
- **Stop Word Removal:** Remove frequent stop words, such as "is," "the," as well as "and," from the written information. Stop words contain minimal lexical information that can inject interference during the model's training process.
- **Stemming or Lemmatization:** Convert inflected terms to the foundation as well as source forms to standardize differences in word morphology. This stage consolidates words with comparable meanings, boosting feature extraction efficiency and lowering the feature space dimensionality.

METHODOLOGY

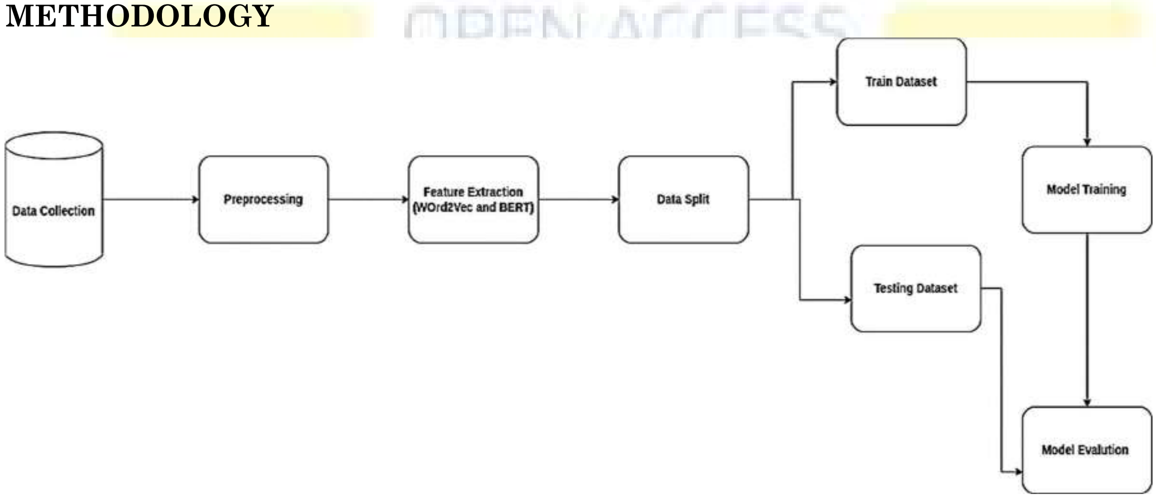

Figure 1: Architectural Design

ACTIVITY DIAGRAM

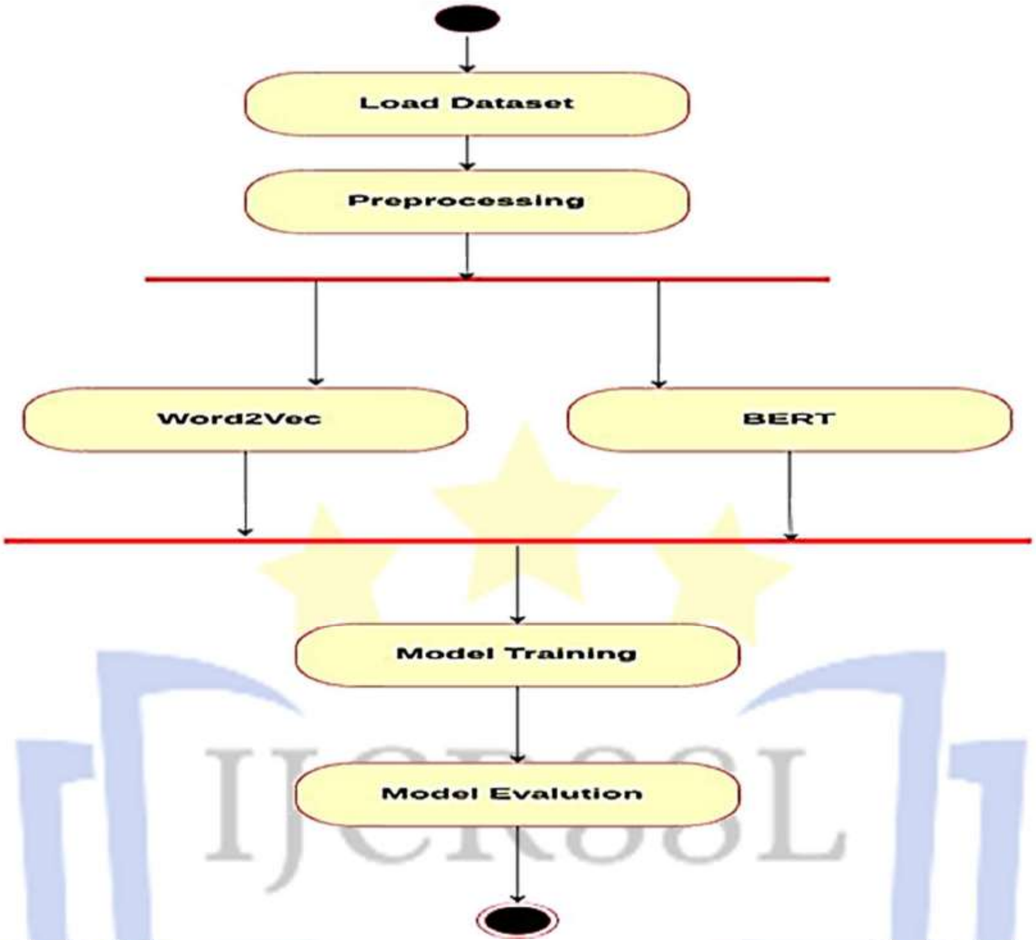

Figure 2: The Activity Diagram of the Model

MODEL EVALUATION

Since this research focuses on classification, the metrics utilized for assessing the efficiency of model comprises precision, recall, accuracy and F1 score. All produced models, whether developed from origin or utilizing transferable knowledge, will be evaluated based on these measures to select the best one. Below is a quick description of each metric in the context of this project:

- **Accuracy:** This is a typical metric for evaluating classification model effectiveness. It reflects the fraction of accurate projections generated by the framework compared to the entire amount of samples. Accuracy represents the proportion of the samples tested that have been properly categorized, acting as a crucial indicator to fulfill some of the research objectives indicated earlier.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

- **Precision:** Precision is the proportion between any number of situations where the model successfully predicted the class of the test data to the entirety of correct predictions plus the faulty predictions the model believed to be correct. It is logically determined as shown in the formula below:

$$\Pr ecision = \frac{TP}{TP + FP}$$

- **Recall:** Recall is an evaluation statistic that shows the proportion of accurately anticipated cases based on the entire amount of accurate projections plus the wrongly classified cases. It is mathematically described as shown in the equation below:

$$\text{Re}\,call = \frac{TP}{TP + TN}$$

- **F1-Score:** For this multiclass classification project, the precision as well as recall were calculated for every category. The F 1 score, which is the average of recall and precision, offers an accurate basis for comparing the produced models. It is logically determined as shown in the formula below:

$$F - Measure = \frac{TP}{TP + \frac{1}{2} + FP + FN}$$

DISTRIBUTION OF THE DATASET

Figure 3 illustrates the arrangement of entries across the set of data used in this research, which is comprised of two categories of articles: false news and factual news. The dataset includes 21,417 actual news pieces and 23,481 fraudulent news stories, For the purpose of training and assessing the false information identification model, this distribution offers information into the ratio of genuine to fraudulent news samples.

