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Research Article

Deep Learning and Transformers Accuracy in Rumor Detection on Social Media

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Abstract: The increasing popularity of social media platforms has revolutionized how news and information are shared. While these social platforms facilitate rapid dissemination, they also provide fertile ground for the proliferation of rumors and unverified information. False information spreads as quickly as accurate news, often influencing public opinion and decision-making processes. Identifying rumors early is critical to limiting their potential harm and mitigating negative consequences. This study evaluates the practical application and scalability of transformer-based models, specifically GPT-2, in detecting rumors on social media platforms alongside traditional deep learning (DL) models. We explore various deep learning models such as Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), ALBERT, and GPT-2. Performance was assessed using standard evaluation metrics, including accuracy, precision, recall, F1-score, and analysis of Receiver Operating Characteristic (ROC) curves. The comparative results reveal that transformer-based approaches significantly outperform traditional DL models in detecting rumors with higher accuracy and reliability. Among the evaluated models, GPT-2 achieved the highest scores across all performance metrics, demonstrating exceptional capability in identifying and predicting rumor-laden content. This study introduces key innovations, including a direct comparative analysis of transformer-based and traditional DL models, highlighting GPT-2's advanced attention mechanisms that capture nuanced linguistic and contextual features. Additionally, it underscores GPT-2's scalability for real-world misinformation mitigation and critically examines dataset biases and adaptability challenges. Future advancements, such as multimodal approaches integrating text, images, and videos, as well as hybrid models combining transformers with traditional DL techniques, are proposed to enhance detection accuracy and efficiency. These findings underline the transformative potential of advanced AI techniques in combating misinformation on social media platforms. The research emphasizes the potential for scalable and practical implementation of GPT-2-based tools in mitigating false information dissemination, contributing to a more reliable and resilient digital ecosystem. This work advances the understanding of AI's role in mitigating the spread of false information.

Keywords: *Deep Learning (DL); GPT-2 Model; Rumor Detection; Social Media Misinformation; Transformer-Based Models*

1. Introduction

The undeniable role of social networks in today's world, on various aspects of human social life, is not hidden from anyone. The emergence and increasing popularity of social media and its services, such as Facebook and Twitter, have transformed the way news and information are shared. Now more than ever, people rely on social media for real-time updates, particularly during breaking news events. However, the rapid and extensive spread of hoaxes and rumors on these platforms has now become a very critical challenge in many situations that demand time, such as natural disasters, pandemics, and elections.

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Conventional rumor detection methods based on manual fact-checking and user reports usually cannot keep pace with the scale and speed of misinformation spread. In particular, to address this, there is an increasing surge of advanced computing techniques, such as deep learning and transformer-based architectures, toward automated and scalable rumor detection solutions [1-4]. In today's world, news media play a significant role in shaping public opinion and influencing governmental policies. The complex development of misinformative content online has stoked more recent state-of-the-art improvements with the application of NLP and deep learning for rumor detection. While capturing sequential patterns in text has proven to be effective, with promising performance seen by LSTM and CNN models, transformer-based models such as BERT, ALBERT, and GPT-2 have shown much more contextual understanding through self-attention. These approaches allow for much finer differentiations between true and false information, significantly enhancing the detection accuracy [5]. Ensuring the accuracy of information on the Internet and virtual networks has gained importance in recent years. Easy access to information by users and the ability to share content freely have facilitated the rapid dissemination of both verified and unverified news. The expansion of the Internet and the widespread adoption of social networks have turned these platforms into powerful information hubs. Traditional models for rumor detection, however, cannot cope with such a dynamically changing informational landscape and require adaptive and scalable solutions. Recent works combine NLP with transformer models to enhance robustness against variation in context and the evolution of linguistic patterns in misinformation. These AI-driven methodologies represent the huge shift from rule-based or statistical approaches, hence yielding a much more efficient and automated way of fighting against false information [5-6].

In this respect, considering the harmful consequences of spreading rumors among the general public, this paper will focus on recent advances of transformer-based architectures in rumor detection and emphasize their superiority over traditional deep learning models. We propose GPT-2 with improved attention mechanisms to improve the accuracy and scalability of misinformation detection for a more reliable digital ecosystem.

Without any verification, rumors have the potential to spread quickly among thousands of people and inflict significant harm. Rumor is a term for untrue information. According to some experts, a rumor is an unsubstantiated remark or piece of incorrect information that was either purposefully or mistakenly made and frequently contains damaging facts. Some define rumor as unsubstantiated claims about people, groups, events, and institutions [7-8]. Rumors may alternatively be described as unverified informational claims and associated instruments that circulate in an environment of risk, uncertainty, or possible harm and serve to educate about risk and help them manage it. Spreading rumors or false news may have a major detrimental effect on people's lives and on society as a whole. For instance, rumors can undermine the credibility of the news industry and raise people's suspicions about all social media content. People's perceptions of and reactions to actual news can be affected by fake news. Readers can be misled by rumors about a variety of things or individuals [7-8]. Readers can be misled by rumors about a variety of things or individuals. For instance, a person's political party beliefs can alter the findings of a survey. Also, sometimes, rumors can spread very quickly on social media, and recently, rumor-mongering has received attention in both academia and industry. Government officials and social media platforms are also trying to eliminate the negative effects of rumors [9-10]. Social networks can be risky for consuming news. Existing detection algorithms from modern and conventional news networks are rendered worthless or ineffective when it comes to identifying false news on social networks since they provide unique traits and difficulties. The purpose of fake news is to deliberately convince readers to believe erroneous information [10-11]. Online interaction through social networking platforms has increased, and most people tend to search and consume news from social networks instead of traditional news organizations. The reasons for this change in consumer behavior are inherent like these social network systems. For example, the consumption of social networks is compared to traditional networks such as newspapers or television. On the other hand, social networks make it simple to share, discuss, and debate news with friends or other readers [12-13]. It is also known that social networks are now using television as the main source of news. Social network news is of lower quality than that available in traditional professional groups, despite the advantages they provide. However, due to the cheapness of providing news online, it is much faster and easier through social networks. Major networks publish large amounts of fake news, that is, news articles with intentionally false information, online for various purposes, such as financial and political gain [14-15].

