Fake News Detection And Summarization Using Deep Learning

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Date: January 2026

1. ABSTRACT

This paper presents a hybrid deep learning approach combining Recurrent Neural Networks (RNN) and Graph Neural Networks (GNN) for fake news detection, integrated with transformer-based text summarization. Using Kaggle's Fake News dataset, our RNN achieves 85.2% accuracy while GNN reaches 87.1%. The Pegasus transformer generates coherent summaries (ROUGE-L: 0.75) for verified articles. The integrated pipeline provides both classification and digestible summaries, addressing the dual challenges of misinformation detection and information overload in the digital age.

Keywords: Fake News Detection, Text Summarization, Deep Learning, RNN, GNN, Transformers, Natural Language Processing

2. INTRODUCTION

Perhaps for the first time in history, accessing information is unprecedented. Anyone, with or without any credentials, can read news about what is happening in the world instantly. Thanks to social media and online news websites, an individual can read news as it happens in virtually every corner of the globe. But with that surge in instant information comes this pressing concern: fake news.

False news is information, written or spoken, that gives out false or misleading information for the purposes of misleading readers. More seriously, it affects society as a whole through distortion of public opinion, influencing elections, undermining trust in other institutions, and even promoting violence. Fake news was made worse by the spread on social media, considering the mechanisms of verifying authenticity are much less rigorous than many other platforms.

The detection of fake news is of a complex nature. Unlike spam and misinformation, pieces of fake news assume the news's format, tone, and style with much finer fineness, which makes it difficult to be detected by rule-based techniques. Thus, more advanced methods are being searched by researchers, especially in the forms of artificial intelligence and natural language processing, to come up with models that can correctly identify fake news. With techniques in deep learning, which can handle large data inputs and capture subtle patterns in text, it is proving to be one of the powerful tools in this domain.

Information overload is yet another critical challenge one faces in this new information landscape. The constant flow of news updates has overwhelmed humans to cope with it all. It has increased interest in automatic text summarization techniques, which can represent massive amounts of information in a concise manner summarizing the main points of a text. Conveniently, the combination of text summarization with detection of fake news is another valuable remedy because it detects not only potentially misleading content but also delivers it in a consumable format.

This paper addresses two key issues facing the fake news problem: (1) the detection of fake news by deep learning models and (2) the generation of concise text summaries. These two complementary tasks should help create a system to enable users to make informed decisions while navigating the vast and often confusing information space.

3. RELATED WORK

3.1 Fake News Detection

Recent years have seen enormous strides in research regarding the detection of fake news, primarily as deep learning techniques emerged. Old approaches for detecting fake news involved rule-based methods or keyword matching; though useful in many senses, they were very limited and led to a failure in handling the intricacies that make human language complex. Most of these approaches failed when it came to sarcasm, the ambiguous phrasing of fake news, and the subtle cues indicating a difference between fake news and actual reporting.

The modern approaches to fake news detection extensively employ machine learning along with deep architectures like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), mostly with Long Short-Term Memory (LSTM) units, where the patterns within the textual data might have been difficult to identify. Recently, Kaliyar et al. (2020) proposed a deep learning model using Gated Recurrent Units (GRUs) in an effort to detect fake news in the process of capturing long-term dependencies in the text. The study found this deep learning model more accurate and precise as compared with traditional machine learning classifiers, such as Support Vector Machines (SVMs) and Naive Bayes, which are generally used in text classification tasks.

Ajao et al. (2020) employed a Hybrid CNN-RNN model for fake news detection. This model mainly captures local features with the help of the CNN component and also tracks sequential patterns with the RNN component. The hybrid recognition of both local and global patterns was what made the model move ahead better compared to the models based solely on one type of architecture.

Graph Neural Networks (GNNs) have also been experimented on for fake news detection since they can model the relationship between news articles, users, and sources. Thus, by having a graph with news articles as nodes and their interactions as edges, GNNs can identify structural patterns that might tell whether a given news is fake or real. Zhou and Zafarani (2022) proposed a GNN-based model that learns to make use of such relational information to enhance the detection of fake news. This work is therefore more representative of the shift toward working on graph-based models for more complex dependency-based tasks.

3.2 Text Summarization

Text summarization is one of the major tasks in Natural Language Processing (NLP), which is highly critical in this digital age, where humongous content is being produced each day. Early solutions to this problem relied on extractive-based methods, whereby key sentences or phrases were chosen from the original text to form the summary. This type of method was straightforward to implement but generally culminated into incoherent or context-irrelevant summaries.

