Scientific Journal of Computer Science
futuristech PT. Teknologi Futuristik Indonesia
Date of publication March 6, 2026, date of current version March 6, 2026.
Digital Object Identifier 10.64539/sjcs.v2i1.2026.400

Article

Hybrid Deep Learning Model for Fake News Detection on Social Media Using CNN-GRU on X formerly known as Twitter

Lawan Jibril Muhammad[1,*], Isa Umar Mohammed[2], Nura Muhammad Sani[3]

[1] Department of Information Technology, Bayero University of Kano, Kano State, Nigeria; e-mail: mljibril.it@buk.edu.ng
[2] Department of Computer Science, Gombe State University, Gombe State, Nigeria; e-mail: isaumarm@gsu.edu.ng
[3] Department of Computer Science, School of Science, Federal Polytechnic Kaltungo, Gombe State. Nigeria; e-mail: nuramuhammad07061@gmail.com
* Correspondence

The authors received no financial support for the research, authorship, and/or publication of this article.

Abstract: The spread of fake news on social media platforms has created a dilemma for the world community by spreading false information and eroding public confidence. Fake news spreads quickly and seriously harms society. Predicting and identifying fake news is crucial for preserving the integrity of information ecosystems in the wake of an epidemic of multiple high-profile disinformation efforts. In order to detect fake news, this work suggests a hybrid deep learning algorithm called Convolutional Neural Network - Gated Recurrent Unit (CNN-GRU), which combines the Convolutional Neural Network (CNN) and Gated Recurrent Unit (GRU) learning algorithms in an efficient manner. Models for identifying fake news were developed using deep learning-based methods, such as CNN, GRU, and CNN-GRU deep learning algorithms. Four standard performance metrics—accuracy, precision, recall, and F1-score—were used to evaluate the models. Nevertheless, the CNN-GRU deep learning-based detection model outperformed models created with CNN and GRU, achieving the maximum accuracy of 98.77%, 98.68%, 98.73%, and 98.71% for precision, recall, and F1-score, respectively. With a combined accuracy of 98.77%, precision of 98.68%, recall of 98.73%, and F1-score of 98.71%, the CNN-GRU deep learning-based false news detection model performs better than the two other deep learning-based models.

Keywords: Fake news; CNN; GRU; CNN-GRU, Deep learning.

1. Introduction

A part of machine learning called deep learning is inspired by how a human brain operates and is organized. It enables computer systems to generate outcomes by learning from previously available examples [1]-[4]. This powerful capability has allowed deep learning to achieve groundbreaking milestones that were previously unimaginable. It serves as the driving force behind many modern innovations, including self-driving cars, voice-controlled devices like smartphones, smart appliances, and televisions [5]. In deep learning, computer systems are trained to classify tasks directly from data in various formats, such as images, text, or audio. Deep learning models consistently deliver state-of-the-art accuracy and performance, often surpassing human capabilities [6]-[9].

Microblogging and social media platforms have witnessed exponential growth over the past decade, with Facebook alone surpassing 2 billion monthly active users worldwide. These platforms have become primary sources of information, with users dedicating significant time to them daily [6], [7], [10]-[12]. However, the advent of social media has raised concerns about the increasing dissemination of misleading and false information, particularly during critical events such as elections. The previously uploaded files have expired and are no longer accessible. If you'd like me to continue working on your document, kindly re-upload the files or provide specific sections for immediate assistance.

Fake news refers to falsified information that mimics genuine news articles or content, although no universally accepted definition exists [13]. It manifests in various forms, including misleading content, fabricated reviews, rumors, and political propaganda [14], [15]. The rapid dissemination of fake news on social media, far outpacing traditional media, presents significant challenges for detection [7], [10], [16], [17]. The COVID-19 epidemic has compounded this issue even more, during which the spread of misinformation reached alarming levels [3], [18], [19].

While manual fact-checking systems exist, their scope and timeliness are limited [20]-[23]. The vast volume of information created, shared, and commented on across social media platforms makes the detection of misinformation an increasingly challenging task. To address this issue, researchers are developing innovative approaches, including deep-learning models, to analyze textual data and determine the authenticity of news [24]-[26].

The battle against fake news remains ongoing, with technological solutions playing a pivotal role in safeguarding the integrity of information in the digital age [9], [26]-[28]. As social media platforms continue to evolve, the demand for efficient and reliable false news detection and prevention methods grows. Such advancements are crucial for ensuring the dissemination of accurate information and preserving public trust in online platforms [17], [27], [29]

In today's social media-driven world, the rapid spread of fake news presents a significant concern, undermining information integrity and distorting public perception [14], [30]. The complexities of fake news, requiring advanced algorithms capable of distinguishing genuine information from fraudulent textual content [13], [14]. Traditional text-based methods often fall short in addressing the dynamic nature of social media posts, motivating the development of hybrid deep learning approaches [15], [16], [30]-[32].

Convolutional Neural Networks (CNNs), renowned for their image recognition capabilities, struggle with sequential data and long-range relationships [16], [33], [34]. Conversely, Gated Recurrent Units (GRUs) are proficient at modeling temporal dependencies but face challenges in processing visual data [24], [28], [35], [36]. This necessitates a comprehensive solution that leverages the synergies between CNNs and GRUs to overcome their respective limitations.

The proposed Hybrid CNN-GRU model addresses these challenges by combining the strengths of both architectures. While the GRU component captures sequential and temporal dependencies in the textual input, the CNN component extracts local n-gram-like features from the narrative flow of social media posts. This integration aims to create a sophisticated and accurate classification system for detecting fake news, effectively addressing the shortcomings of traditional approaches.

This study aims to create a hybrid deep learning model competence to detect and classify news as either real or fake on social media channels, especially X (formerly known as Twitter). The specific objectives include designing and implementing a hybrid CNN-GRU model that integrates the strengths of CNN and Gated GRU for effective fake news classification.

The study involves the use of a dataset to build and train models based on the Hybrid CNN-GRU architecture, as well as standalone CNN and GRU models. Each model's performance will be assessed and compared using accuracy as the primary metric, with additional consideration of how the hybrid model outperforms the individual CNN and GRU models in classifying fake news.

