

Fake News Detection Using CNN/GRU Deep Learning Model

Amina Yusuf Umar¹, Ibrahim Said Ahmad^{2*}, Khadijah Muhammad³
^{1,2,3}Department of Information Technology, Bayero University Kano, Kano, Nigeria.
aminayusuf625@gmail.com¹, isahmad.it@buk.edu.ng^{2*}, naanasx@gmail.com³

*Corresponding Author

Abstract

Social media platforms enable the creation and sharing of news, information, ideas, and other expressions. However, it also facilitates the dissemination of fake news and misinformation. Therefore, there is a need for effective methods of detecting fake news on social media platforms. Consequently, fake news detection has attracted many studies in recent years. Notwithstanding, there exist various flaws due to the characteristics of the algorithms used and the nature of the data. This work addresses some of the limitations of a hybrid Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) approach in fake news detection. Specifically, large computational complexity and storage of a large number of redundant intermediate variables of the LSTM algorithm. The limitations are addressed by proposing a hybrid of CNN and Gated Recurrent Unit (GRU) instead. GRU is similar to the LSTM, but with fewer computational complexities. The proposed approach was evaluated using four existing datasets based on accuracy, precision, and recall. The result of the evaluation shows the superiority of the proposed approach over the baseline approach.

Keywords: Deep learning, Fake news detection, Misinformation, Disinformation, Rumors, CNN, GRU.

1. Introduction

The technological advancement in computing technologies has revolutionized how societal challenges are being tackled. Artificial Intelligence (AI) fields like machine learning and deep learning are playing a vital role in solving many challenges in our daily lives. One important application of machine learning is in fake news detection. Fake news is news that is intentionally and verifiably false (Shu et al., 2017). Traditionally, fake news is transmitted through print media, however, nowadays fake news is also rapidly and massively transmitted through social media (Agrawal et al., 2017; Galli et al., 2022).

The proliferation of misinformation on social media presents a complex challenge in effectively identifying and differentiating fake news. Detecting and distinguishing such content, whether through manual or automated means, becomes increasingly challenging. One common tactic employed in the propagation of fake news is the use of click-bait headlines, enticing users to click on potentially biased articles with the intention of generating revenue through increased viewership (Bondielli & Marcelloni, 2019).

Fakes news has many negative implications to the society. Recent studies have shown that exposure to fake news can lead to the creation of false memories regarding events that never actually occurred, but were deliberately fabricated by the researchers (Greene et al., 2021; Murphy et al., 2019). In relation to the Covid-19 pandemic, there are arguments suggesting that being exposed to fake news related to COVID-19 could have detrimental effects, such as undermining adherence to social distancing guidelines or influencing individuals to self-administer unapproved treatments (Elhadad et al., 2021; Kouzy et al., 2020). Furthermore, in 2017, the implementation of a Nigerian Army program providing free medical services, which encompassed polio vaccinations, was significantly disrupted by the spread of rumors and fake news. These unfounded claims alleged that the army was conducting visits to schools with the intention of injecting students with the monkeypox virus. Regrettably, the circulation of these rumors triggered widespread panic, resulting in the closure of numerous schools in response to the perceived threat (Okoro & Emmanuel, 2018).

Similarly, the dissemination of false information on Facebook had severe consequences in Plateau State, located in central Nigeria, as it sparked an inter-ethnic crisis. Specifically, a distressing image of a mutilated

baby, which originated from a tragic incident in Congo Brazzaville back in 2012, was shared alongside a claim that it depicted an act carried out by Fulani individuals targeting the Berom community in Jos in 2018. Media reports revealed that this post triggered a reaction from Berom youths who took to the streets and launched retaliatory attacks specifically targeting Fulani men. Authorities believed that the Facebook post played a significant role in inciting the violence. It is important to note that this same image has been exploited in other African regions to fuel deadly conflicts as well (Destiny Apuke & Omar, 2020). Consequently, the importance of fake news detection cannot be overemphasized.