False information may be widely disseminated with positive effects on individuals and society. First, fake news has the ability to upset the natural balance of the ecosystem. Second, deceptive information aims to persuade readers to believe things they shouldn't. Advertisers frequently use fake news to spread divisive or powerful messages [16]. Fake news has become more potent as web-generated news has become more prevalent on social networks. A few features of this problem make automatic detection quite challenging. First of all, fake news is deliberately produced to mislead readers, making it challenging to identify based just on the content of the story. The goal of fake news is to suppress real news while distorting the truth in a variety of ways. The themes, methods, and network platforms of fake news content are widely varied.

For instance, insufficient textual factual evidence may be used by fake news to bolster an untrue assertion. Therefore, the existing and manipulated textual features of the data are usually not suitable for identifying fake news. The user's knowledge base and social vocations should be used as extra information to enhance detection. Due to a lack of supporting information or confirmed assertions, fake news frequently relates to recent and important events that may not be accurate despite existing knowledge bases. Users' social interactions with bogus news also generate a lot of unstructured, noisy, and incomplete information [16-17]. Addressing the challenges mentioned above, new research into the advancement of ML and DL provided more refined methods to identify fake news. A number of transformer-based systems with different architectures, such as BERT, ALBERT, and GPT-2 attained high performances by exploiting the contextual embeddings along with the attention mechanisms for better extraction of features from the textual data. These models outperform traditional ML approaches, such as decision trees and SVM, reliant on handcrafted features and are often ineffective against evolving tactics of misinformation. More recently, hybrid models that combine multiple learning paradigms, such as ensemble learning with CNNs and LSTMs, have also been proposed to enhance detection accuracy. These models capture both semantic and sequential dependencies and are more robust against adversarially generated fake news. Since a few years ago, false news has been prevalent on social media, yet the phrase "fake news" is undefined. False information is produced with the goal of misleading customers. In recent research, this term has received widespread acceptance. The veracity or aim of the news material is the main emphasis of general definitions of false news [18-19]. Social media is a significant source of false information. In social networks, certain new patterns may be utilized to identify bogus news. Graph-based methods also came into vogue, where network structures and propagation patterns make a difference between fake and legitimate news. Relationship analysis between users, content, and sources gives insight into discrepancies in dissemination trends, thus helping to enhance model reliability. Advanced false news detection techniques can be better understood by looking at how they are now used in various social network contexts [20]. Recent political events have led to the popularity and spread of fake news. Some of this news spreads in such a way that they are very close to reality and affect many people. Various methods have been proposed to automate the process of discovering fake news, the most popular of which are blacklists of unreliable sources and authors. While these tools are useful, more needs to be considered to create a complete solution for discovering such news. Explainable AI (XAI) techniques have recently been explored to improve interpretability in fake news detection models, helping researchers and policymakers understand how predictions are made. The detection of false news can be aided by Machine Learning and NLP algorithms [20-22]. The development of techniques that automatically identify bogus news on social networks is crucial to reducing the detrimental consequences of fake news. Given the significance of the issue of spotting fake news on social networks, this study tried to use an intelligent model to identify false news on Twitter [16].

In the following, several studies related to the topic of the research are reviewed. Ma and Gao [23] presented a model to improve the identification of rumors using the tree transformer approach. The findings demonstrated that the suggested method is accurate enough to identify rumors on Twitter and PHEME platforms. Malhotra and Vishwakarma [24] proposed a model based on graphic convolution networks and transformers to identify fake tweets by examining the structural and graphic features of tweet text. The results of investigations on 2 different datasets from Twitter showed that the proposed approach has appropriate accuracy. Al-Yahya *et al*. [25] investigated and compared the accuracy of NN-based models with Transformer-Based models in identifying Arabic fake news. The results and evaluation indicators showed that Transformer-based approaches are more accurate. A model was given by Kar *et al*. [26] to forecast bogus news about COVID-19 that is shared on Twitter. The proposed model is based on the BERT algorithm, which has high accuracy in identifying fake tweets in the Hindi and Bengali languages.

Abdelminaam *et al*. [27] used an updated Deep Neural Network based on LSTM and GRU algorithms to automatically predict fake news related to COVID-19 on Twitter. Finally, the results of 6 ML-based algorithms were compared to the accuracy of the suggested technique. The results proved the superiority of DL approaches. Wani *et al*. [28] presented a model to identify fake news related to COVID-19 on Twitter using DL approaches. For this purpose, CNN, LSTM, and BERT algorithms were used. The results indicated an improvement in the evaluation indicators. Ashraf *et al*. [29] used ML-based approaches to detect rumors in tweets related to COVID-19. Examining tweets based on English and Arabic languages showed that the proposed approach with appropriate extraction of features from text messages is accurate enough to predict rumors. Nassif *et al*. [30] in a study identified fake Arabic news on Twitter. By using the capabilities of transformer classifiers and embedding models, they showed that the proposed approach has appropriate accuracy. Ali and Malik [31] presented a transformer-based approach, the BERT algorithm, to investigate the textual features of Twitter to identify Rumor news. The investigation of the case study confirmed the acceptable accuracy of the proposed approach. The analysis of the literature revealed that some strategies and approaches have been put out in recent years to identify rumors, and the majority of them are based on machine learning techniques. The process of separating features from a dataset is a typical problem in most investigations. The feature extraction procedure is eliminated, and performance is significantly improved, thanks to the DL model. On the other hand, transformers are one of the common approaches in the fields of NLP and computer vision, which weigh the importance of each part of the input data by using the mechanism of attention to itself. The literature review showed that DL methods are heavily used in detecting fake news due to the automatic selection of features. Fake news is now seen as one of the biggest threats undermining public trust in governments. Fake news on Twitter spreads faster, deeper, and wider than real news. Therefore, in this study, by using approaches based on DL and transformers, a model was presented to predict and detect fake tweets on Twitter.