2. Related Work

Various strategies for detecting fake news have been used in the literature, demonstrating the efficiency of a variety of deep-learning algorithms. The growing frequency of disinformation on social media platforms needs better detection methods, prompting the development of hybrid models that integrate various deep learning architectures.

In [6] Naive Bayes classifiers were applied, resulting in an 87% classification accuracy, which increased to 92% with enriched corpora. However, they underlined the significant costs of training and labeling data, implying that future research should focus on developing more cost-effective model training methods.

In [10], they made considerable progress in false news classification by optimizing and merging CNN and LSTM approaches. Their study centered on strengthening model architecture, implementing sophisticated optimization algorithms, and improving feature engineering to better capture the intricacies of disinformation. The hybrid CNN-LSTM model they constructed outperformed earlier state-of-the-art approaches regarding efficiency and accuracy, demonstrating the possibility of fine-tuning existing deep-learning techniques for this complicated problem. Their algorithm obtained an outstanding 93.85% accuracy on a broad collection of news stories, a 2.5% increase over the previous best-performing model. This study is part of a larger trend in the field of false news detection, in which researchers are increasingly focusing on fine-tuning and integrating existing models rather than creating whole new structures. This method acknowledges the changing nature of misinformation and the need for increasingly advanced, context-aware categorization systems. Researchers like Emmy et al. are pushing the frontiers of performance and accuracy by optimizing existing models, as well as tackling difficulties like model interpretability and real-time detection capabilities. Emmy et al. revealed a considerable accuracy improvement, highlighting the approach's potential to enhance the sophistication of fake news identification.

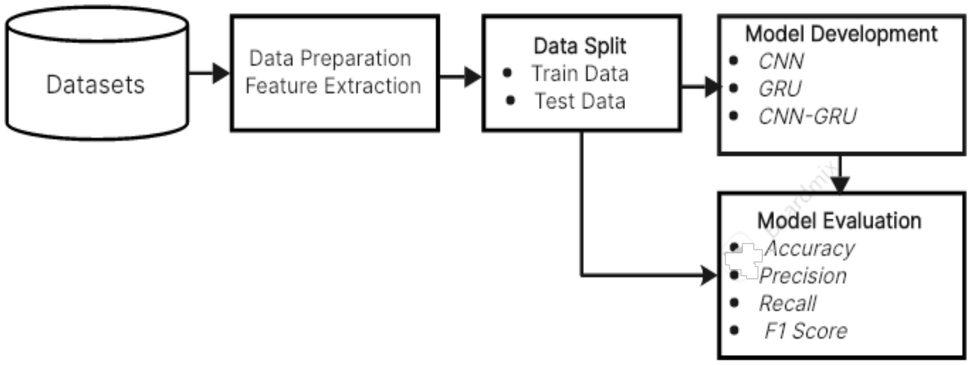

Figure 1. Methodology.

In the work of [7] C-DSSM and Deep CNN models were used. They made a big contribution to the detection of fake news with their automated hybrid deep neural network model for social networks. This novel approach combines several neural network topologies to capitalize on their complementary qualities, resulting in a more robust and accurate classification system. The model obtained an astonishing 92.60% accuracy on their test dataset, suggesting a significant advance above previous techniques. By combining different neural network types, such as convolutional and recurrent layers, the researchers were able to capture both local and sequential patterns in social media information, improving the model's capacity to discern between genuine and fake news. The model displayed outstanding performance.

Study [31] recognized the ongoing challenge of user prejudice in fake news identification, emphasizing the necessity for additional studies to solve this issue and the work besides improving the technological capacity of fake info detection systems, but it also highlighted the need to take human elements into account when designing holistic solutions to combat misinformation on social media platforms.

Work [9], [37] proposed a method for detecting online false news using n-gram analysis and machine learning approaches. They looked at two feature extraction approaches, TF and TF-IDF, as well as six different machine learning classifiers, such as SVM, KNN, and Decision Trees [37]. The authors compiled a collection of 25,200 articles (12,600 fraudulent and 12,600 real) on political news in 2016. Their studies changed the n-gram size from unigrams to four grammes, as well as the number of top features selected. The best result was achieved with TF-IDF features, unigrams, and Linear SVM, with a 92% accuracy. The study's authors discovered that linear classifiers outperformed non-linear ones and that TF-IDF was more successful than TF for feature extraction. They also discovered that accuracy decreased when n-gram size rose beyond unigrams. When evaluated on an external dataset, their approach exceeded earlier results, obtaining 87% accuracy versus the 71% stated originally. This article shows how n-gram analysis and traditional machine learning approaches can be used to detect fake news, as well as several crucial aspects that influence model success.

Many works employed a variety of deep learning techniques, including Naive Bayes, CNN, LSTM, and SVM, to detect bogus news [38]. While hybrid CNN-GRU architectures have been explored in other domains [39]-[42], the specific application of a CNN-GRU model to fake news detection on X (formerly Twitter), utilizing a preprocessing pipeline tailored to informal social media language and evaluated against standalone CNN and GRU baselines, represents the novel contribution of this work. This study addresses the urgent need for more precise and trustworthy fake news identification techniques in today's dynamic information world, marking a significant step in the fight against false information.

3. Proposed Methodology

This study outlines the methodologies employed in using a hybrid CNN and GRU for fake news classification on social media platform X, formerly Twitter. It includes data collection methods, data pre-processing techniques, model architecture, and evaluation metrics.

3.1. Proposed System Architecture

Our proposed system will classify news on the X platform from a text corpus and execute it using deep learning techniques. The Figure 1 presents the proposed architecture of the research. First and foremost, the dataset will be collected and preprocessed to ensure that it very ready for machine learning and deep learning training and testing tasks. It will be split into two groups; for training and testing. After that, the individual deep learning model, CNN, and GRU will be applied individually for training, testing, and evaluation. Performance metrics will then be applied to measure the performance of the various approaches. The two models; CNN and GRU will then be combined to form a hybrid CNN-GRU for training, testing, and evaluation using the common metrics precision, accuracy, recall, and f1-score. The hybrid results will then be compared with the individual model and also with existing literature.