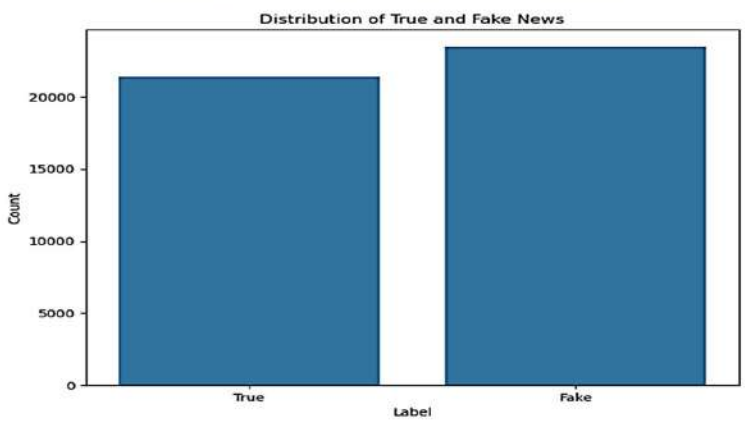

Figure 3: The Bar Chart of the Distribution of the Dataset

PIE CHART OF THE DATASET

Figure 4 presents a Pie chart illustrating the distribution of articles in the dataset between fake and true news categories. The pie chart shows that fake news articles constitute approximately 52.3% of the dataset, while true news articles make up the remaining 47.7%. This distribution visually represents the ratio of real to fraudulent news stories, which sheds light on the balance and content of the dataset.

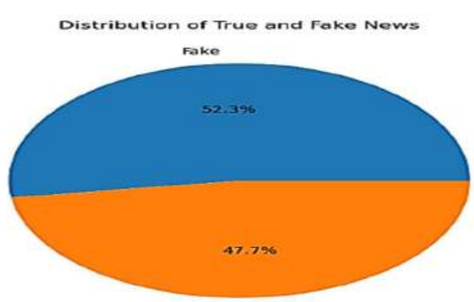

Figure 4: Pie Chart of the Dataset

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SUBJECT-WISE DISSEMINATION OF AUTHENTIC AND COUNTERFEIT NEWS

Figure 5 displays a chart with stacked bars that depicts the distribution of genuine and fabricated news stories based on their topic. The stacked bar chart provides a visual representation of the distribution of true and fake news articles across different subjects. True news articles are categorized under "politicsNews" and "worldnews," while fake news articles are classified into various subjects, including "Government News," "Middle-east," "News," "US_News," "left-news," and "politics." This visualisation enables an exact analogy of the prevalence of authentic and fabricated news pieces across different topic areas, hence emphasising any discrepancies in coverage between the two groups.

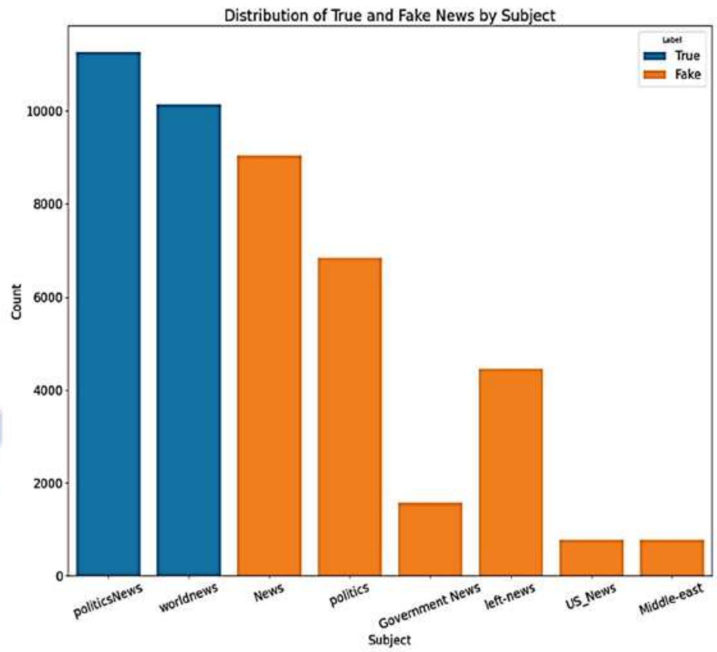

Figure 5: Stacked Bar Chart of the Dataset

TRAINING PROGRESSION OF THE MODEL

Fig. 6 illustrated the training progression of the propose model, offering detailed insights into the changes in loss and accuracy metrics over the course of 10 epochs. The suggested algorithm's train sequence, as shown in Fig 6, unfolds over 10 epochs and demonstrates a gradual refinement in both loss and accuracy metrics. Initially, the model has an accuracy of 0.9773 and a rather significant loss of 0.0688. The model's progressive learning is seen by the steady decline in loss and rise in accuracy during the next epochs. By the time the training is over, the loss decreases to 0.0177, signifying a significant reduction in prediction errors, while the accuracy increases to 0.9937, reflecting enhanced predictive performance. Despite fluctuations in performance metrics occasional peaks in loss and dips in accuracy the overall trend shows a convergence towards improved model performance. These findings highlight the efficacy of the proposed model in effectively capturing underlying patterns in the data and making accurate predictions, thereby establishing a solid foundation for robust fake news detection.