Various approaches, such as machine learning, deep learning, retweet behavior, diffusion pattern, anomaly detection, crowd-sourcing, and computational fact-checking, can be utilized for fake news detection. While classical machine learning algorithms have been previously employed (Ajao et al., 2019; Choudhury & Acharjee, 2023), deep learning models have become more prevalent (Luvembe et al., 2023; Nasir et al., 2021). Hybrid deep learning models, which combine different techniques, have also demonstrated effectiveness in detecting fake news (Ajao et al., 2018; Nasir et al., 2021). Nonetheless, these existing models have limitations. For instance, Nasir et al. (2021) achieved favorable outcomes with a hybrid CNN/LSTM model, but it had a complex algorithm. To address this issue, we propose a hybrid deep learning model that leverages the advantages of a convolutional neural network (CNN) and a Gated Recurrent Unit (GRU). GRU has been shown to possess lower computational complexity than the LSTM algorithm in binary classification (Girgis et al., 2018).

The rest of this paper follows this organization: Section 2 provides a review of the existing literature, Section 3 introduces the proposed model and its components, Section 4 presents the results and discussion, and Section 5 concludes the paper.

2. Literature review

Fake news is referred to as those stories that are fabricated with no verifiable source with the intent to mislead the readers. Any news that is intentionally and verifiably false is referred to as fake news (Shu et al., 2020). The impact of spreading false information on the internet extends to various aspects of society, such as citizens, governments, organizations, and businesses. In the age of social media, where anonymity, user-generated content, and geographical boundaries can facilitate the rapid spread of fake news, the issue of fake news and its widespread dissemination has emerged as a significant and concerning problem (Talwar et al., 2020).

Social media provides simple access to information at a cheaper cost and faster than traditional sources like broadcast and print. Because of these characteristics, many individuals prefer to get their news via social media rather than traditional news sources like television or newspapers. The characteristics of social media platforms make the dissemination of fake news remarkably effortless. Users have the ability to share fake news stories with their friends, who, in turn, can continue the cycle by sharing it with their own networks. This creates a ripple effect, amplifying the reach of fake news. Moreover, the presence of comments on these fabricated stories can contribute to a false perception of credibility, leading to a heightened likelihood of rapid sharing and the subsequent proliferation of additional instances of fake news (Albright, 2017; Jarrahi & Safari, 2023).

The dissemination of this fake news in social media makes researchers study ways of detecting fake and real news to reduce the spread of this news in society.

2.1. Related Works

Numerous frameworks have been proposed and developed for the detection of fake news. Traditional machine learning classifiers, such as SVM, Logistic Regression, and Random Forest, have commonly been employed for this purpose (Gravanis et al., 2019; Nasir et al., 2021; Trueman et al., 2021). Some of the prominent related works include the work of (Ahmed et al., 2017), where they presented a model that leverages n-gram analysis and machine learning techniques. The authors explored various feature extraction approaches and evaluated multiple machine classification methods. Through their experimentation, they identified the Term Frequency-Inverted Document Frequency (TF-IDF) as the most effective feature extraction technique. Additionally, they found that employing the Linear Support Vector Machine (LSVM) as the classifier yielded the highest accuracy, achieving an impressive 0.92. Similarly, (Gravanis et al., 2019) contributed to the field by

proposing a model that employs content-based features and Machine Learning algorithms for fake news detection. Their study emphasized the importance of enhancing linguistic features and leveraging ensemble algorithms, along with the SVM algorithm, to achieve highly accurate classification of fake news. These findings highlight the potential for improved accuracy in detecting fake news by utilizing these techniques.

While these methods have shown effectiveness, there remain several research challenges that need to be addressed. For example, most of the existing studies overlooked the importance of context representation in the data and rely on manual feature identification (Trueman et al., 2021). To address this limitation, utilizing deep learning approaches allows for effective learning of data representations and automatic feature extraction by the classifier.