Probably, abstractive summarization methods have lately gained much importance. In fact, because abstractive methods deviate from extractive ones, which merely pick existing text, abstractive methods formulate entirely new sentences to express the main ideas of the original text. So, there is a need for an understanding of the text itself and of sentences formulated grammatically and pragmatically in their environments. For this task, sequence-to-sequence (Seq2Seq) models combined with attention mechanisms are prevalently used. Nallapati et al. (2016) was among the early implementations of a Seq2Seq architecture for automatic summarization using RNNs with added attention layers that would be able to generate quality summaries.

More recently, transformer-based models have achieved state-of-the-art performance in the realm of text summarization tasks, mostly because of their ability to capture long-range dependencies in the text through self-attention mechanisms. This is far more effective than the traditional models that depend on RNN, which become struggle-prone for long sequences. Attention mechanisms enable a model to focus on the relevant parts of the text, making their summaries coherent and content-suitable. In Chen and Bansal's work (2018), reinforcement learning was used in text summarization to enhance the quality of summaries by training the model to optimize summary quality.

3.3 Combining Fake News Detection and Text Summarization

While tasks of fake news detection and text summarization are generally considered rather separately within the domain of NLP, much attention nowadays is centered on integration between the two in order to eventually gain better control over digital information streams. Processing detected fake news through a summary would enable users to quickly understand what the core message of the article is and then make better decisions based on that basis. This also reduces the cognitive load when users would otherwise have to wade through long articles in order to establish whether the contents are authentic.

Li et al. (2020) explored a hybrid model with fake news detection coupled with text summarization. It used both extractive and abstractive summarization techniques and approached to summarize the article's content first and then judged its veracity. This method proved that the summarization of the article before filtering it for fake news improved the overall accuracy of the fake news detection model by filtering the redundant or less relevant information.

Kaur and Chopra (2020) apply attention mechanisms for both of these tasks. This shows that models trained to pay attention on key parts of the text can perform well on both short summary generation, as well as fake news detection.

It has been through transformer models that the integration of these tasks will even have a further boost. According to Nguyen et al. (2023), fine-tuning pre-trained transformer models on news datasets should enable effective fake news detection and summarization in one pipeline primarily because state-of-the-art performance on both tasks was accomplished by capturing long-range dependencies and contextual relationships within the text.

4. METHODOLOGY

This section describes the methodology adapted for both tasks that we executed: fake news detection and text summarization. To this end, we use deep learning models to establish that these two tasks can be accomplished by integrating multiple architectures, preprocessing, and evaluation metrics. The following subsections detail the models adopted, the datasets, and the training and testing steps we used.

4.1 Fake News Detection via Recurrent Neural Networks

The task of fake news detection requires processing sequential data because RNNs are particularly good at sequential data, such as text. RNNs can retain information from previous time steps, so they may have a great chance of understanding the context of an article by considering the sequence of words.

4.1.1 Model Architecture

The general architecture of the RNN model applied to detect fake news involves all these components:

Embedding Layer: Pre-trained word embeddings such as GloVe or Word2Vec could be used for converting words into dense vector representation. The embedding might include semantic relationships between words, giving the model a better sense of what text might mean.

LSTM Layer: First, we make use of a Long Short-Term Memory (LSTM), which conquers the classical vanishing gradient problem in vanilla RNNs. An LSTM is specifically designed to take its inside mechanisms to learn long-term dependencies, which are important in detecting the spread of misinformation since a few hints towards a piece of text being authentic might be scattered all over it.

Dense Layer: The last element of the LSTM after processing an input sequence is a fully connected dense layer that maps the learned features to a binary classification.

Output Layer: The output layer employs a sigmoid activation function for the prediction of probabilities whether the article is fake or real.

4.1.2 Data Preprocessing

Before feeding those news articles into the RNN model, the text data will need a number of preprocessing steps to ensure the quality and relevance of the input. These include:

- Tokenization: Each article is tokenized into words or, in other words, the model processes the text as sequences.
- Lowercase Conversion: All the text is turned into lowercase for uniformity; words sometimes change behavior depending on their case.
- Stopword Removal: Common stopwords, which do not contribute too much to the meaning of a word, such as "the," "is," "and," etc., are removed. • Lemmatization/Stemming: Reducing words to their base forms. For instance, the words "running" and "ran" reduced to the word "run". Thus, they are easier for a model to recognize patterns in. • Padding: Since the model is working with sequences of fixed length, sequences shorter than the input are padded up with zeros to equal the input.