1.1. Innovation and Novelty

The present study innovates by showing that transformer-based GPT-2 performs much better than traditional deep learning methods such as LSTM and CNN in identifying rumors. Further, advanced attention mechanisms in GPT-2 have the potency of capturing nuanced linguistic and contextual features from the text, thereby attaining better performance with high accuracy and reliability. The paper presents a comparison of both types of models, pointing out the inability of conventional deep learning to handle the complexities of misinformation.

It is a vital contribution because it emphasizes the scalability of GPT-2 for real-world applications, demonstrating its great potential to be more widely deployed in misinformation mitigation. The study also critically examines dataset limitations, recognizing biases in labeled data and the challenge of adapting to the ever-changing nature of rumors. This ushers in further research on more diverse and adaptive training datasets.

It also goes ahead and gives an overview of the future of the methodologies, which will involve multimodal methodologies where text, image, and video will be included to do comprehensive rumor detection. This work also hybridizes transformers with traditional deep learning techniques for more efficiency. Finally, the study underlines the need to reduce computational cost by enhancing real-time detection for practical implementation in social media monitoring and public policymaking.

2. Methodology

The current research aims to investigate and compare several deep learning models in spotting rumors on social media. Figure 1 shows the flowchart of the research methodology. Data gathering is the initial phase, based on this figure. The Kaggle database was utilized to gather a set of textual data that was taken from social media and employed in this investigation. 2 classes of tweets are identified in this dataset: Both rumors and truth. After collecting the data, the data is pre-processed. Data preprocessing is a fundamental step in the learning process based on artificial intelligence methods, which increases the accuracy of predictions and classifications by improving the learning process.

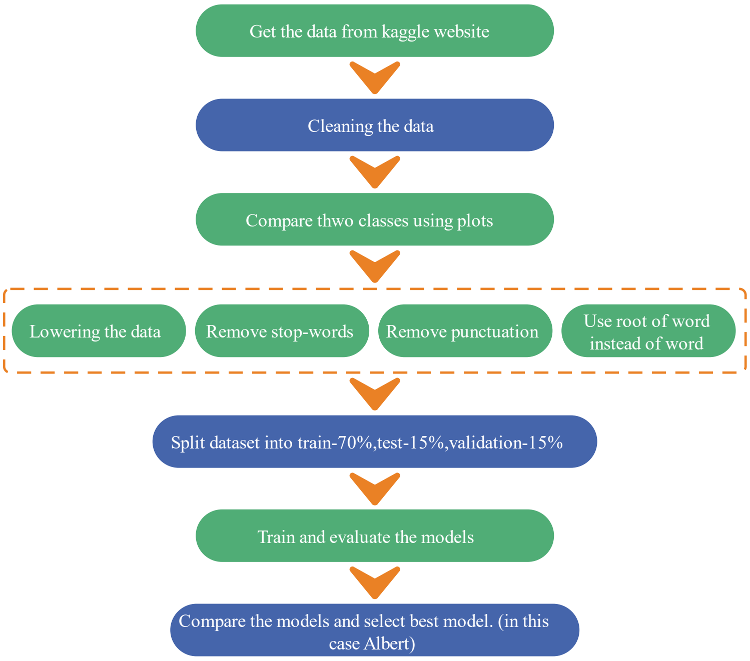

Figure 1. Flowchart of research methodology

In this study, lowering the texts, normalizing the texts, removing punctuation and stop words, and using the root of the word instead of the word were done for pre-processing. To find the roots of the words, the Lemmatization method was used. Stop words are frequently used and often unimportant words that come across a lot when working with text. Despite their frequent usage, these words have little significance in terms of meaning. Because of this, NLP activities typically remove them during the preprocessing phase when handling large amounts of data. Stop words are really frequently used terms that search engines, such as Google, are intended to ignore while indexing web pages and when retrieving them in response to a search query. Among these common words, "the, a, an, in" can be mentioned. Stop words have no propensity to occupy database space or consume important processing time when using NLP. For this reason, these words can be easily removed by saving the list of stop words [31-32]. The main goal of text normalization is to integrate and make characters uniform to have more control over the results of more advanced text processing. More precisely, these integrations include things such as character refinement, extra spaces, removing extra spaces, removing extra newlines, removing extra semi-spaces, and removing letter stretches and carriage returns [33-34]. Lemmatization groups several variants of the same word and breaks it down to its most basic form. For instance, past tense verbs are changed to present tense, and synonyms are combined to create words that have the same meaning as their roots. Lemmatization takes an alternative route to determine words' root forms, even though it appears to be closely tied to the rooting process. The advantage of the Lemmatization method is not to produce irrelevant words as roots. Of course, the speed of this method is lower than Stemming because a search must be done [34-35].

The data provided in three classes—rumor and non-rumor—were analyzed and contrasted in the following. Additionally, the correctness of various models was verified by dividing the data into three sections: training, testing, and validation, with 70%, 15%, and 15%, respectively. The models used in this study were 4 different models based on 2 main approaches, i.e., DL and transformer (which are subset of DL), to provide a 2-class classification model. Algorithms based on DL include LSTM and CNN and algorithms based on transformer include Albert and GPT-2 from huggingface. The 2 LSTM layers in the given LSTM have 100 units each. Also, the presented CNN model consists of 2 convolutional layers with 100 filters for each. In the definition of these 2 models, the embedding size was considered equal to 128. The maximum vocabulary is set to 10,000 words and the maximum length is equal to the length of the longest sentence, i.e., 30. Different language models can learn word embedding, which is a dense representation of words in the form of numerical vectors. The word embedding representation can show a variety of hidden connections between various words.

In the following, after learning each of the algorithms, the accuracy of the proposed approaches was checked and compared using different evaluation indices, and the best approaches were selected. These indices include ROC-AUC, Precision-Recall AUC, Accuracy, Precision, Recall, and F1-score. The Receiver Operating Characteristic (ROC) curve is a key technique for evaluating binary classification models, integrating Sensitivity (True Positive Rate) and Specificity (1 - False Positive Rate) into a single curve. It quantifies the model's overall discriminative ability, with higher values indicating better separation between rumors and legitimate content.