(Trueman et al., 2021) introduced an innovative approach called AC-BiLSTM, which combines attention-based convolution with bidirectional long short-term memory, for the purpose of detecting fake news. They applied this approach to the Liar dataset, capturing the nuanced meaning of sentences by considering local, global, and temporal context. The incorporation of an attention mechanism enables the model to effectively handle long input sequences.

Similarly, (Sahoo & Gupta, 2021) proposed a deep learning-based method specifically designed to detect fake news on Facebook within the Chrome environment. They conducted experiments using various features associated with Facebook accounts and news content. Their results were highly promising, showcasing the efficacy of their approach.

(Nasir et al., 2021) devised a hybrid deep learning model, leveraging both CNN and RNN algorithms, to classify fake news. They evaluated the model on two distinct fake news datasets and achieved favorable results, highlighting the potential of their approach.

(Kaliyar et al., 2020) introduced a CNN-based methodology for detecting fake news. Their model was designed to automatically extract discriminative features from fake news articles using multiple hidden layers within a deep neural network. The model demonstrated exceptional performance, achieving a classification accuracy of 0.98 on test data using benchmarked datasets.

Lastly, (Raza & Ding, 2022) proposed a Transformer-based framework specifically tailored for early detection of fake news, even when training data is limited. Their model takes into account both the content of the news and social contexts, achieving high accuracy when evaluated with real-world data.

Although these deep learning methods have shown promising results, they suffer from certain limitations inherent to the algorithms. For instance, Nasir et al. (2021) proposed a hybrid CNN-RNN model for fake news detection, but LSTM, being computationally intensive and memory-consuming, requires significant training time and storage space. Additionally, LSTM has a strong reliance on historical information, limiting its ability to effectively utilize future information. Combining CNN with a more efficient RNN variant has the potential to enhance fake news detection while mitigating these drawbacks. By addressing these challenges and considering the context representation of data through deep learning techniques, improvements can be made in the detection of fake news.

3. Methodology

This paper proposed a model of fake news detection which leverages the advantages of two deep learning algorithms. The model uses the advantages of CNN and GRU to detect fake news. The development of this model undergoes 4 stages: data preprocessing, word embedding, classification, and evaluation. The model architecture is illustrated in Figure 1.

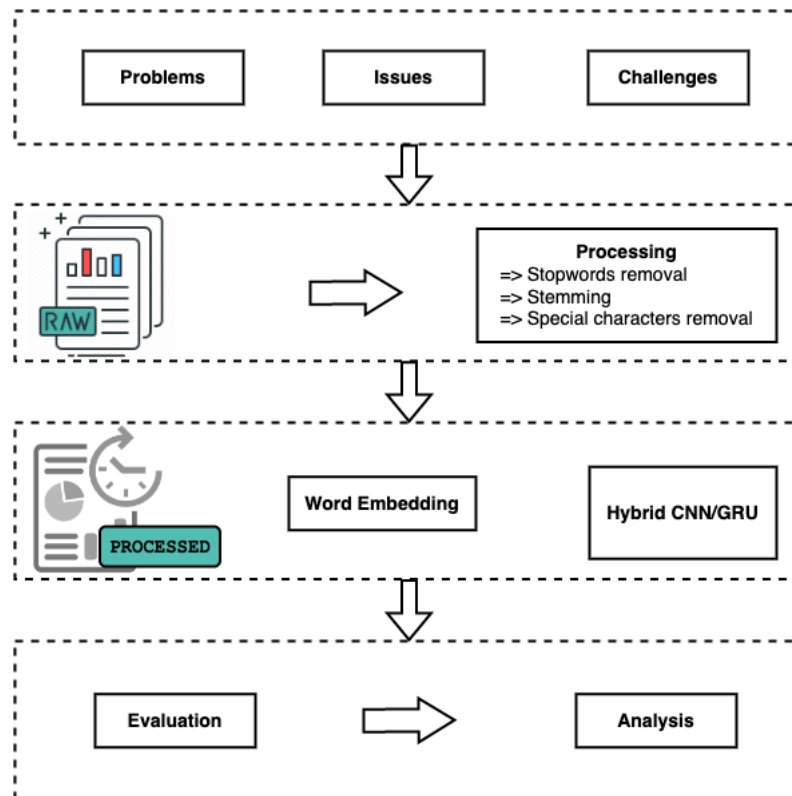


Figure 1. Model Architecture

3.1. Datasets

Four publicly available datasets were used to evaluate the proposed model. The datasets used are ISOT, FA-KES, WELFake and BuzzFeed.