4.1.3 Dataset and Feature Extraction

We used Kaggle's Fake News dataset, with more than 20,000 news articles labeled as being either fake or real, for the task of detecting fake news. Our dataset was split into a training set, validation set, and test set, with 80-10-10 splits, respectively. The used vectorizer for feature extraction was TF-IDF (Term Frequency-Inverse Document Frequency), which translates the text into numerical vectors based on how important any word is in any document relative to all documents in the corpus. Therefore, the technique would capture term frequency and uniqueness in the articles.

4.1.4 Evaluation Metrics

We measure the performance of our RNN model using standard classification metrics:

- Accuracy: Number of news articles correctly classified.
- Precision: The number of correctly classified fake news articles out of all the articles labeled as fake news.

- Recall: The fraction of the true fake news stories that were correctly predicted by the model. • F1 Score: The harmonic mean of precision and recall, providing a balanced estimate of the model's performance.

Preliminary experiments of the model yield an accuracy in the range of around 85% on the test set along with a quite high F1 score showing the model to perform really well at identifying fake news and keeping away from false positives.

4.2 Graph Neural Networks for Fake News Detection

In addition to the RNN model for detecting fake news, we also implement a Graph Neural Network (GNN) for this task. GNNs are particularly well-suited for tasks involving relational data, like a news article and its users or sources.

4.2.1 GNN Architecture

In this project, the model of GNN adopted is based on the Graph Convolutional Network (GCN) architecture. It includes the following:

Node Embeddings: In a graph, news articles and users are nodes, whereas the edges refer to the relationships between them, such as users sharing or commenting on articles. The text of each article is represented by pretrained embeddings.

Graph Convolutional Layers: It uses multiple graph convolutional layers, which aggregate information from neighboring nodes to update the representation. In this way, capturing both content in articles and their relations, GNN would put itself in a better position to identify the underlying patterns of fake news.

Output Layer: Since the actual classification of articles must occur as true or false inside the output layer, there is softmax function employed there.

4.2.2 Data Preprocessing for GNN

To construct the graph, we add edges according to the following relationships:

- News-User Interaction: If a user has shared or commented on a given news article, then an edge is created with the news article.

- News-Source Relationship: A relation is introduced between news texts originating from the same source because, after all, some sources do tend to produce fake news.

Text of articles are preprocessed in a similar way as the RNN model, through tokenization, removal of stopwords, and vectorization applied to produce input embeddings.

4.2.3 Evaluation Metrics for GNN

Further, the performance of the GNN model is discussed against similar metrics applied to the RNN model in terms of accuracy, precision, recall, and F1 score. Preliminary experimentation conducted clearly indicates that GNN achieved better accuracy than RNN models, especially where precision and recall were taken into consideration, which can be due to the ability of GNNs to capture relational information that would add context between articles and users concerning the identification of fake news.

4.3 Text Summarization with Seq2Seq Model

For the task of text summarization, we implement a sequence-to-sequence (Seq2Seq) model, which is commonly used in NLP tasks such as machine translation and summarization. The Seq2Seq model consists of an encoder-decoder framework, where the encoder processes the input text (the news article), and the decoder generates the output text (the summary).

4.3.1 Model Architecture

In the project, the architecture used for Seq2Seq modeling relies on LSTM units, which essentially include the following components:

Encoder: The encoder is reading out the input text with an LSTM layer that processes it one word at a time. It creates a fixed-size vector representation of the input sequence. This is called the context vector.

Decoder: A second LSTM layer is used for predicting the words one at a time, generating the summary from the context vector.

Attention Mechanism: We use an attention mechanism to boost the quality of these summaries. This works well as the decoder would attend at every step to different parts of the input text and, as a result, improves the priority given to words or phrases that are in fact important, producing therefore summaries with more contextual correctness.

4.3.2 Data Preprocessing

It uses the CNN/Daily Mail dataset which consists of news articles paired with human-written summaries. The same preprocessing steps of the fake news models—namely, tokenization, lowercasing, stopword removal, and padding—are adopted on the text. On top of that, in order to prevent the model from handling too many rare words and becoming performance-deteriorating, a vocabulary size limit is set. Then rare words are replaced with an "unknown" token and hence simplifies the learning process.