However, ROC-AUC may not fully reflect performance in imbalanced datasets, where false positives and false negatives carry different risks. In such cases, Precision-Recall analysis provides deeper insight, especially when identifying rare instances of misinformation. PR-AUC measures how well a model balances precision (how many detected rumors are truly rumors) and recall (how many actual rumors are correctly identified), making it particularly useful for misinformation detection [36].

By considering both ROC-AUC and PR-AUC, we ensure a more comprehensive evaluation of rumor detection models, balancing sensitivity, specificity, and real-world applicability [37-40]:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}m \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{P} = \frac{TP}{TP+FN} \tag{3}$$

$$F1\ Score = \frac{2\times Recall \times Precision}{Recall+Precision} \tag{4}$$

Evaluation metrics are highly important in establishing practical performance for systems that automatically detect rumors. While accuracy is more general as a measure of the correctness of a model, it does not represent performance when the dataset is imbalanced, where one class dominates the other. Thus, precision, recall, F1-score, and ROC-AUC are important for a more nuanced evaluation.

Precision is defined as the ratio of correctly detected rumors among all reported as such; high precision will prevent the situation of losing trust on social media sites by mislabelling true content as fake. The recall, in this case, gives the percentage of true rumors which the model has correctly identified. A high recall score means that fewer examples of misinformation will slip by undetected; the possibility of continuing to spread false information is thereby lowered.

While F1-score is a balanced measure in which precision and recall are combined, therefore, it is more suitable for cases of imbalance in the number of instances of rumor and non-rumor. Moreover, ROC-AUC actually quantifies how well the model can classify between rumors and legitimate content across different classification thresholds. A higher AUC indicates a better trade-off between a true positive rate and false positive rate, translating into the fact that the model can effectively discriminate between rumors and non-rumors under differing scenarios.

By including such evaluation metrics, we make certain that the theoretical grounds for the proposed models sound and their effectiveness in performing real-world rumor detection tasks is practical as well.

2.1. Experimental Setup

The experiments were done on a system with an NVIDIA Tesla P100 GPU, 16GB VRAM, 13GB RAM, and a 2-core CPU. In the training process, we have used the Adam optimizer. For Transformer-based models (ALBERT and GPT-2), we take the learning rate to be 1e-5 and 1e-4 for the deep learning model. The fact that Transformers are usually much bigger in size implies the usage of lower learning rates. The models used were trained with 100 epochs and binary cross-entropy objective loss.

2.2. Description of the Dataset

The dataset used in this study consists of a total of 62,443 samples, all in English. The class distribution is 48,619 samples labelled as non-rumor and 13,824 samples labelled as rumor, as visualized in Figure below based on topic. Among these samples, 471 samples were in French, and since ALBERT is English in nature, they were removed. The dataset used in this study is the textual dataset of social media, which is available under the name "PHEME Dataset for Rumor Detection" through the Kaggle database. This dataset contains 61,371 data, which focuses on **two** main events, including the Germanwings crash and Charlie Hebdo, and labels the data into **two** classes: rumor and non-rumors. Figure 2 shows a bar plot related to the frequency of data in each class for data of test.

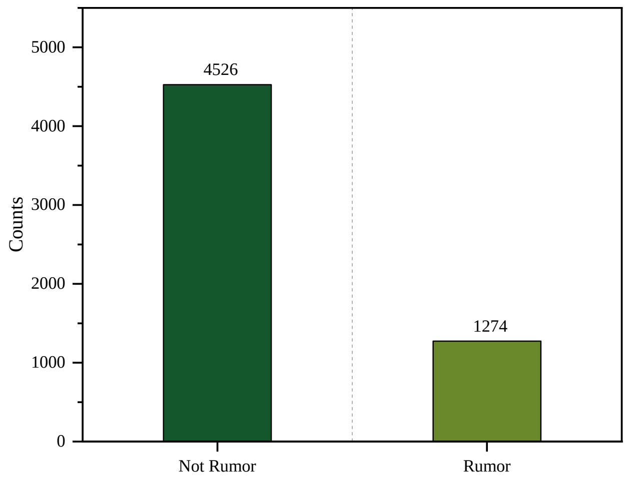

Figure 2. Bar plots Comparing the Frequency of Data in Classes for testing

Figures 3 and 4 show 30 frequently used words applied in the rumor and non-rumor classes, respectively.