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```
Epoch 1/10
1011/1011 [==============================] - 29s 22ms/step - loss: 0.0688 - accuracy: 0.9773 - val_loss: 0.0404 - val_accuracy: 0.9869
Epoch 2/10
1011/1011 [==============================] - 6s 6ms/step - loss: 0.0330 - accuracy: 0.9884 - val_loss: 0.0337 - val_accuracy: 0.9891
Epoch 3/10
1011/1011 [==============================] - 4s 4ms/step - loss: 0.0284 - accuracy: 0.9898 - val_loss: 0.0278 - val_accuracy: 0.9919
Epoch 4/10
1011/1011 [==============================] - 5s 5ms/step - loss: 0.0253 - accuracy: 0.9916 - val_loss: 0.0307 - val_accuracy: 0.9889
Epoch 5/10
1011/1011 [==============================] - 5s 5ms/step - loss: 0.0249 - accuracy: 0.9912 - val_loss: 0.0342 - val_accuracy: 0.9889
Epoch 6/10
1011/1011 [==============================] - 5s 4ms/step - loss: 0.0224 - accuracy: 0.9922 - val_loss: 0.0486 - val_accuracy: 0.9825
Epoch 7/10
1011/1011 [==============================] - 5s 4ms/step - loss: 0.0217 - accuracy: 0.9927 - val_loss: 0.0340 - val_accuracy: 0.9883
Epoch 8/10
1011/1011 [==============================] - 4s 4ms/step - loss: 0.0188 - accuracy: 0.9933 - val_loss: 0.0214 - val_accuracy: 0.9925
Epoch 9/10
1011/1011 [==============================] - 5s 5ms/step - loss: 0.0176 - accuracy: 0.9942 - val_loss: 0.0198 - val_accuracy: 0.9933
Epoch 10/10
1011/1011 [==============================] - 5s 5ms/step - loss: 0.0177 - accuracy: 0.9937 - val_loss: 0.0355 - val_accuracy: 0.9894
```

Fig 6: Train Report of the Model

TRAINING AND VALIDATION LOSS GRAPH

Figure 7 displays training and validation loss graph, with training loss shown in blue and validation in orange. This graph visually shows the models loss progression throughout the procedure for coaching, enabling assessments of over fitting or under fitting tendencies. In this graph, the training loss curve, shown in blue, illustrates the progression of the loss metric across training epochs. It begins at a relatively high value of 0.01 and steadily decreases, showing how well the model was able to reduce mistakes on the training set. On the other hand, the orange validation loss curve shows our model performance with unseen validation of data. Which starts from 0.022 and, albeit with some oscillations, follows a similar declining pattern to the training loss. This curve measures the model's generalization capability, showing how well it performs on new, unseen data. The convergence of the training and validation loss curves suggests that the model effectively learns from the training data without overfitting, as evidenced by their close alignment. This alignment indicates concurrent improvement in the model's performance on both training and validation sets, resulting in a well-generalized and accurate fake news detection model.

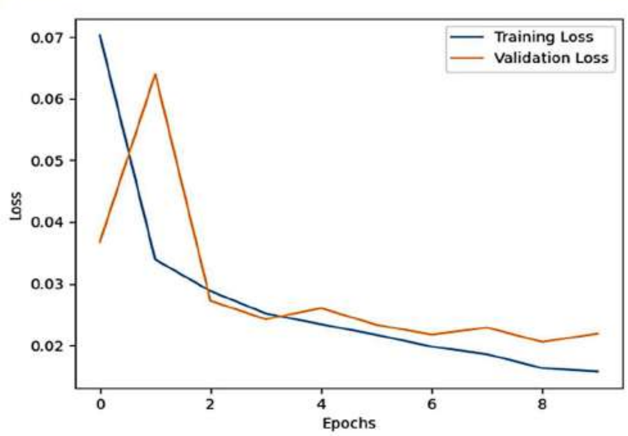

Figure 7: Training and Validation Loss Graph of the Model

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TRAINING LOSS AND VALIDATION ACCURACY GRAPH

Figure 8 displays the training and validation accuracy graph, visually illustrating the progression of the model's accuracy metrics throughout the training process. The model's accuracy throughout several training dataset epochs is represented by the training accuracy curve in this graph, which is shown in blue. The graph, which begins with a high accuracy of 0.99 and gradually increases across the training cycles, demonstrates how well the model is able to categorise instances within the training data. On the other hand, the