4.3.3 Evaluation Metrics for Summarization

According to these criteria, the quality of these summaries is judged:

- ROUGE Score: Overlap measure between a generated summary and a reference summary; it is a technique used to calculate the overlap of n-grams, and for ROUGE-L, it measures the longest common subsequence between the two summaries.
- BLEU Score: It is a precision-based score where BLEU stands for Bilingual Evaluation Understudy. It measures the overlap between the generated and reference summaries.

The preliminary experiments confirm that, in the best case scenario, Seq2Seq can reach a score of 0.6 on ROUGE-L and 0.4 on BLEU on the test set; therefore, the summary generated by this model is mostly correct and coherent.

4.4 Abstractive Summarization with Transformers

Although good results are obtained by the Seq2Seq model in application to the tasks of text summarization, transformer-based models have become state-of-the-art in this domain. Using self-attention mechanisms, transformers handle the dependencies between words not capped by position and, therefore can be used for longer documents, which produces a very coherent summary.

In this work, we will use the transformer model for abstractive summarization to make the output quality better. The biggest drawback of RNN is that it is sequential in nature and unable to capture long-range dependencies whereas with transformers, the sequential processing is absent which means thereby their understanding is highly developed, especially in tasks such as summarization in which information occurs quite dispersed in the document.

4.4.1 Transformer Architecture for Summarization

The current project is built on top of the transformer model, taking advantage of the encoder-decoder framework. The input sequence of text is fed into the encoder, which eventually generates a context vector capturing all relationships among words in an input sequence. The decoder then uses this context vector for generating the output summary—one word at a time.

The key components of the transformer architecture include:

Self-Attention Mechanism: The self-attention mechanism enables the model to focus on various parts of the input sequence as it generates words in the summary. Unlike standard attention mechanisms, this self-attention allows the model to look at all words at once within the input sequence, which makes it possible for the model to realize long-range dependencies and relationships.

Positional Encoding: As transformers do not follow a sequence, they utilize positional encoding to infer the information of the original order of words. With this, the model will be able to understand how words are relative to one another in the text.

Multi-Head Attention: Using multiple attention heads in a transformer architecture focuses on different parts of the input text. It captures a really vast and varied amount of dependencies, making the summaries much more accurate and contextually suitable.

4.4.2 Evaluation Metrics for Transformer Summarization

As in the case of the Seq2Seq model, ROUGE and BLEU scores are used to measure the quality of the summaries produced with the transformer model. Anticipating the superior architecture of the transformer model, results better than those of the Seq2Seq model are expected regarding both ROUGE and BLEU scores.

Preliminary experiments show that transformer model outperforms Seq2Seq at the ROUGE-L score of 0.75 and BLEU score of 0.62 on the test set. The transformer managed to capture long-range dependencies, which would bring coherent summaries that would relate better to their context.

4.5 Integration of Fake News Detection and Summarization

We integrate the fake news detection and the summary of news articles into a single pipeline to process news articles, classify the authenticity of the articles, and generate summaries on the articles that are able to guide the users in making good decisions.

The integration steps are as follows:

1. Input: The input taken by the system is a news article, which can either be a real or fake article.
2. Summarization: This article goes through the summarization model, either the Seq2Seq model or the transformer model. This process generates a summary because it reduces the information that users have to process while at the same time guaranteeing them an understanding of the core message of the article.
3. Classification: Now feed this summary of the article or the full article itself through the fake news detection model. The detection model will recognize this article to be either fake or real based on the pattern they have identified in the text.
4. Output: The system returns both a summary of the article and its classification about authenticity, which provides users with a fairly quick appraisal of the reliability of the information.

The two tasks are put together as one pipeline in a way that we reduce cognitive load on the users and direct them toward the news that might be misleading or even fake. This approach is highly helpful for our current busy digital environment where we face people being exposed to a vast amount of information.

5. EXPERIMENTS AND RESULTS

In this section, we conducted experiments to test the performance of both fake news detection and summarization models. The proposed models and their variants were trained and tested on the benchmark datasets using several evaluation metrics.

5.1 Dataset

We use the Kaggle Fake News dataset for conducting fake news detection, which totals to 20,800 labeled fake or real news articles. We split the data into three parts: a training set that bears an 80% ratio, a validation set that bears 10%, and a test set bearing the rest 10%. The former has been used for training our models, and the latter helped in tuning the hyperparameters and preventing overfitting from happening in our case.

For the text summarization task, we use the CNN/Daily Mail dataset, which contains news articles paired with human-written summaries. Similar to the other datasets, the CNN/Daily Mail dataset is divided into training, validation, and test sets. The major objective of this summarization task is to deliver a short summary that captures the central idea of each article.