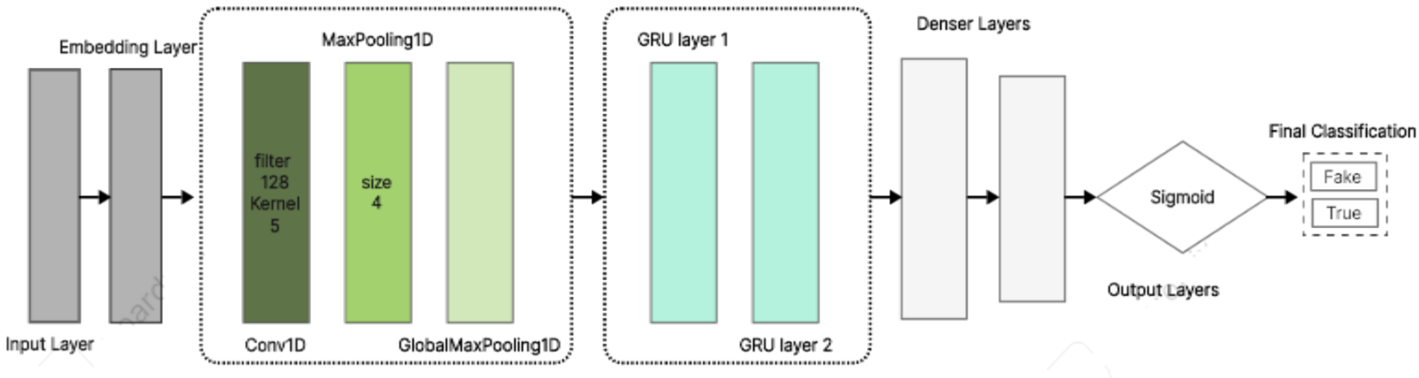

Figure 2. CNN-GRU Architecture.

3.2. Data Collections

The dataset used for this research comprises news articles from various online sources, labeled as either fake or real. The dataset is sourced from kaggle.com (https://www.kaggle.com/datasets/algord/fake-news)[43]. The collected data includes news headlines, content, and metadata such as publication date and source.

3.3. Data Pre-processing

Data pre-processing is a crucial step in preparing the dataset for model training. The following steps are implemented:

- Text Cleaning, Tokenization: Splitting the text into individual words (tokens).
- Stop Words Removal: Removing common words that do not contribute to the model's predictive power.
- Stemming and Lemmatization: Reducing words to their base or root form.
- Vectorization: Converting text data into numerical vectors using techniques such as TF-IDF (Term Frequency-Inverse Document Frequency).

3.4. CNN-GRU

The potent combination of CNN-GRU has been proposed to harness the feature extraction capacities of CNN and the efficient sequential-learning of the GRU algorithm. This architecture is designed to dramatically detect and model the dataset's encoding of both short- and long-term temporal correlations, particularly for applications like false news classification.

The proposed CNN-GRU is made up of the following two main essential components to accomplish the aforementioned goal:

- One-dimensional (1D) CNN that consists of convolutional Max and Global Max pooling layers to process the input data mathematically to extract features.
- GRU and dense layers to make use of the generated features.

In the adopted CNN-GRU algorithm, GRU functions as a sequence processor and CNN as a feature extractor. From the incoming data, the feature extractor extracts meaningful patterns, which it then feeds into the sequence processor (GRU). Next, the sequence processor finds and models the dataset's intrinsic short- and long-term temporal relationships.

The following is a quick summary of each step's sequence of events, as seen in Figure 2:

a) Input layer: receives the tokenized text data;
b) Embedding layer: converts tokens into dense vector representations;
c) 1st Convolutional layer: examines the embedded input data before applying feature maps to the results;
d) Max pooling layer: simplifies the feature maps by eliminating particular features from (c) above and producing a matrix of smaller dimensions;
e) GlobalMaxPooling1D layer: creates a single vector from feature maps that can be used as input for sequence processing purposes;
f) Dropout layer: improves the learning network to prevent overfitting of the model;
g) GRU sequence processor: comprises two 64-unit hidden layers capable of processing the full arrangement, serving as the foundation for modeling temporal relationships in the input sequence;
h) Fully connected layer: comprehends the combined features to interpret the complex patterns for classification purposes;
i) Output layer: Sigmoid-activated single neurons for binary news classification: fake or real.

This CNN-GRU architecture leverages the CNN's ability to extract invaluable knowledge from local patterns in the text, combined with the GRU's learning efficiency. The result is a model capable of capturing both specific linguistic cues and overarching narrative structures, essential for task like fake news detection.

3.5. Model Training and Evaluation

The model is trained using supervised learning techniques. Training, validation, and test sets make up the dataset. The model is trained using the training set, its performance is determined using the test set, and

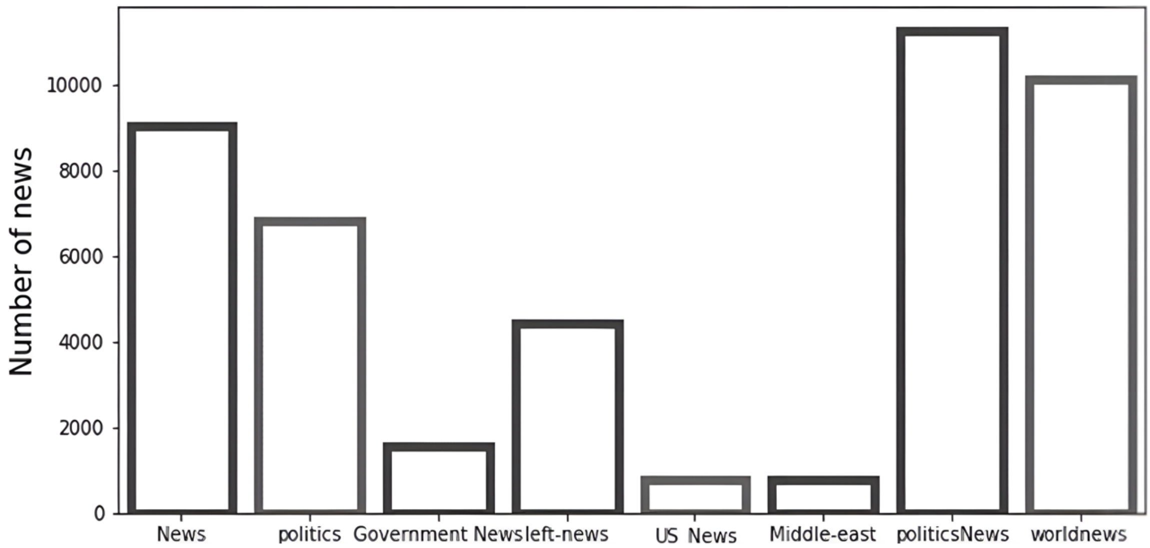

Figure 3. Types of News Count of the Data.