model's performance on unseen validation data is shown in the orange validation accuracy curve. It starts off with an accuracy of 0.978 and, while it fluctuates a little, follows the same rising trend as the training accuracy curve. This curve measures the model's generalizability, indicating its efficiency on previously encountered data. The convergence of the training and validation accuracy curves suggests that the model effectively learns from the training data without over fitting, as evidenced by their close alignment. This alignment indicates simultaneous improvement in the model's performance on both the training and validation sets throughout the training process, resulting in a well-generalized and accurate fake news detection model.

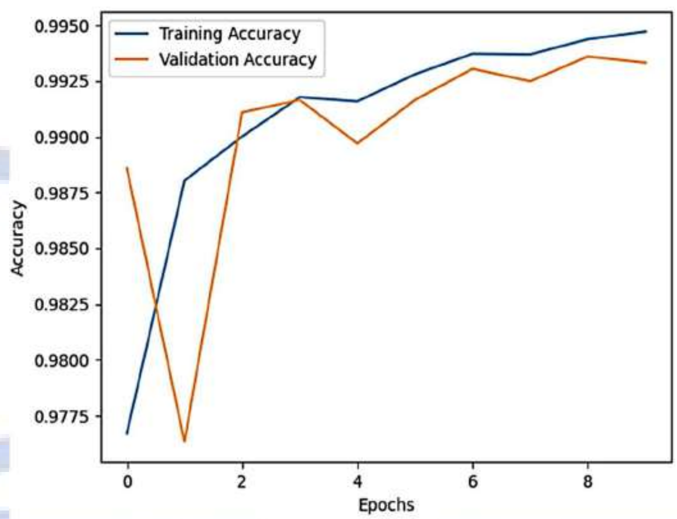

Figure 8: The Training and Validation Accuracy Graph of the Model

CONFUSION MATRIX OF THE MODEL

Figure 9 showcases the confusion matrix of the proposed fake news detection model.
This matrix offers a detailed breakdown of the model's predictions compared to the actual labels in the test dataset.

- **True-positive results (TP):** The program correctly identified 4624 instances of bogus news.
- **Real negative (TN):** The algorithm used correctly predicted 4301 occurrences of real news.
- **False Positives (FP):** The algorithm misidentified 26 occasions as incorrect information when they were really factual news.
- **False Negatives (FN):** The system incorrectly classified 29 instances of fake news as real.

Figure 9 depicts the recommended algorithm's matrix of disorientation visually. giving a clear picture of how well it performs in terms of both accurate and inaccurate classifications. The efficiency of the suggested fake news detection model is shown by the noteworthy numbers of actual positives and true negatives as well as the low incidence of false positives and false negatives.

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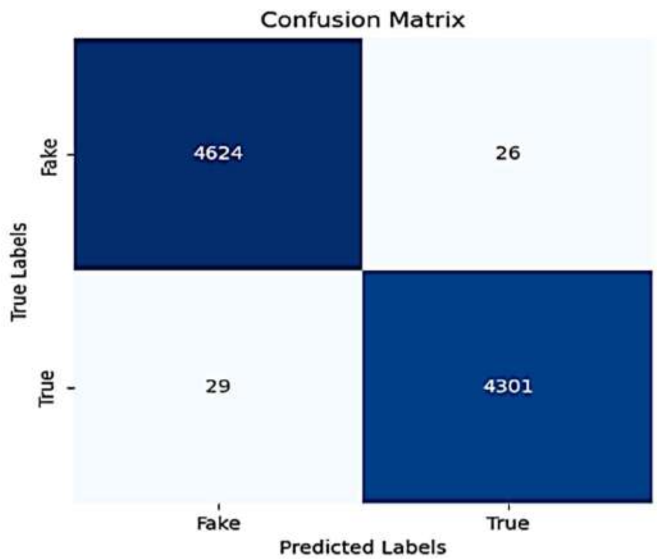

Figure 9: Model Confusion Matrix

MODEL PERFORMANCE METRICS

In figure 10, the suggested false news detection model's performance metrics are compiled. These metrics offer a comprehensive evaluation of the model's performance in classifying fake and true news articles. The precision for fake news (0.98) indicates that 98% of articles predicted as fake are indeed fake, while the precision for true news (1.00) signifies that all articles predicted as true are true. The recall for fake news (0.98) suggests that the model correctly identifies 98% of all actual fake news articles, and the recall for true news (1.00) indicates that the model correctly identifies all true news articles. Both fake and true news have an f1-score of 0.99, demonstrating high accuracy and reliability in classification by balancing precision and recall. The model's accuracy stands at 0.99, indicating that 99% of all news articles are correctly classified. The macro and weighted averages of precision, recall, and f1-score further confirm the model's robustness across both classes, highlighting its balanced performance. Figure 10 provides a visual representation of these performance metrics, showing a screenshot of the model's evaluation results. The suggested false news detection model's efficacy and reliability are validated by its high accuracy rate, recall, F1-score, and precision values.

	precision	recall	f1-score	support
Fake	1.00	0.98	0.99	4650
True	0.98	1.00	0.99	4330
accuracy			0.99	8980
macro avg	0.99	0.99	0.99	8980
weighted avg	0.99	0.99	0.99	8980