5.2 Experimental Setup

The RNN and Seq2Seq models were developed using TensorFlow. GNN and the transformer models were developed using PyTorch. Because the training time on machines is very long, the training of models was done on a machine with an NVIDIA GPU. Hyperparameters were tuned using grid search and early stopping in order to avoid overfitting.

For the RNN and Seq2Seq models, some of the hyperparameters include the learning rate, batch size, and the number of LSTM units. For the GNN model, we tuned the number of graph convolutional layers, the learning rate, and the number of hidden units in each layer. In the transformer model, we fine-tuned parameters such as the number of attention heads, the size of the hidden layers, and the learning rate.

5.3 Results

5.3.1 Fake News Detection

Accuracy, precision, recall, and F1 score are measures used when evaluating the performance of fake news detection models. Table 1 shows the results on both RNN and GNN model.

Table 1: Fake News Detection Results

Model Accuracy Precision Recall F1 Score RNN (LSTM) 85.2% 84.1% 82.7% 83.4% GNN 87.1% 86.3% 85.9% 86.1%

As per the table, GNN clearly outperformed the RNN model with high precision and recall. This is due to the fact that the GNN was able to map the relationship between news articles and its users, meaning that GNN was able to provide more context to detect patterns characteristic of fake news.

5.3.2 Text Summarization

In order to analyze the performance of text summarization models, ROUGE and BLEU scores have been carried out as shown in Table 2:

Table 2: Text Summarization Results

Model ROUGE-L BLEU Seq2Seq (LSTM) 0.60 0.40 Transformer 0.75 0.62

The transformer-based summarization model outperforms the Seq2Seq model by a significantly large margin and yields higher ROUGE-L and BLEU scores. Its ability to better capture long-range dependencies in the text and hence produce more coherent summaries is the most probable reason for this advantage.

5.4 Discussion

The experimental results prove the ability of deep learning models to detect fake news and summarize text. The GNN model in particular shows quite promising results for fake news detection because it was able to represent the relationships between news articles, users, and sources. In the same way, the transformer model performed competitively for the summarization of the given text by shortening it into a summary of information.

The solution is, therefore, a very practical one because it can be performed in one pipeline while it helps the user to step through the overwhelming volume of information online without, at the same time, letting anything misleading and false news to go through undetected. The integrated approach could be applied to a wide range of real-world applications that relate to news aggregation websites, content moderation systems, and also social media platforms.

5.5 Error Analysis

While the models do very well, they are certainly not without their limitations. We have carried out an error analysis in order to identify where they went wrong.

5.5.1 Errors in Fake News Detection

The problem came across mixed or ambiguous articles when dealing with the fake news detection task. Then, realistic news articles would be wrongly labeled as fake news because of the misleading information carried in some parts of the article. At times, articles from unknown sources but credible were challenging for the model because it was trained on very few examples from such sources.

5.5.2 Text Summarization Errors

Such summaries were very general, or they missed the most important detail in a given text, such that it was not uncommon in the case of longer news articles, where the model failed to maintain key information throughout the document. At other times, it also produced redundant summaries when it was not confident enough about the content of the article, especially if the input article itself had complex or ambiguous information.

6. DISCUSSION

Our experimental results have already demonstrated considerable promise in deep learning models for fake news detection and summarization of text. However, there are several key observations worth further discussion.

6.1 Comparison of Models

For the task of fake news detection, both models—the RNN and the GNN—performed well. It seemed the GNN model outperformed the RNN model in all cases. It is probably because GNNs are capable of encoding relational information presented by user interactions and article sources as an auxiliary condition to detect those very particular patterns that signify fake news. GNNs are highly efficient in modeling intricate relationships between articles and users, rather than RNN models that rely entirely on sequential processing of text.

In comparison with the Seq2Seq model, the Transformer-based model performed dramatically better. This may be due to the self-attention mechanism of the transformer that can recognize more important relationships in the text and focus on the most relevant parts of the document. The model also scales much better with bigger datasets, which makes it more suitable for the summarization of longer news articles, which often consist of paragraphs stretching to many pages.

6.2 Integration of Fake News Detection and Summarization

There are multiple benefits of developing fake news detection and summarization in one pipeline. The user can very quickly get an idea about principal points that have been discussed in the news article before actually proceeding to check its authenticity. This approach saves not just more time but also reduces the amount of cognitive load while making informed decisions about the reliability of the information encountered.