1. ISOT Dataset: The ISOT dataset (Ahmed et al., 2018) is a news dataset classified into two classes: fake news and real News. The dataset covers primarily topics on politics. The dataset contains a total of 44,898 articles¹.
2. FA-KES Dataset: The FA-KES dataset by (Abu Salem et al., 2019) is a labelled fake news dataset that is centered around the conflict in Syria. The dataset comprises of a set of articles labelled as 0 for fake news or 1 for credible news. The credibility of the articles is computed based on ground truth information obtained from the Syrian Violations Documentation Center².
3. WELFake Dataset: The WELFake dataset is a fake news dataset proposed by (Verma et al., 2021). It contains 72,134 news articles out of which 35,028 are labeled real and 37,106 labelled fake news³.
4. BuzzFeed Dataset: (Potthast et al., 2018) created the BuzzFeed dataset, which encompasses news articles shared on Facebook by 9 news agencies during a week leading up to the 2016 U.S. election. The dataset covers the dates from September 19 to 23, as well as September 26 and 27. Notably, a team of 5 BuzzFeed journalists conducted a comprehensive fact-checking process, scrutinizing each post and its corresponding article for accuracy. The BuzzFeed dataset consists of two distinct subsets: one containing fake news articles and the other comprising real news articles⁴.

3.2. Data Preprocessing

The datasets used were preprocessed using different kinds of preprocessing techniques such as stop words removal, stemming, removing symbols URLs and IDs, converting text to lowercase, and tokenization.

¹ <https://onlineacademiccommunity.uvic.ca/isot/2022/11/27/fake-news-detection-datasets/>

² <https://zenodo.org/record/2607278>

³ <https://zenodo.org/record/4561253>

⁴ <https://zenodo.org/record/1239675>

First, we used the case converter to convert the text into lowercase, secondly, we removed all symbols, URLs and ids from the text then finally we applied the tokenization process to convert the input text into tokens. The preprocessing techniques were performed using the NLTK toolkit in python.

3.3. Word embeddings

Word embedding is a technique used in text analysis to represent words. These embeddings are trained on large, domain-specific datasets to capture statistical relationships between words. Rather than training new embeddings, pre-trained embeddings can be employed, such as Google's Word2Vec and GloVe word embeddings.

For this research, we utilized the glove.6B.100d word embedding, an unsupervised learning algorithm introduced by (Pennington et al., 2014). It enables the measurement of word proximity in a vector space based on co-occurrence statistics. This particular embedding was trained on a corpus containing one billion words and a vocabulary size of 400,000. The processed data serves as input to the word embedding layer, generating word vectors used by the classifiers.

3.4. Convolutional Neural Network

Convolutional Neural Networks (CNNs) are a popular deep learning architecture extensively used for hierarchical document classification and text classification tasks. CNNs operate by performing matrix multiplication, which is known as convolution, to generate outputs that contribute to the training process. In the context of Natural Language Processing (NLP), textual data is represented as word vectors and utilized for training a CNN.

During the training phase, a CNN defines the kernel size and the number of filters. In text classification tasks, a one-dimensional CNN (Conv1D) is commonly employed. Conv1D deals with one-dimensional arrays that represent word vectors. By iterating a fixed-size window filter over the training data, the input is multiplied with the filter weights at each step, resulting in an output stored in an output array. This output array, also referred to as a feature map or output filter, captures relevant features from the input training data. The kernel size determines the size of the filter, while the number of filters specifies the number of feature maps used.