Figure 10: Screenshot of the Performance Metrics of the proposed model

FINDINGS

Several interesting findings arise from the testing and assessment of the proposed misleading information detecting methodology. First, the model has a phenomenal accuracy rate, averaging about 99%, suggesting its ability to distinguish between phoney and authentic news pieces. This high degree of accuracy demonstrates the efficacy of using a hybrid technique that combines Word2Vec and BERT embeddings to capture semantic and contextual subtleties in textual information. Furthermore, examining accuracy and recall rates demonstrates the model's capacity to reduce false positives and false negatives, hence increasing its dependability in real-world applications. The results also highlight the importance of visualisations like bar charts, line graphs, and confusion matrices in offering insights into the model's performance across different metrics and epochs.

CONCLUSIONS

To address the widespread problem of false information in digital media, this work presents a reliable false information identification algorithm which includes the advantages of Word 2 Vector as well as BERT embedding's. By harnessing Word2Vec's capacity to capture semantic relationships and BERT's contextual comprehension, the model exhibits improved performance in distinguishing between fake and true news articles. Through meticulous experimentation and evaluation. The utilization of a diverse dataset, comprehensive pre-processing techniques, and concurrent feature extraction methodologies contribute to the model's resilience and applicability. The findings highlight the importance of integrating sophisticated methods of spoken linguistic analysis into the systems for identifying misleading information, the algorithm can accurately differentiate true and false information, reducing the spread of disinformation and maintaining the legitimacy of digital conversation. The suggested approach marks a big step forward in the field of fake news identification, offering a viable way to counteract the spread of incorrect information in the media. As digital platforms expand, continual research and development efforts are required to improve the model's effectiveness and adaptation to new difficulties in the dynamic world of digital communication.

FUTURE RESEARCH

When evaluating future research paths, there appear to be numerous options for further investigation and progress in the area of false news detection:

- **Enhanced Model Designs:** Investigate new neural network designs and deep learning approaches for detecting bogus news. This entails looking at attention processes, neural networks with graphs, and transformer-based models to improve the model's ability to grasp complex verbal patterns and contextual interactions.
- **Multimodal Analysis:** Enhance false news detection systems by incorporating multimodal data sources such as text, photos, and videos. By assessing both textual information and supporting multimedia features, the model may gain a more complete knowledge of the context, enhancing its accuracy in detecting false news.
- **Cross-Lingual Detection:** Tackle the challenge of fake news detection in multilingual environments by developing models capable of detecting misinformation across different languages. This entails adapting existing detection techniques to a variety of linguistic contexts and investigating transfer learning approaches for transferring information from one tongue to another.

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