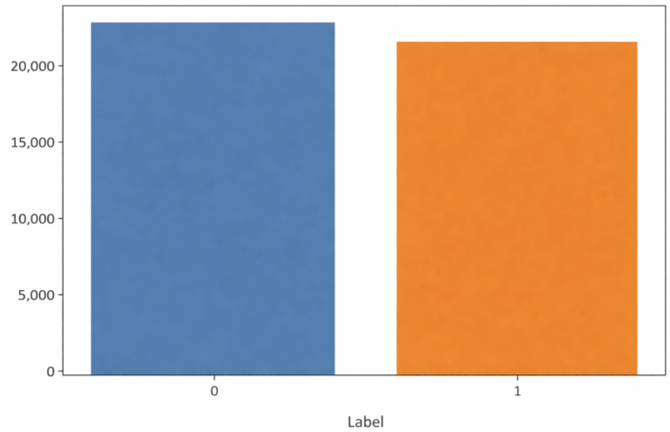

Figure 4. Distribution of target class.

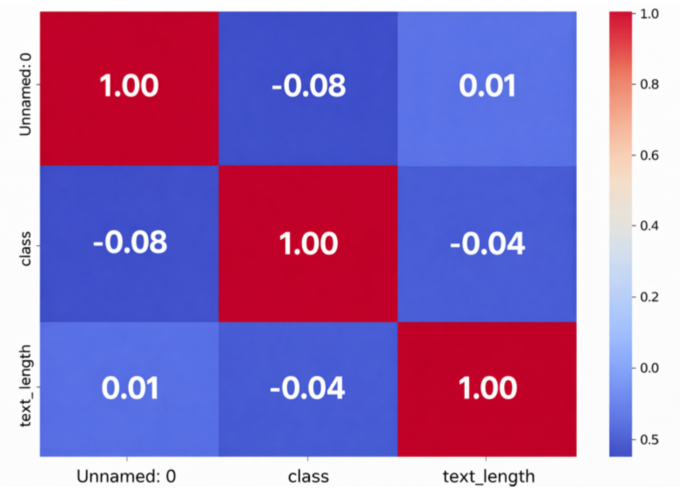

Figure 5. Correlation Matrix.

hyperparameters are adjusted using the validation set. Key evaluation metrics include precision, accuracy, F1-score and recall.

Confusion Matrix:

To evaluate the performance of the proposed model; a confusion matrix was used. It is made up of precision, accuracy, recall, and f1 scores. It is calculated as shown below:

a) Accuracy

Accuracy is the most straightforward intuitive performance statistic; it is just the ratio of correctly predicted observations to all observed.

$$Accuracy = \frac{tp + tn}{tp + tn + fp + fn} \tag{1}$$

b) Precision

Precision measures how many correctly predicted positive observations there are out of all expected positive observations.

$$Precision = \frac{tp}{tp + fp} \tag{2}$$

c) Recall

The percentage of correctly predicted positive observations relative to all observations in the class is known as recall. Another name for the recollection is sensitivity.

$$Recall = \frac{tp}{tp + fn} \tag{3}$$

d) F1-Score

Recall and precision are calculated as an average and weighted. Therefore, both false positives and false negatives are taken into account in this score. F1 is often more valuable than accuracy, even if it is less obvious, particularly when the distribution of classes is uneven.

$$F1 - Score = 2\left(\frac{precision * recall}{precision + recall}\right) \tag{4}$$

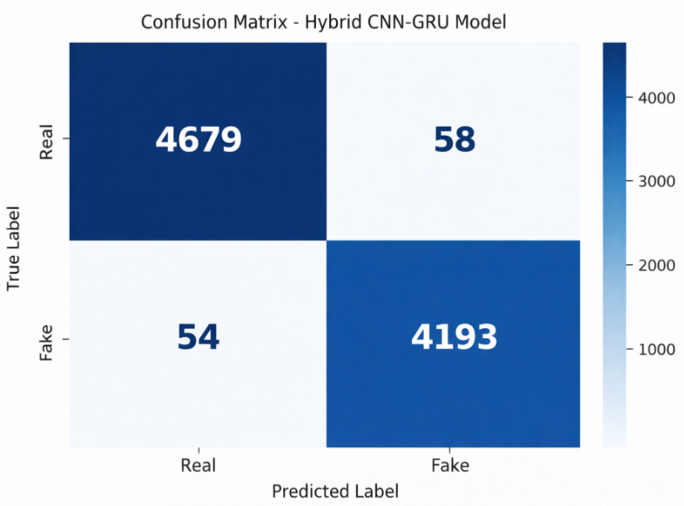

Figure 6. Confusion Matrix.

Table 1. Dataset Basic Information.

#	Column	Non-Null Count	Dtype
0	Unnamed: 0	44919 non-null	int64
1	title	44919 non-null	object
2	text	44919 non-null	object
3	subject	44898 non-null	object
4	date	44898 non-null	object
5	class	44919 non-null	int64

RangeIndex: 44919 entries, 0 to 44918
Data columns (total 6 columns)
dtypes: int64(2), object(4)

Table 2. Dataset Basic Statistics.

Statistic	Unnamed: 0	class
count	44,919.000000	44,919.000000
mean	11,253.444801	0.476792
std	6,525.299017	0.499467
min	0.000000	0.000000
25%	5,614.500000	0.000000
50%	11,229.000000	0.000000
75%	16,844.000000	1.000000
max	23,501.000000	1.000000

Table 3. Result Comparison.