This approach allows a CNN to effectively learn local features directly from the training data, enhancing its ability to analyze and classify text.

3.5. Gated Recurrent Unit

RNN, short for Recurrent Neural Networks, has been extensively utilized by researchers in the field of text mining and classification. It stands out for its ability to assign greater importance to previous data points within a sequence, making it well-suited for handling text, string, and sequential data. Notably, RNN has various variants, including LSTM and GRU.

GRU, which stands for Gated Recurrent Unit, is a specific variant of RNN that addresses the vanishing gradient problem encountered in traditional RNNs. It introduces two essential gates, namely the update gate and the reset gate. The update gate (referred to as z) determines the relevant information to be carried forward to the next time step (t). It achieves this by considering the previous output (h_{t-1}) and applying a sigmoid function to obtain an output value ranging between 0 and 1. On the other hand, the reset gate (referred to as r) determines the information to be forgotten at the current time step (t) based on the previous output (h_{t-1}). It, too, employs a sigmoid function to produce an output within the range of 0 to 1. Figure 2 illustrates the architecture of the GRU model.

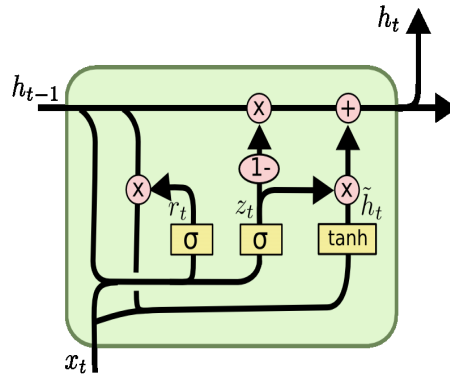


Figure 2. Gated Recurrent Unit (Sit et al., 2020)

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \tag{1}$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \tag{2}$$

$$\tilde{h}_t = \tanh(W \cdot [r_t \times h_{t-1}, x_t]) \tag{3}$$

$$h_t = (1 - z_t) \times h_{t-1} + z_t \times \tilde{h}_t \tag{4}$$

3.6. Hybrid CNN/GRU model

The proposed model leverages the strengths of CNN for extracting local features and GRU for capturing semantic representations and long-term dependencies. Firstly, the input vectors are processed through a Conv1D layer in the CNN, which effectively captures the local features present at the textual level. The output of this CNN layer, comprising the feature maps, is then fed into the subsequent GRU layer. In the GRU layer, the extracted local features in the form of vector representations are utilized to learn the long-term dependencies within the news article, enabling accurate classification as either fake or real. The transformed vector is partitioned into training, validation, and test data sets. To compile the model, binary cross-entropy is employed as the loss function, along with the Adam optimizer, while F-measure is used as the evaluation metric. A concise overview of the model architecture is depicted in Figure 3.

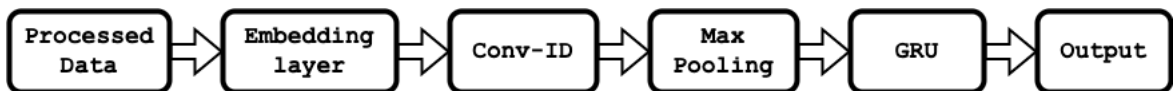


Figure 3. Model Summary

3.7. Evaluation metrics

The performance of this research study was assessed using various evaluation metrics, including accuracy, precision, recall, and F-measure. These metrics are calculated based on the number of True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) instances, which are essential in binary classification predictions. Table 1 illustrates a visual representation of the confusion matrix utilized in the evaluation process.

	Predicted positive	Predicted negative
Actual positive	True Positive (TP)	False Negative (FN)
Actual negative	False Positive (FP)	True Negative (TN)

Accuracy: Accuracy is the percentage of true (correct) predictions. Accuracy can be determined using Equation (5).