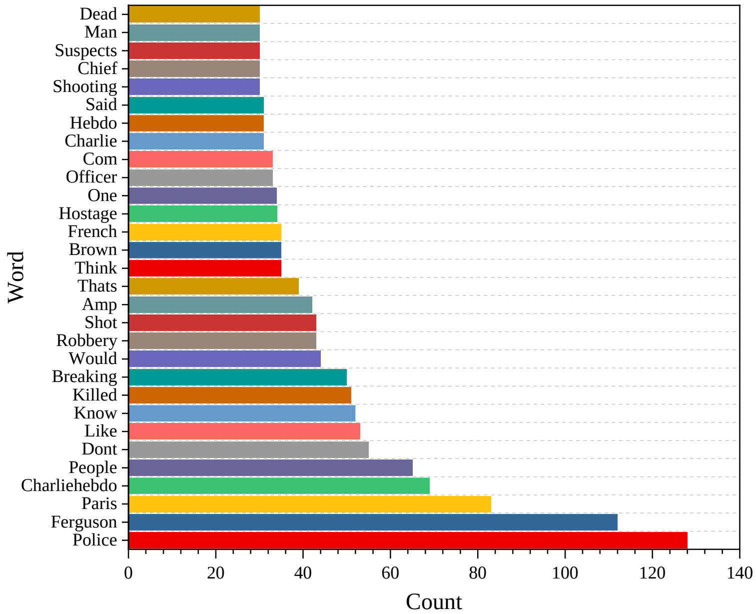

Figure 3. Thirty of the most frequently used words were used in the rumor class

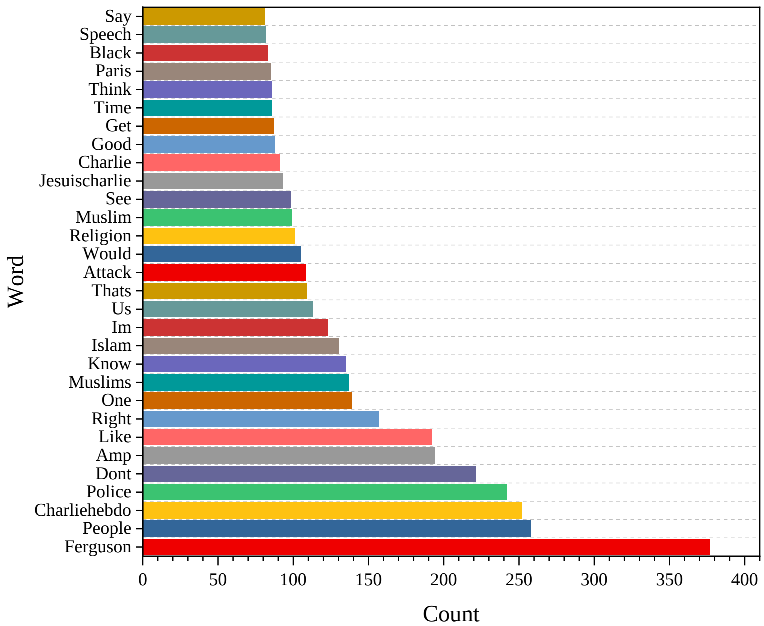

Figure 4. Thirty of the most frequently used words were used in the non-rumor class

According to these figures, the most tweeted words were Police, Ferguson, and Paris for rumors and Ferguson, People, and Charlie Hebdo for non-rumors. Figure 5 demonstrates the distribution of the dataset based on the topic.

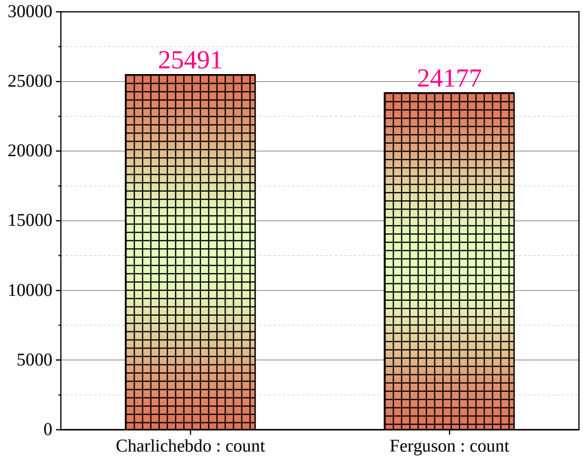

Figure 5. Bar plots Comparing the Distribution of the Data for each Topic

We fix the maximum sequence length for deep learning models as 35, which corresponds to the longest sentence length, and embedding dimension as 128. In Transformer-based models, we did not change these parameters and used the default values for these hyperparameters in order to make full utilization of their pretraining.

Also, stop symbols were removed before training and replaced with placeholders. Since most tweets would have contained stop words, which usually are neutral in embedding and feature extraction, their replacement with placeholders helped reduce both the embedding matrix dimensions and maximum sequence length and hence the computation costs. For GPT-2 and ALBERT, their respective tokenizers were used by default and ignored or replaced the stop words where necessary. Besides, because these models have already been pre-trained on raw text, usually minimal preprocessing is necessary.

3. Description of the Models

A brief description of the utilized DL models, including the transformer-based models such as ALBERT and GPT-2 along with the LSTM and CNN are introduced in the following.

3.1. Transformer-Based Models

Several transformer models have appeared in AI. The DL model known as the transformer uses the attention mechanism. NLP research typically uses this model. The basic transformer architecture is a special form of encoder-decoder model. This model has a group of encoders and decoders that are connected together. The Self-Attention layer and the Feed-forward neural network are the 2 distinct sub-layers that make up each encoder. A Self-Attention layer is the first thing the encoder input goes through. A feed-forward neural network layer receives the output of the Self-Attention layer. Each decoder also has 2 layers of Self-Attention and Feed-forward neural network. After each input word is converted into the desired vector and so-called after the embedding process, each of the 2 sub-layers in the encoders is passed. Here it is important that these words enter the encoder in parallel, which is one of the distinguishing features of the Transformer Model. Since the development of the transformer model, popular models such as BERT and GPT-2 have adopted aspects of the original architecture using encoder or decoder components. The main similarity between these models lies in the layered architecture, which incorporates self-awareness mechanisms and feed-forward layers [41-42]. In the following, the transformer models including Albert and GPT-2 are briefly described.

3.1.1. A Lite BERT (Albert)

The BERT model uses the Transformer architecture but differs from it in several ways. The point to be noted is that all these models are different from Transformer. Designed to help computers understand complex text, BERT is an open-source ML framework for NLP. The BERT system may be designed to use question-and-answer datasets and was pre-trained on Wikipedia text [43]. This model, which draws inspiration from Transformers, is a dual-link model (DL) where each output and input element is connected, and the weight between them is dynamically decided based on their connection (this process is known as attention in NLP). Prior to now, language models could only analyze text input sequentially—that is, from left to right or from right to left—rather than concurrently. BERT is unique in that it can simultaneously read in both directions. Transformers activate this feature, known as bi-directionality. The model is pre-trained using only a simple text collection (i.e., Wikipedia). BERT can react to user requirements and the ever-growing volume of searchable material and queries. Transfer learning is the term for this procedure [44]. Google Research created the open-source NLP model Albert. It stands for "A Lite BERT". The Albert model was designed to be more memory-efficient and computationally faster than the original BERT model while maintaining similar performance. It achieves this by implementing parameter-sharing techniques and reducing the model size. Using self-attention processes, the Albert model architecture employs the transformer-based methodology to capture contextual connections in text. Unsupervised techniques, like masked language modeling and sentence order prediction, are used to train it on large-scale corpora [45].