Model	Accuracy	Preci-sion	Recall	F1 Score
CNN_GRU	98.77%	98.68%	98.73%	98.71%
CNN	98.65%	97.71%	99.48%	98.59%
GRU	97.74%	98.44%	96.77%	97.60%

4. Results and Discussion

The result obtained from the experiment and analysis is presented as shown below. The various data exploration techniques applied were also presented, cleaned data and other data preprocessing tasks were displayed for ease of understanding, and performance measures.

4.1. Data Exploration

This study's dataset was obtained from the popular and reliable machine learning repo known as Kaggle. The distribution of news types within the dataset is shown in Figure 3. The data obtained has been used in various previous studies for classification, identification, and prediction of real and fake news. As shown in Table 1, the dataset comprises six columns; these include the serial number, title, text, subject, date, and class. It has a total of forty-four thousand nine hundred and ninety entries (rows).

In the following Table 2, further information regarding the dataset was displayed (descriptive statistics). Such as the total number of entries (count), mean value, minimum (min) and maximum (max) values, standard deviation (std) and percentages (twenty-five, fifty and seventy-five).

Figure 4 displays the target distribution of classes as contained in the dataset. Zero (0) in the distribution represents the fake news corpus whereas one (1) represents the real news corpus in the dataset for the design, creation, and implementation of the hybrid CNN and GRU unit; that is the hybrid CNN-GRU model. Figure 5 presents the correlation matrix of the dataset features, illustrating the degree of linear relationships between the variables.

4.2. Confusion Matrix

Confusion metrics can help evaluate the effectiveness of classification algorithms by providing a more complete insight of the model's accuracy and errors. The confusion matrix can be used to calculate a variety of performance metrics, including precision, accuracy, recall, and F1. Figure 6 is a confusion matrix of results obtained from the hybrid CNN-GRU model. The hybrid CNN-GRU model has correctly made 4689 true positive predictions and correctly made 4212 true negative predictions. However, it failed to create 48 false positive and 35 false negative predictions. As a result, the hybrid CNN-GRU model made an extremely accurate forecast.

4.3. Performance Measure

In Table 3, the individual models that were proposed to be used in the study, CNN, and GRU were trained and tested individually and then later hybridized to get the proposed hybrid convolutional neural network and gated recurrent unit. After the experiment, it was observed that the model performed well individually but better performed when hybridized or concatenated as one. The result of which can be found in the following figures.

The performance measure was used to measure the performance of the hybrid convolutional neural network and gated recurrent unit on the testing data to determine how effective the proposed model was in detecting fake news on social media platforms. Table 3 shows the result of the measure as reported by the model. Accuracy is the

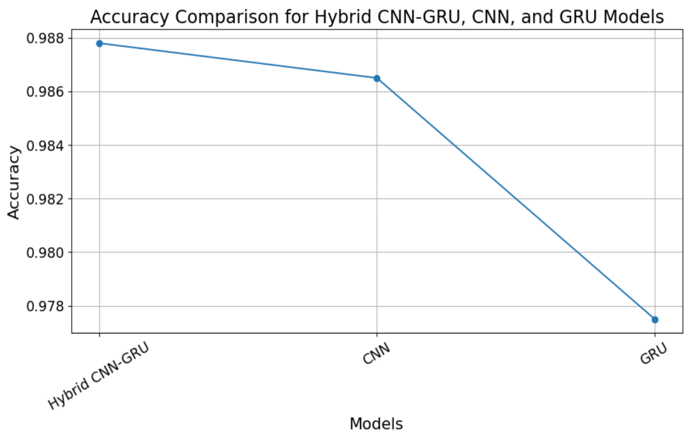

Figure 7. Accuracy Comparison for Hybrid CNN_GRU, CNN and GRU.

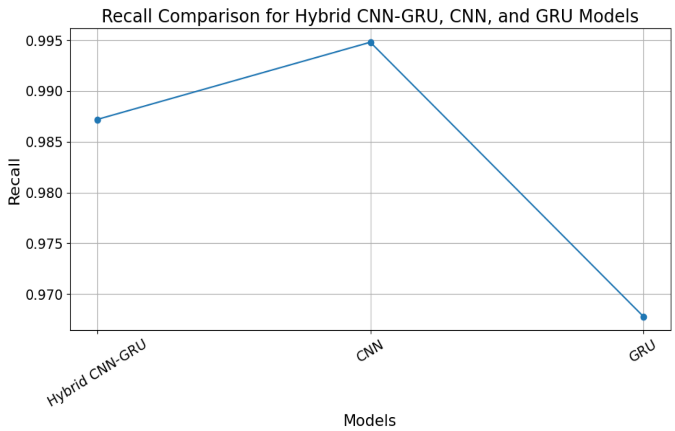

Figure 9. Recall Comparison for Hybrid CNN_GRU, CNN and GRU.

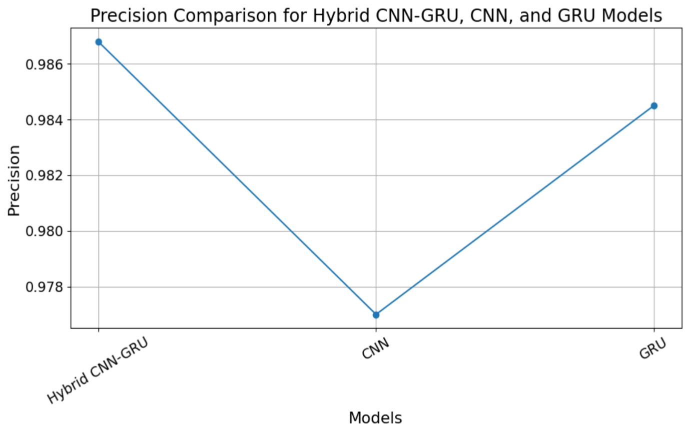

Figure 8. Precision Comparison for Hybrid CNN_GRU, CNN and GRU.