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{5}$$

Precision: Precision is the ability of the classifier not to label a negative sample. Precision can be determined using Equation (6).

$$\text{Precision} = \frac{TP}{TP + FP} \tag{6}$$

Recall: Recall captures the ability of the classifier to find all positive samples. Recall can be determined using Equation (7).

$$\text{Recall} = \frac{TP}{TP + FN} \tag{7}$$

F-Measure: F-measure is the harmonic mean of precision and recall. F-measure can be determined using Equation (8).

$$F - \text{measure} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{8}$$

4. Results

The proposed CNN/GRU hybrid model was implemented using python programming language, and the performance was evaluated using four real-world datasets. The following subsections describe the results of the experiments conducted.

4.1. Experiment 1a: Performance of Existing Algorithms in Fake news Detection using ISOT dataset

The performance of different algorithms in detecting fake news using the ISOT dataset was evaluated, and the results are presented in Table 2. It is evident from the table that, apart from LR and GRU, all the algorithms performed satisfactorily. The CNN algorithm exhibited the highest F-measure. The poor performance of LR can be attributed to the dataset's non-linear variables. RF and DT yielded comparable results, which can be attributed to their similar operational characteristics.

Table 2. Result of existing algorithms based on the ISOT dataset

Models	Accuracy	Precision	Recall	F-measure
LR	0.52	0.50	0.50	0.41
RF	0.94	0.95	0.95	0.94
DT	0.96	0.96	0.97	0.96
GRU	0.52	0.26	0.5	0.35
CNN	0.98	0.99	0.99	1.00

4.2. Experiment 1b: Performance of Existing Algorithms in Fake news Detection using FA-KES dataset

The performance of various algorithms in detecting fake news using the FA-KES dataset was examined. The findings presented in Table 3 indicate that all the algorithms achieved moderate performance, with F-measure values ranging from 0.47 to 0.59. Surprisingly, the results show that GRU performed the best, which contradicts the results obtained from the ISOT dataset in Experiment 1a. This discrepancy in performance could potentially be attributed to the relatively small size of the FA-KES dataset.

Table 3. Result of existing algorithms based on FA-KES

Models	Accuracy	Precision	Recall	F-measure
LR	0.50	0.49	0.49	0.49
RF	0.48	0.47	0.46	0.47
DT	0.55	0.55	0.55	0.54
GRU	0.58	0.42	0.50	0.59
CNN	0.56	0.53	0.52	0.51

4.3. Experiment 1c: Performance of Existing Models in Fake news Detection using WELFake dataset

The objective of this experiment was to assess the effectiveness of established algorithms in detecting fake news using the WELFake dataset. The results, displayed in Table 4, reveal that CNN outperformed all other algorithms, achieving an impressive F-measure of 0.92. Conversely, LR exhibited the poorest performance, with

an F-measure of 0.58. These findings align with those obtained in Experiment 1a, confirming the consistency of the results across different datasets.

Table 4. Result of existing algorithms based on WELFake

Models	Accuracy	Precision	Recall	F-measure
LR	0.58	0.57	0.58	0.58
RF	0.81	0.81	0.81	0.81
DT	0.78	0.78	0.78	0.78
GRU	0.49	0.48	0.99	0.64
CNN	0.90	0.92	0.92	0.92

4.4. Experiment 1d: Performance of Existing Algorithms in Fake news Detection using BuzzFeed dataset

Similarly, the performance of established algorithms in detecting fake news was evaluated using the BuzzFeed dataset. The findings, illustrated in Table 5, align with the results obtained in Experiments 1a and 1c. Once again, the CNN algorithm demonstrated superior performance with an F-measure of 0.72, confirming its effectiveness in fake news detection.