3.1.2. Generative Pre-trained Transformer 2 (GPT-2)

Researchers and programmers have enthusiastically embraced GPT-2 for a range of NLP applications, including text completion, summarization, translation, and more. It has significantly advanced the field of language generation and continues to be a prominent model in the NLP community [46]. The cutting-edge language model GPT-2 was created by OpenAI. It is a successor to the original GPT model and has gained significant attention for its impressive language generation capabilities. GPT-2 employs a transformer-based design, like the BERT and Albert models. Numerous layers of feed-forward NNs and self-attention processes make up its structure. GPT-2 can capture long-range relationships and produce language that is logical and contextually appropriate thanks to the transformer design. Unsupervised learning is used to pre-train GPT-2 using a sizable corpus of text data. It gains the ability to anticipate the following word in a phrase based on the preceding words. This process helps GPT-2 develop a deep understanding of language, grammar, and semantic relationships between words [47-48].

3.2. Description of DL-Based Models

DL has proven to be a very powerful tool due to its ability to handle large amounts of data. In the following, the DL-based algorithms used in this study will be briefly described, including LSTM and CNN algorithms.

3.2.1. Long Short-Term Memory (LSTM)

A particular type of RNN is the long short-term memory, or LSTM. One of the classes of neural networks that are defined by the internal memories are called recurrent neural networks or RNN. In essence, this is an expansion of a regular neural network whereby the internal loop is feeding the previous output and current new input to maintain the context for the next output. The network can access both new and old data through this loop, enabling it to produce the required output. This RNN network capability enables working with sequential data, including text, audio, and other types of media [49]. The model resolves the RNN network's long-term memory issue. Gates are intrinsic components of the LSTM network. These gates regulate the information flow. Additionally, they outline which sequenced data should be destroyed and which should be maintained for importance. The network does this to transfer crucial data along the chain of events in order to get the desired result [50]. Because of LSTMs, RNNs have long-term memory for inputs. This is because LSTMs store information in memory similarly to a computer's memory. Data may be read, written to, and removed from the memory of the LSTM. The cell that decides to store or delete information (i.e., open or shut gates) depending on the value it assigns to the information may be thought of as a gate in this memory. Weights are used to assign importance, and the model learns these weights. It thereby learns to make a difference between important information and irrelevant data progressively. LSTM networks include feedback connections unlike the classic feed-forward neural networks used broadly in deep learning and AI. Like RNNs, they also process in sequences of input data or discreet data such as speech or video. For example, LSTM is employed in the fields of healthcare, robotics, speech recognition, machine translation, and video gaming. In the LSTM design, cells, which are repeating modules, interconnect like links in a chain. Each cell's 3 main components are an input gate, an output gate, and a forget gate. These gates regulate the information flow through the cell so that the LSTM knows which information to accept, reject, or output to the next cell [51-52].

3.2.2. Convolutional Neural Network (CNN)

The most widely used DNN is perhaps the convolutional neural network. A CNN is a special type of neural network, designed to emulate human vision. Over time, they have grown to become a core component of many machine vision applications. CNN has a variety of applications, and in addition to photos and videos, it can also be used in the analysis of other types of data, such as text or voice processing. These networks use convolution layers to extract features from images and have been successful in tasks such as object detection and image segmentation. DL employs these networks to evaluate visual data. Images, audio, texts, movies, and other media can all be handled via these networks. A system of hardware or software known as a neural network is based on how neurons in the human brain work. This model arranges its neurons more like neurons in the frontal lobe, the region responsible for processing visual stimuli in humans and other animals [53]. The structure of a CNN is modeled by the arrangement of the visual cortex and resembles the neuronal connections in the human brain. Only a small portion of the visual field, known as the receptive field, is used by individual neurons to react to stimuli. These fields cross over one another to fill the whole visual field. Convolutional layers are the fundamental components of CNNs. Input vectors like images, filters like feature detectors, and output vectors like feature maps are frequently seen in this layer. In actuality, a CNN's convolution layer serves as its central building component and is where the majority of computations take place. Other layer types, such as pooling layers and fully linked layers, are also used by CNNs. By combining layers, feature maps' spatial dimensions are reduced, thus down-sampling the data and strengthening the network's resistance to changes in the input. Max pooling, which chooses the maximum value inside each pooling window, is a frequent pooling method. The final classification or regression operation based on the retrieved characteristics is carried out by fully linked layers. The capability of CNNs to automatically learn hierarchical representations of the incoming data is one of its benefits. The deeper layers of a CNN learn more complicated and abstract properties, whereas the top levels learn low-level features like edges and textures. CNNs are proficient in identifying spatial correlations and patterns in pictures because of this hierarchical feature extraction [54-55].

4. Results and Discussion

In this section, the accuracy of different approaches is analyzed based on evaluation indices. The values of the assessment indices for the models under investigation are displayed in Figure 6. This graphic illustrates how the evaluation index values of transformer-based models are higher than those of DL-based models. Consequently, it can be said that transformer-based models perform better when it comes to categorizing and recognizing rumor news on social media. According to this, it can also be found that the GPT-2 algorithm has the best performance compared to other algorithms. All the index values of the GPT-2 algorithm are higher than the values corresponding to the ALBERT algorithm. Conversely, the LSTM method performs worse than other algorithms since its evaluation index values are the lowest when compared to the comparable values in other models.