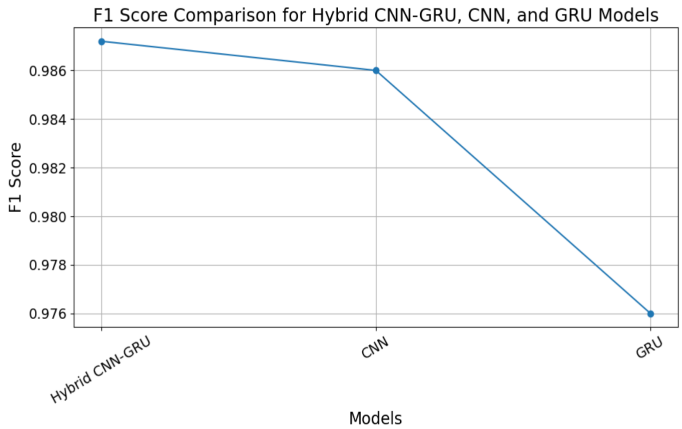

Figure 10. F1 Score Comparison for Hybrid CNN_GRU, CNN and GRU.

Table 4. Comparison of the proposed hybrid CNN-GRU and results accessed in the literature.

Model	Accuracy	Precision	Recall	F1 Score
CNN_GRU (Proposed)	**98.77%**	**98.68%**	**98.73%**	**98.71%**
(Adiba et al., 2020)	96.00%	97.00%	95.00%	96.00%
(Karwa & Gupta, 2022)	92.60%	92.40%	92.50%	92.50%
(Emmy et al, 2023)	95.16%	95.17%	95.16%	95.16%

proportion of instances that are correctly predicted out of the total number of instances. The 98.77% accuracy means that approximately 98.77% of the predictions made by the proposed model are correct. Precision is the proportion of correct positive predictions out of all the positive predictions made. 98.68% precision implies that when the CNN-GRU model predicts a positive class, it is correct about 98.68% of the time. Recall is the proportion of actual positive instances that are correctly identified as positive by the model. 98.73% recall means the hybrid CNN-GRU model can correctly identify 98.73% of the actual positive instances. F1-score is referred to as the harmonic mean of precision and recall. 98.71% F1-score offers a balanced measure that considers both precision and recall. It is useful when there is an imbalance between the classes.

To ensure the reliability of the reported results, several measures were taken to prevent data leakage and overfitting. The dataset was partitioned into non-overlapping training (80%) and testing (20%) sets prior to any preprocessing or feature extraction. Importantly, TF-IDF vectorization was fitted exclusively on the training set and then applied to the test set, preventing any information from the test partition from influencing the feature representation. No future facing data or temporal information was incorporated into the training pipeline. While k-fold cross-validation was not applied in this study due to computational constraints, this is acknowledged as a limitation, and future work will incorporate cross validation to provide more robust generalization estimates. Furthermore, baseline comparisons with standalone CNN and GRU models, as presented in Table 3, confirm that the performance improvement is attributable to the hybrid architecture rather than data artifacts. The high classification accuracy (98.77%) is consistent with the benchmark dataset's characteristics, which has also yielded comparably high scores in related studies [6], [7], [10]. Figures 7, 8, 9, and 10 illustrate the accuracy, precision, recall, and F1-score comparisons respectively among the Hybrid CNN-GRU, CNN, and GRU models across training epochs.

The results indicate that the Hybrid CNN-GRU model outperforms both the individual CNN and GRU models in terms of accuracy, precision, and F1 score. This suggests that combining the strengths of both CNN and GRU architectures leads to a more robust model capable of capturing both spatial and temporal features effectively.

The CNN-GRU hybrid model combines CNN's capacity to capture spatial data with GRU's ability to interpret temporal relationships. While CNNs excel at recall and GRUs at precision, the hybrid approach balances their respective strengths, resulting in higher overall performance. This combination of spatial and temporal feature extraction produces higher precision, F1 score, and accuracy, outperforming separate models and resulting in a more complete and reliable false news detection system. Table 4 compares the performance of the proposed hybrid CNN-GRU model against existing methods reported in the literature, demonstrating its superior classification performance.

5. Limitations and Future Work

This study has limitations that should be acknowledged as:

i) the current model relies exclusively on textual features extracted via TF-IDF vectorization. Although effective, this approach does not capture semantic nuances, contextual relationships, or non-textual signals such as user metadata, posting patterns, or network propagation features that could further improve detection performance. Future work should explore the integration of such multimodal or social graph features.

ii) the dataset used in this study is sourced from a single repository (Kaggle) and is limited to the X (formerly Twitter) platform. This restricts the models generalizability to other social media platforms or news domains. Cross platform and cross domain evaluation should be conducted in future studies to assess the models robustness.

iii) while a holdout train/test split was employed and data leakage prevention measures were applied, k-fold cross-validation was not used due to computational considerations. Future iterations of this work should incorporate cross validation to provide more statistically reliable performance estimates.

iv) the model does not currently support multilingual content, limiting its applicability in non-English-speaking contexts where fake news also proliferates. Multilingual fake news detection using models such as multilingual BERT or cross lingual embeddings is a promising direction for future research.

v) real-time deployment and scalability of the proposed model remain unexplored. Future work should address integration into live platforms, latency optimization, and continuous model retraining to adapt to evolving disinformation patterns.

6. Conclusion

The CNN-GRU model has demonstrated exceptional effectiveness in classifying social media news as real or fake, with robust performance metrics reflecting high accuracy and minimal false positives. Its success lies in the seamless integration of convolutional and recurrent neural networks, enabling the model to capture both localized and sequential text patterns. High precision and recall ensure accurate identification of fake news, thereby reducing the spread of misinformation online.

To further enhance the model's capabilities, it is recommended to evaluate its performance on diverse datasets, implement continuous monitoring for sustained accuracy, and improve interpretability to build user trust and ensure compliance. These enhancements aim to maintain the model's relevance as data dynamics evolve and to solidify its role in fostering a more informed online community.

7. Declarations

7.1. Author Contributions

Lawan Jibril Muhammad: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing Original Draft, Writing – Review & Editing, Supervision; **Isa Umar Mohammed:** Formal analysis, Investigation, Resources, Data Curation, Writing Original Draft; **Nura Muhammad Sani:** Writing Review & Editing, Visualization, Supervision, Project administration.

7.2. Institutional Review Board Statement

Not applicable.

7.3. Informed Consent Statement

Not applicable.

7.4. Data Availability Statement

The data presented in this study are available upon request from the corresponding author (Lawan Jibril Muhammad, mljibril.it@buk.edu.ng). The dataset is publicly accessible at: https://www.kaggle.com/datasets/algord/fake-news.