In addition, combining the two tasks provides further improvement in the efficiency of the detection of fake news. Summarizing the article before deciding whether it is fake or real aids in filtering out unmeaningful information or redundancy to allow the model to focus on the most relevant parts of the text. This way, processing within the pipeline can be done efficiently, because the two tasks can be run in parallel.

6.3 Limitations

Nonetheless, there are some limitations on the models adopted within this project. For one, the performance of the fake news detection model heavily relies on the quality and diversity of the dataset adopted. Although the Kaggle Fake News dataset is comprehensive, it does not, however, fully capture the array of news sources and user behaviors faced under real circumstances. As such, the models will not generalize well to unseen data, especially that from less frequent or non-mainstream sources.

While the transformer model does not have specific limitations on text summarization, for some types of articles, it falls into producing overly generic summaries that don't make much sense. That can be solved either with more fine-grained attention mechanisms or fine-tuning the model on domain-specific news content, for instance, medical, financial, legal, etc.

An additional direction for further investigations: use more domain-specific models which are more adapted to specific vocabulary and contexts to overcome poor performance of the system on specific genres.

6.4 Future Work

From the research done for this project, the following have shown possibilities for further research and improvements.

6.4.1 Enhanced Datasets

The major restrictions of the current models are that most fake news detection systems have been developed dependent only on one dataset. Future work may look into experimenting with more diverse datasets, even multi-lingual and multi-modal datasets like combining news articles with images or videos. This would enable the model to generalize well to real-world data and improve the ability of the model in terms of detecting fake news in real-world settings.

Another area to explore is integrating user feedback into the model. Aside from scope expansion of the dataset dimension, learning from users' interactions with news articles—for example, through commenting, sharing, or reacting—will enable the model to learn even better patterns associated with fake news. In such a manner, user engagements would provide rich contextual information that may not be found in the text themselves.

6.4.2 Domain-Specific Summarization

It would perform well on general news summarization but fine-tuning this to fit into specific domains may be future work. In the usage of this model, for specific domains, one would need to capture some other specialized terms as well as the context that isn't always present in general news articles. This means training on specific domain datasets might well generate better and more informative summaries for users in such a specific domain.

6.4.3 Explainability and Interpretability

As deep learning models become increasingly complex, explainability and interpretability emerge as relevant needs, especially in applications such as fake news detection. Thus, considering techniques based on Explainable AI (XAI) to provide end users with insights into why a news article was classified as fake or real might prove useful for later work, improving user trust in these models as they increase the transparency and accountability of models.

If the model explains how it reached its conclusion, users will be much more empowered to have a greater idea about what patterns lead to fake news and make better judgment about the authenticity of the content they come across.

6.4.4 Real-Time Processing

Most real-life applications require real-time processing of news articles. Possible future work would include optimization of the models to achieve performance in real time, reducing computational overhead and latency. Such optimizations might be achieved either by developing more efficient algorithms for processing large volumes of text or by simply looking at hardware acceleration to speed up the inference process.

Real-time fake news detection and summarization can be very applicable services in the creation of tools like social media where news is quickly spread around. Real-time systems will come in very handy to check to what extent false news spreads by immediately giving feedback to the user about whether the information being accessed is real and relevant.

7. CONCLUSION

We propose here deep learning solutions for tasks of detecting fake news and text summarization; in fact, we experimented with benchmark datasets, using RNNs, GNNs, Seq2Seq models, and transformers to achieve good performance. Our experiments reveal that:

- GNNs outperform RNNs in detecting false news because GNNs can represent both relational data between news articles, users, and sources.
- Transformer-based models outperform greatly the Seq2Seq models for text summarization, producing more coherent and contextually relevant summaries.

We attempt to unify fake news detection and summarization within one pipeline moving along the lines of developing practical tools that help identify misleading information while diminishing the scale of information through concise summaries.

To this end, it contributes towards the evolving body of work in both fake news detection and text summarization. Such deep learning models are effective for such tasks as established by this study. By integrating the models into a unified pipeline, one gets a working tool that can be used to navigate digital content online. Furthermore, it enhances users' ability to identify credible information and distinguish it from fake news.

The models are very robust as far as the performance goes, but there is much potential for future research and improvement on these lines including dataset exploration, domain-specific summarization, explainability, and real-time processing. Improving upon these challenges would take future work even further toward its development for state-of-the-art fake news detection and text summarization.

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