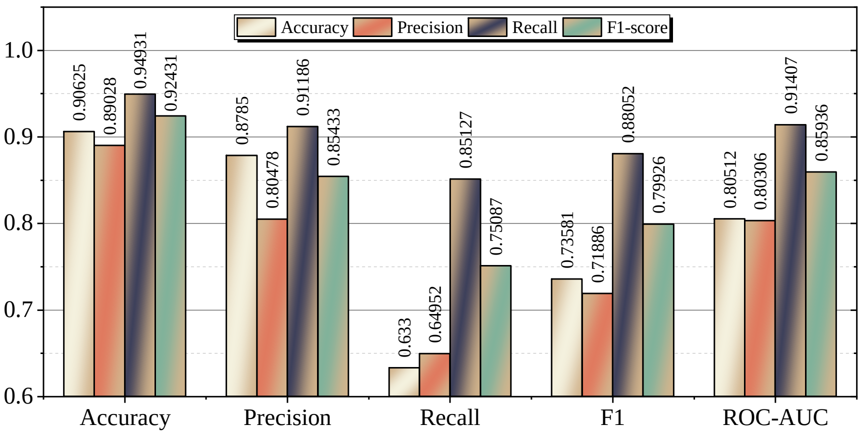

Figure 6. Comparation of Models Based on the Evaluation Metrics Denoting the Outperformance of the transformer-based models such as GPT-2

GPT-2 outperforms traditional models, such as LSTM and CNN, by a large margin in performance due to its advanced contextual learning capabilities and superior handling of sequential data. Unlike LSTM, which is designed to process information in a step-by-step manner, GPT-2 uses a transformer architecture that processes entire sequences of data at once, capturing long-range dependencies more effectively. Especially useful in rumor detection, where the meaning and subtle relations between words are critical over a long stretch of text, this proves helpful. Because GPT-2's attention mechanism can focus on the most relevant pieces of input, it is able to capture more nuanced linguistic features than those that traditional models might have captured. Besides, GPT-2 is scalable, hence it can handle large datasets with more efficiency, making it a powerful tool in the detection of rumors on social media platforms when compared to LSTM and CNN-based models.

In the other hand, such poor performance of LSTM in rumor detection could be for several reasons: sparsity of data, limitations in model depth, and computational constraints. An LSTM model, while pretty good for sequential data, fails to recognize long-range dependencies in a sparse dataset or even when sufficient context is not provided. This might eventually result in the failure to provide realistic performance in identifying the subtle patterns related to rumor-based content. Additionally, shallow architectures in LSTM models restrict their capability to learn complex relationships within the data, which is a significant drawback for rumor detection. Further, LSTM models tend to involve more computational resources, especially when working with larger datasets, restricting scalability and efficiency compared to transformer-based models like GPT-2. These factors lead to the overall lower accuracy with LSTM that was observed in our study.

In Figures 6 and 7, the performance of the models is checked based on ROC curves and Precision-Recall curves, respectively. In Figure 7, the point with coordinates (0, 1) in this graph will have the best classification performance since it has the highest recovery or sensitivity rate and the lowest error rate. This point represents perfect classification. In this curve, the ROC space is divided into 2 parts by a diagonal line. The area above this line constitutes the favorable area (better than random classification) and the unfavorable area (worse than random classification) of these sections. In Figure 8, the point with coordinates (1, 1) represents the ideal classification point in Precision-Recall curves. The closer the Precision-Recall curves are to this point, the better the classification performance of this model.

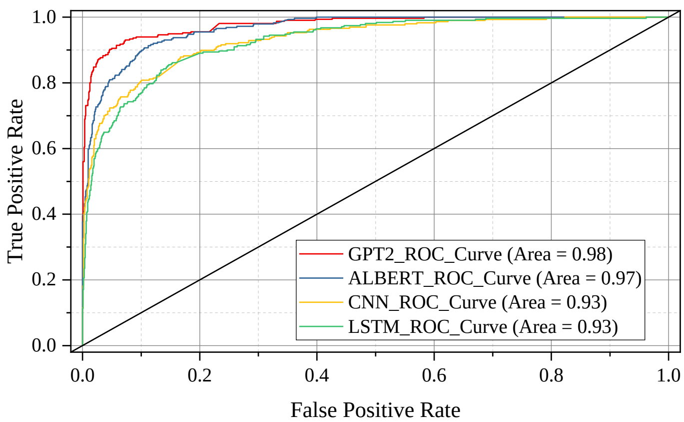

Figure 7. Model's performance as determined by ROC curves Indicating better performance of GPT-2

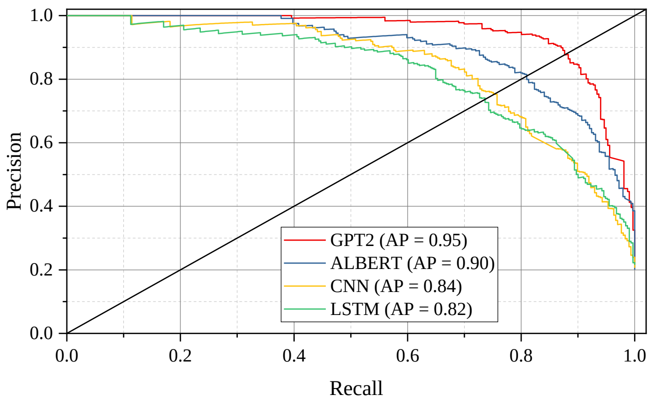

Figure 8. Model's performance on the basis of Precision-Recall curves showing the Outperformance of GPT-2

According to Figure 6, it is clear that the ROC curves of transformer-based models are higher than the ROC curves of learning-based models. The area enclosed by the ROC curve related to the GPT-2 algorithm is equal to 0.98, which has the highest value compared to the others. As a result, the ROC analysis likewise supports the GPT-2 algorithm's superiority over other methods. According to the results of Figure 7, Precision-Recall curves also confirm the superiority of transformer-based models. Also, the area enclosed by the Precision-Recall curve related to the GPT-2 algorithm is equal to 0.95, which has the highest value compared to the others. The Precision-Recall curve related to this algorithm is in a higher relative position than other algorithms, which shows the superiority of this algorithm over others.

Ethical considerations should, therefore, be at the forefront when deploying automated rumor detection systems, especially on social media platforms. Among these, privacy is a major concern, where personal data used for training these models may lead to unintended violations of user privacy unless handled appropriately. Data anonymization and users' consent are required where necessary.