7.5. Acknowledgment

Not applicable.

7.6. Conflicts of Interest

The authors declare no conflicts of interest.

8. References

[1] A.O. Alsayed *et al*, "Selection of the Right Undergraduate Major by Students Using Supervised Learning Techniques". *Appl. Sci.* Vol. 11, no. 22, art. No. 10639, 2021. https://doi.org/10.3390/app112210639.

[2] P. Jiang, Y. Chen, B. Liu, D. He and C. Liang, "Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks," *IEEE Access*, vol. 7, pp. 59069 – 59080, 2019. https://doi.org/10.1109/ACCESS.2019.2914929.

[3] L. J. Muhammad, A. A. Haruna, U. S. Sharif, M. P. Mohammed, "CNN-LSTM deep learning based forecasting model for COVID-19 infection cases in Nigeria, South Africa and Botswana," *Health and Technology*, vol 12, pp. 1259–1276 2022. https://doi.org/10.1007/s12553-022-00711-5.

[4] S. Sreejith, K. Nehemiah, A. Kannan, "A. Clinical data classification using an enhanced SMOTE and chaotic evolutionary feature selection," *Computers in Biology and Medicine*, vol. 126, art no. 103991. 2020. https://doi.org/10.1016/j.compbiomed.2020.103991.

[5] J. A. Nasir, O. S. Khan, I. Varlamis "Fake news detection: A hybrid CNN-RNN based deep learning approach". *International journal of information management data insights*, vol. 1, no. 1, 2021. https://doi.org/10.1016/j.jjimei.2020.100007.

[6] F. I. Adiba, T. Islam, M. S. Kaiser, M. Mahmud, M. A. Rahman, "Effect of Corpora on Classification of Fake News using Naive Bayes Classifiers," *International Journal of Automation, Artificial Intelligence and Machine Learning*, vol. 1, no. 1, pp. 80-92, 2020. https://doi.org/10.61797/ijaaiml.v1i1.45.

[7] R. R. Karwa, S. R. Gupta, "Automated Hybrid Deep Neural Network Model for Fake News Identification and Classification in Social Networks," *Journal of Integrated Science and Technology*, vol. 10, no. 2, pp. 110-119, 2022, https://doi.org/10.5875/ausmt.v13i1.2409.

[8] E. Tacchini, G. Ballarin, M. L. Della Vedova, S. Moret, and L. de Alfaro, "Some like it hoax: Automated fake news detection in social networks," *arXiv preprint arXiv:1704.07506*, 2017. https://doi.org/10.48550/arXiv.1704.07506.

[9] L. Alzubaidi et al., "A survey on deep learning tools dealing with data scarcity: definitions, challenges, solutions, tips, and applications," *Journal of Big Data*, vol. 10, Article no. 46, 2023. https://doi.org/10.1186/s40537-023-00727-2.

[10] E. D. Ajik, G. N. Obuandike, F. O. Echobu, "Fake News Detection Using Optimized CNN and LSTM Techniques," *Journal of Information Systems and Informatics*, vol. 5, no. 3, pp. 1044-1057, 2023, https://doi.org/10.51519/journalisi.v5i3.548.

[11] F. W. R. Tokpa, B. H. Kamagaté, V. Monsan, S. Oumtanaga, "Fake news detection in social media: Hybrid deep learning approaches," *Journal of Advances on Information Technology*, vol. 14, no. 3, pp. 606-615, 2023. https://doi.org/10.12720/jait.14.3.606-615.

[12] F. C. Akyon and M. E. Kalfaoglu, "Instagram fake and automated account detection," in *Proc. Innovations in Intelligent Syst. Applications Conf. (ASYU)*, 2019. https://doi.org/10.1109/ASYU48272.2019.8946437.

[13] M. Aldwairi and A. Alwahedi, "Detecting fake news in social media networks," *Procedia Computer Science*, vol. 141, pp. 215-222, 2018. https://doi.org/10.1016/j.procs.2018.10.171.

[14] H. Allcott and M. Gentzkow, "Social Media and Fake News in the 2016 Election," *Journal of Economic Perspectives*, vol. 31, no. 2, pp. 211-236, May 2017, https://doi.org/10.1257/jep.31.2.211.

[15] M. Akay, Y. M. Akay, and W. Wolfowitz, "Neural networks for the diagnosis of coronary artery disease," in *Proceedings of the IEEE International Joint Conference on Neural Networks (IJCNN)*, 1992, vol. 2, pp. 419-424. https://doi.org/10.1109/IJCNN.1992.226952.

[16] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-Based Learning Applied to Document Recognition," *Proceedings of the IEEE*, vol. 86, no. 11, pp. 2278-2324, Nov. 1998. https://doi.org/10.1109/5.726791.

[17] F. S. Prity *et al*., "RvXmBlendNet: A multi-architecture hybrid model for improved skin cancer detection," *Human-Centric Intelligent Systems*, vol. 4, pp. 545–570, 2024. https://doi.org/10.1007/s44230-024-00083-1.

[18] O. A. Sarumi, O. Aouedi, L. J. Muhammad. "Potential of Deep Learning Algorithms in Mitigating the Spread of COVID-19". *In: J. Nayak, B. Naik, A. Abraham (eds) Understanding COVID-19: The Role of Computational Intelligence*. Studies in Computational Intelligence, vol 963, 2022. https://doi.org/10.1007/978-3-030-74761-9_10.

[19] A. Bhagat, D. Dangi, V. Suman, D. K. Dixit, S. Sharma, "Fake News Detection Using ARO and LSTM Algorithms," *SN Computer Science*, vol. 6, p. 36, 2025. https://doi.org/10.1007/s42979-024-03574-x.

[20] B. A. Tanawala and D. C. Dalwadi, "Harmonic synergy: Leveraging deep convolutional networks, long short-term memory networks, and recurrent neural networks for multi-genre piano roll generation with generative adversarial networks," *SN Computer Science*, vol. 6, p. 297, 2025. https://doi.org/10.1007/s42979-025-03855-z.

[21] C. S. Lakshmi, S. Saxena, and K. B. Kumar, "Sentiment analysis and classification of COVID-19 tweets using machine learning classifier," *Journal of Autonomous Intelligence*, vol. 7, no. 2, 2024.