Table 5. Result of existing algorithms based on BuzzFeed

Models	Accuracy	Precision	Recall	F-measure
LR	0.57	0.60	0.59	0.57
RF	0.46	0.47	0.47	0.46
DT	0.57	0.56	0.56	0.56
GRU	0.47	0.46	1.00	0.63
CNN	0.73	0.74	0.72	0.72

4.5. Experiment 2: Performance of Proposed Model in Relation to Baseline Model

In this section, we provide an evaluation of the proposed model's performance compared to the baseline model across four established datasets. The outcomes, presented in Table 6, reveal that the proposed model surpasses the baseline model's performance when applied to the WELFake and BuzzFeed datasets. However, it achieves a slightly lower accuracy when used with the ISOT dataset. These results indicate that the proposed model is equally effective in detecting fake news compared to the baseline model, while also possessing the advantage of lower computational complexity. This outcome is further depicted in Figure 4, visually representing the comparative performance of the two models.

Table 6. Performance of the proposed model in relation to the baseline model

Dataset	Models	Accuracy	Precision	Recall	F-measure
ISOT	CNN-RNN (Baseline)	1.00	0.99	0.99	1.00
	CNN/GRU (Proposed)	0.99	0.96	0.96	0.99
FA-KES	CNN-RNN (Baseline)	0.58	0.29	0.53	0.45
	CNN/GRU (Proposed)	0.59	0.80	0.50	0.38
WELFake	CNN-RNN (Baseline)	0.86	0.87	0.87	0.86

Table 6 Cont'd

	CNN/GRU (Proposed)	0.91	0.91	0.92	0.92
	CNN-RNN (Baseline)	0.57	0.75	0.62	0.53
BuzzFeed	CNN/GRU (Proposed)	0.70	0.77	0.68	0.67

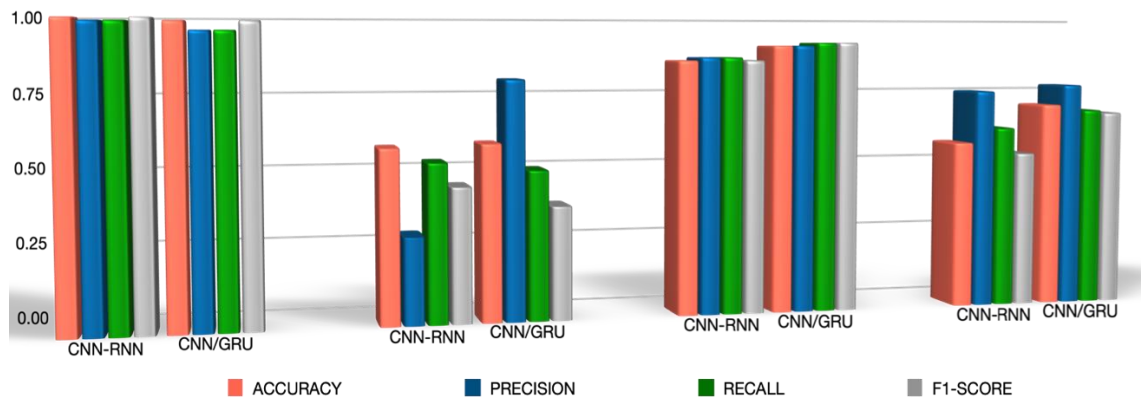


Figure 4. Performance of the proposed model in relation to the baseline model

5. Conclusion

In addition to good prediction accuracy, the computational complexity of machine learning or deep learning algorithms is equally an important factor being considered when choosing an algorithm. In this paper, we focus on improving the work of (Nasir et al., 2021) by reducing the computational complexity of their model of fake news detection. Their model already achieved a competitive performance; however, it has a large computational complexity due to its use of the LSTM algorithm which is known to have a large computational complexity. Our proposed model, CNN-GRU is based on a more efficient variant of the LSTM algorithm and achieved superior results using the WELFake dataset and the BuzzFeed datasets and achieved a competitive result using the ISOT dataset.

Our results further strengthen the findings of previous studies that hybrid deep learning algorithms are superior to traditional deep learning or machine learning algorithms in fake news detection. Our results show the superiority of the proposed CNN-GRU and the baseline CNN/LSTM over the traditional algorithms. For future work, the performance of the proposed model with optimization algorithms like particle swarm optimization or crow search could be studied.

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