Another important problem is that of the biases in the dataset, which, if not taken care of, can lead to biased outputs. For instance, if some social groups or topics are overrepresented in the training data, the model will tend to overclassify rumors from those underrepresented groups, compromising fairness and accuracy. Alike biases would be pacified if the training dataset is kept under continuous curative state and monitoring performance continuously in diverse settings.

In addition, the false positives and false negatives in rumor detection may have severe real-world consequences. For example, false positives refer to flagging factual information as a rumor, which might cause harm to legitimate discourse and damage reputations, while false negatives refer to failing to detect rumors, which may allow misinformation to spread. A balance of these risks is important, and it really underscores the need for fine-tuning these systems to reduce such mistakes, especially since they are finding applications in real life where they shape public opinion and decision-making.

Compared to previous studies, our proposed models for rumor detection on social media demonstrate significant improvements in performance metrics.

Shu *et al*. [16] achieved an accuracy of 0.689 and an F1-score of 0.717 using the SAF model for fake news detection. Our best model, GPT-2, outperforms this study substantially, reaching a ROC-AUC of 0.98 and a precision-recall value of 0.95, indicating a much higher reliability in distinguishing rumors.

Reddi and Eswar [18] employed a geometric deep learning approach and attained a ROC-AUC of 92.7% for fake news detection on social media. Our GPT-2 model surpasses this result with a ROC-AUC of 98%, showing enhanced classification capabilities.

Malhotra and Vishwakarma [24] used a RoBERT model for rumor detection based on a transformer. The accuracy was 0.865, while the F1-score value was 0.874 for the non-rumors data. While their approach demonstrates strong performance, the ROC-AUC value of 0.98 suggests a more robust discrimination capability of our GPT-2 model; likewise, the precision-recall of 0.95 depicts better reliability in handling imbalanced datasets of rumors.

Nasir *et al*. [21] developed a hybrid CNN-RNN-based deep learning approach, which achieved precision of 0.59 and a recall of 0.6. In contrast, our GPT-2 model attains a much higher precision-recall score of 0.95, reflecting a significant improvement in both precision and recall, which are critical for minimizing false positives and false negatives.

The Table 1 in the following presents a tabular comparison of the aforementioned studies with the presented results in this paper.

Table 1. Comparing the proposed study with state-of-the-art studies

Study	Model	Accuracy	Precision	Recall	F1 Score	ROC-AUC
Shu *et al.* [16]	SAF	0.689	-	-	0.717	-
Monti *et al.* [18]	Geometric deep learning	-	-	-	-	92.7%
Malhotra and Vishwakarma [24]	RoBERT	0.865	-	-	0.874	-
Nasir *et al.* [21]	CNN-RNN	-	0.59	0.6	-	
Proposed Study	GPT-2	-	**0.95**	**0.95**	-	**98%**

Overall, our study achieves state-of-the-art results, especially with GPT-2, demonstrating superior classification performance in rumor detection on social media. Our improvements stem from leveraging advanced transformer architectures, effective model fine-tuning, and a well-structured dataset, leading to a more accurate and reliable detection system.

In general, LSTM and CNN work with very minimal computing, hence making them efficient to work with in resource-constrained environments. However, ALBERT is even more efficient compared to LSTM and CNN but at the cost of high computational resources. GPT, being the largest model in this comparison, requires the highest computational cost in training and inference.

Considering the system latency, simpler architectures like CNN and LSTM support faster inferences. They are much more suitable for real-time applications in detecting rumors. ALBERT is a moderate trade-off against precision in processing speed. Contrasting, due to its massive model size, GPT provides the longest time for processing with the highest accuracy.

Among these, deployment challenges vary: CNN and LSTM are relatively easy to deploy because they do not need high hardware resources; ALBERT is optimized for efficiency, but careful tuning is nevertheless required for actual deployment; and GPT-which has quite high computational resource demands-almost always requires a distributed solution if one wants a real-time application.

5. Conclusion

Rumor news is spread on websites and social media just like accurate information. As a result, rumors can significantly influence choices and public opinion. The most common types of misleading and unverified information are fake news and rumors, which must be identified as quickly as possible to prevent negative consequences. In recent years, there has been a sharp rise in interest in efficient detection methods. In NLP and text mining, the challenge of identifying fake news is referred to as a classification problem. Its goal is to separate and identify false from true news in extracted texts and increase the accuracy of identifying false news. Therefore, this study aims to present a model for detecting and identifying fake news by examining models based on DL and transformers. DL models include LSTM and CNN and transformer algorithms such as ALBERT and GPT-2. Examining evaluation indices and analysis of ROC curves showed that transformer-based approaches are more accurate than traditional deep learning models. The results showed that the GPT-2 algorithm has the highest values of evaluation indices and thus the highest accuracy in predicting and detecting rumor tweets.

Although the proposed model is very effective, there are a few shortcomings. First of all, this research study relies on the data provided by social media. Its performance is not evaluated for any other social networking site like Facebook or Instagram. In future, one might test its adaptability on various platforms where rumors would look different. Further, the dependency on labeled datasets for training restricts the model's generalizability due to the dynamic nature of the distribution of rumors on social media. Moreover, a bias in the datasets that may not completely represent all possible linguistic or cultural contexts is a limitation. More diverse data sources could be considered in future studies to make the model robust in different languages and regional variations.

Future research will be related to enhancing the capability of the model by introducing multimodal approaches, such as the inclusion of images and videos along with text for more comprehensive rumor detection. Further, hybrid models that combine the strengths of both traditional DL techniques and transformers may provide more efficient and scalable solutions. The main direction for the future is expanding the dataset to other social media platforms and making the model more flexible in terms of other types of rumors. Finally, reducing the computational cost and improving real-time detection of the rumors would be a big step toward a successful application of the model in both social media monitoring tools and public policy-making initiatives.

CRediT Author Contribution Statement

Long Yu: Data curation; Jiarui Dai: Writing – original draft; Jiaqi Dai: Formal analysis; Yanan Wang: Software.

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