[22] D. K. Dixit, A. Bhagat, and D. Dangi, "Automating fake news detection using PPCA and levy flight-based LSTM," *Soft Computing*, vol. 26, no. 22, pp. 12545–12557, 2022. https://doi.org/10.1007/s00500-022-07215-4.

[23] S. Raza and C. Ding, "Fake news detection based on news content and social contexts: A transformer-based approach," *International Journal of Data Science and Analytics*, vol. 13, no. 4, pp. 335–362, 2022. https://doi.org/10.1007/s41060-021-00302-z.

[24] M. S. Hossain, L. J. Armstrong, D. M. Cook, P. Zaenker, "Application of histopathology image analysis using deep learning networks," *Human-Centric Intelligent Systems*, vol. 4, pp. 417–436, 2024. https://doi.org/10.1007/s44230-024-00077-z.

[25] Q. Chang, X. Li, and Z. Duan, "Graph global attention network with memory: A deep learning approach for fake news detection," *Neural Networks*, vol. 172, p. 106115, 2024. https://doi.org/10.1016/j.neunet.2024.106115.

[26] B. Gülmez. "Stock price prediction with optimized deep LSTM network with artificial rabbits optimization algorithm," *Expert Systems with Applications*. vol. 227, art. no. 120346, 2023. https://doi.org/10.1016/j.eswa.2023.120346.

[27] H. Ahmed, I. Traore, and S. Saad, "Detection of Online Fake News Using N-Gram Analysis and Machine Learning Techniques," in *International Conference on Intelligent, Secure, and Dependable Systems in Distributed and Cloud Environments*, 2017, pp. 127-138. https://doi.org/10.1007/978-3-319-69155-8_9.

[28] K. Cho, B. van Merrienboer, C. Gulcehre, D. Bahdanau, F. Bougares, H. Schwenk, and Y. Bengio, "Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation," in *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 2014, pp. 1724-1734. https://aclanthology.org/D14-1179.pdf.

[29] E. Lesyk, T. Arias-Vergara, E. Nöth, A. Maier, J. R. Orozco-Arroyave, and P. A. Perez-Toro., "Empathetic deep learning: Transferring adult speech emotion models to children with gender-specific adaptations using neural embeddings," *Human-Centric Intelligent Systems*, vol. 4, pp. 633–642, 2024. https://doi.org/10.1007/s44230-024-00088-w.

[30] W. Romsaiyud, H. Schnoor, and W. Hasselbring "Improving k-nearest neighbor pattern recognition models for privacy-preserving data analysis". In *2019 IEEE International Conference on Big Data (Big Data)*, pp. 5804-5813, 2019. https://doi.org/10.1109/BigData47090.2019.9006281.

[31] I. AlShourbaji, P. Kachare, W. Zogaan,, L. J. Muhammed, and L. Abualigah, "Learning features using an optimized artificial neural network for breast cancer diagnosis". *SN Computer Science*, vol. 3, art. No. 229, 2022. https://doi.org/10.1007/s42979-022-01129-6.

[32] K. Shu, et al., "FakeNewsNet: A data repository with news content, social context, and spatiotemporal information for studying fake news on social media," *Big Data*, vol. 8, no. 3, pp. 171–188, 2020. https://doi.org/10.1089/big.2020.0062.

[33] D. Jyoti, D. P. Mahato, and J. Srivastava, "Deep learning-based scientific document summarization considering citation," *SN Computer Science*, vol. 6, art. No. 300, 2025. https://doi.org/10.1007/s42979-025-03821-9.

[34] D. Trandabăț and D. Gifu, "Discriminating AI-generated fake news," *Procedia Computer Science*, vol. 225, pp. 3822–3831, 2023. https://doi.org/10.1016/j.procs.2023.10.378.

[35] R. Kailasam and S. Balasubramanian, "Deep learning for pneumonia detection: A combined CNN and YOLO approach," *Human-Centric Intelligent Systems*, vol. 5, pp. 44–62, 2025. https://doi.org/10.1007/s44230-025-00091-9.

[36] A. Hanson, K. PNVR, S. Krishnagopal, L. Davis, "Bidirectional Convolutional LSTM for the Detection of Violence in Videos" in *Proceedings of the European Conference on Computer Vision (ECCV) Workshops*, 2018.

[37] I. Ahmad, M. Yousaf, S. Yousaf, and M. O. Ahmad, "Fake news detection using machine learning ensemble methods," *Complexity*, vol. 2020, no. 1, p. 8885861, 2020. https://doi.org/10.1155/2020/8885861.

[38] P. Samuels, "Exploring cultural aspects of visual metaphors in doctoral and early career researcher training," in *Proceedings of the 4th International Technical University of Kenya Exploring Visual Cultures Conference*, 2023. https://www.researchgate.net/profile/Peter-Samuels/publication/388315400.

[39] M. Bouchane, W. Guo, and S. Yang, "Hybrid CNN-GRU models for improved EEG motor imagery classification," *Sensors*, vol. 25, no. 5, p. 1399, 2025. https://doi.org/10.3390/s25051399.

[40] N. Pachhala, S. Jothilakshmi, and B. P. Battula, "Cross-Platform Malware Classification: Fusion of CNN and GRU Models," *International Journal of Safety and Security Engineering*, vol. 14, no. 2, pp. 477–486, 2024. https://doi.org/10.18280/ijsse.140215.

[41] R. Puthran, "Spatio-temporal analysis of hybrid convolutional neural network and gated recurrent unit model for prediction of earthquake for disaster management," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 12, no. 3s, pp. 270–281, 2024. https://ijisae.org/index.php/IJISAE/article/view/3705.

[42] J. Yu, X. Zhang, L. Xu, J. Dong, and L. Zhangzhong, "A hybrid CNN-GRU model for predicting soil moisture in maize root zone," *Agricultural Water Management*, vol. 245, p. 106649, 2021. https://doi.org/10.1016/j.agwat.2020.106649.

[43] A. Golovin, "Fake News: Fake News dataset based on FakeNewsNet," [Online]. Available: https://www.kaggle.com/datasets/algord/fake-news.