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RESEARCH PAPER

A Data-Driven Advanced Deep Learning Model For False News Classification and Identification

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***Abstract*—The popularity of fake news has become a significant issue in contemporary society due to the rapid growth of internet social media and the ease of sharing information. The unintended consequences of spreading false information include social unrest, political polarization, and a loss of trust in media sources. The paper explores the performance of a deep learning method for automating the separation of fake and real news articles. The hybrid RNN +GRU model has been proposed and the classification performance of the model is highly reliable with an accuracy, precision, recall and F1-score equal to 99.8 on the test data. Further comparative analysis reveals that the proposed model performs greatly except the models that are currently being used, including CNN, Random Forest, XGBoost, ALBERT, and LSTM model. The findings confirm that the RNN + GRU architecture is an efficient and reliable method for false news detection. The paper provides a useful hybrid RNN+GRU model of the reliable fake news detection and it has high levels of robustness and stability as well as a high level of consistency in comparison to the current systems. In general, the results indicate that hybrid sequential models are indeed appropriate for detecting false news in real-world conditions.**

Keywords—Social Media Analytics, Fake News Detection, Misinformation Analysis, Text Classification, Semantic Feature Extraction, Deep Learning Models.

I. INTRODUCTION

The massive growth of digital communication technologies has essentially transformed the way information is produced, distributed and consumed in the world [1]. With the growing use of social media as a news source, it has also enabled the uncontrolled dissemination of false and misleading information. It is known as fake news when the intention is to create and spread misleading information and make it appear as the real journalism. Therefore, this kind of content may mislead the general public, influence political and social decisions, and cause widespread confusion during essential events, such as elections, pandemics, and natural disasters. Consequently, authenticity and credibility of information in the digital format have become an urgent issue of the contemporary digital societies [2], [3]. Despite the pre-existing misinformation, its effect has been bigger than ever with the digital age because of the rapid and comprehensive distribution of Internet-related information [4], [5]. Social media sites enable information not to be checked and thus propagation of information is easy unlike traditional media [6]. Moreover, platform algorithms tend to promote emotional and sensational content more than facts, which contributes to false news spreading to more users [7]. Consequently, it has led to the inadequacy of manual verification and conventional methods of the fact-checking. Hence, automated and scalable methods for detecting fake news are necessary.

To overcome these shortcomings, machine learning approaches using data have become useful solutions to detecting fake news. Traditional machine learning models are based on handcrafted linguistic and statistical attributes to distinguish between false and authentic news, which is interpretable and computationally efficient [8], [9]. However, despite their advantages, these approaches struggle to capture complex semantic relationships and contextual dependencies inherent in natural language [10], thereby limiting their robustness in dynamic information environments [11]. This limitation has led to the discovery of more modern modeling paradigms [12]. deep learning methods have shown better performance by learning hierarchical representations automatically by using large quantities of textual data [13], [14]. Advanced neural models, through modelling semantic subtleties and long term contextual contingencies, have more discrete patterns that distinguish between genuine and false news. The proposed study, therefore, finds applications in offering a solid data-based advanced deep learning model that can be used to classify and identify false news and enhance accuracy of detection, adaptability, and generalization. The suggested framework can help enhance the trustworthiness and integrity of digital information ecosystems through effective representation learning and contextual awareness.

A. Motivation and Contribution

The inspiration behind this work is the fact that the fake news is rapidly spreading within the online and social media platforms, and this presents severe challenges to the credibility of information and the trust of people. Conventional methods of detection are usually inapplicable at the other end complex linguistic and contextual patterns in misleading news content. As the volume of textual information at scale continues to rise, deep learning models have proven to be a viable solution for automatic and precise fake news detection. This paper, therefore, has the motivation of developing a hybrid RNN+GRU model that can enhance accuracy and reliability of detection. This study makes some important contributions as enumerated below:

- Conducted comprehensive exploratory analysis, including class distribution, word cloud visualization, and word-length analysis, highlighting linguistic patterns in fake versus real news.
- The hybrid deep learning model with Recurrent Neural Network (RNN) and Gated Recurrent Unit (GRU) was

designed to capture sequential and contextual pattern in news text so that they are accurately classified.

- Assesses the strength of the model based on conventional assessment measures Accuracy, precision, recall, and F1-score.
- Validated the computational efficiency of the model on standard hardware, making it practical for real-world implementation.
- Demonstrated balanced generalization with minimal overfitting, supported by aligned training and testing curves and a reliable confusion matrix.

B. *Novelty And Justification*

The proposed research is innovative approach to using a hybrid RNN+GRU architecture in detecting fake news by integrating the advantages of the two recurrent networks to identify and extract both short- and long-term correlations in text. This model unlike traditional ones like CNN, LSTM and ensemble methods has a very high performance and it has a balance between generalization and minimal overfitting. The fact that the work studies linguistic patterns in detail, has effective preprocessing, and represents features with CountVectorizer and GloVe embeddings, which have an overall positive impact on the model's discriminative power, justifies the work. The method is not only better than existing techniques but also a dependable, scalable solution for detecting fake news in real-life scenarios.

C. *Organization of the Paper*

The paper is structured as follows: Section II provides a literature review on fake news detection. Section III presents the dataset; the preprocessing processes and the proposed methodology and Section IV presents the analysis and the experimental results. Lastly, Section V presents the paper's conclusion and outlines directions for future research.

II. LITERATURE REVIEW

The literature review and analysis of the major studies on False News Detection were conducted to inform and improve the construction of the current study.

Arianto *et al.* (2025) designed to capture the syntactic and stylistic patterns commonly found in misinformation. The dataset, collected from TurnBackHoax.id, Komdigi, and Kompas, consists of 32,865 labeled entries. A stratified 10-fold cross-validation was employed to evaluate five machine learning classifiers. Results demonstrate that the Support Vector Machine (SVM) with an RBF kernel achieved the highest performance, achieving an F1-score of 84.4% and outperforming MLP, KNN, Decision Tree, and Naive Bayes. Validation on 15 real news headlines further confirmed the robustness of the framework in low-similarity cases [15].

Vysotska *et al.* (2024) display the results of news analysis in a convenient and understandable format. The article demonstrates better indicators of news analysis based on Long Short-Term Memory (LSTM) with eight epochs compared to similar works with 3–4 epochs (99% vs 85-96%) because a neural network was developed for news classification using bidirectional recurrent neural network LSTM (BRNN) and Bidirectional layers in the model. Deep learning models, such as bidirectional LSTM, have high accuracy in recognising patterns in textual data, allowing for better results [16].

Safdar and Wasim (2024) propose an innovative hybrid model for news titles and user comments, DFN-SCNC (Detection of fake news based on social context and news content), that combines BERT and Bi-GRU models. model, which combines BERT for tokenizing and extracting contextual vectors with Bi-GRU for analyzing post content and social interactions (comments), outperforms various state-of-the-art techniques achieving an F1-score of 97% and 91 % on FNID and FNFD datasets respectively [17].

Malik, Chakraverti and Abidi (2023) evaluating the effectiveness of multiple classification algorithms, including Logistic Regression, Decision Tree, K-Nearest Neighbors (KNN), and Naive Bayes. These models undergo rigorous scrutiny, with Logistic Regression emerging as the top performer, achieving an impressive accuracy rate of 96%. To address concerns about false positives, fine-tune the Logistic Regression model and meticulously assess its performance metrics, including the ROC AUC score, which is 98%, indicating its ability to distinguish genuine news from fabricated narratives. Additionally, explore deep learning techniques, employing Long Short-Term Memory (LSTM) and bidirectional LSTM (BiLSTM) models, which yield accuracy scores of 96% and 98%, respectively [18].

Anand, Kulkarni, and Agrawal (2023) developed a mechanism that combines the prediction probabilities of ML and DL models. achieved accuracy as high as 0.98 and F1 scores as high as 0.98 using approach. also analyze the results of classification using different graphs which give us meaningful insights into the accuracy of the prediction of different models. use flow charts to demonstrate the flow of proposed algorithm in the classification of news. The superiority of model is demonstrated in experimental results [19].

Bonny *et al.* (2022) identification is accomplished using ML algorithms, Logistic Regression (LR) Decision Tree (DT), Random Forest (RF), Extreme Gradient Boosting (XGB), Gradient Boosting (GB), Multinomial Naive Bayes (MNB) and K Nearest Neighbors (KNN). they have determined the precision, recall, F-measure, accuracy for each of the classifiers. To be more specific, employed a total of 44898 distinct news pieces from a dataset of authentic and fake news to train a ML model using Count vectorizer and TF-IDF as feature extraction approaches, with the highest performing model LR achieving an accuracy of 93.86% [20].

Although recent fake news detection models have high levels of accuracy, most methods are based on a high level of supervised learning and include domain-specific features, which restrict their extrapolation to other areas, languages, and real-life situations. A significant number of studies mainly concentrate on content-based analysis whereas less attention is paid to the dynamic social context, the development of source credibility, and the real-time verification. Also, such high accuracy values lead to suspicion of bias and overfitting of the dataset and little is done in terms of validation on unseen or low-similarity news samples. As such, there is a research gap in how to create scalable, explainable, and cross-domain fake news detection systems that combine content, context, and external verification in real-time settings. Table 1 presents an overview of the current literature on False News Detection, including the proposed models, the datasets used, key findings, and the challenges it faces.

TABLE I. RECENT STUDIES ON FALSE NEWS CLASSIFICATION AND IDENTIFICATION USING DEEP LEARNING TECHNIQUES

Author	Approach	Results	Key Findings	Limitations & Future Work
Arianto et al. (2025)	Framework capturing syntactic and stylistic misinformation patterns using ML classifiers on Indonesian datasets	SVM (RBF kernel) achieved F1-score of 84.4%	SVM outperformed MLP, KNN, DT, and NB; effective in handling low-similarity misinformation cases	Performance limited by handcrafted features; future research may incorporate deep learning and larger multilingual datasets
Vysotska et al. (2024)	Bidirectional LSTM-based deep learning model for news classification with optimized epochs	Achieved 99% accuracy, outperforming prior works (85–96%)	Bidirectional LSTM effectively captures contextual dependencies and textual patterns in news data	High computational cost; future work may explore lightweight architectures and cross-domain validation
Safdar and Wasim (2024)	DFN-SCNC hybrid model combining BERT and Bi-GRU using news titles and social media comments	F1-score of 97% (FNID) and 91% (FNFD)	Joint modeling of content and social context significantly enhances fake news detection performance	Requires large labeled social-context datasets; future work can address scalability and platform generalization
Malik, Chakraverti and Abidi (2023)	Evaluation of ML (LR, DT, KNN, NB) and DL (LSTM, BiLSTM) models	LR accuracy 96%, ROC-AUC 98%; BiLSTM accuracy 98%	Logistic Regression remains competitive; BiLSTM improves contextual understanding	Limited analysis of explainability; future work may integrate explainable AI techniques
Anand, Kulkarni and Agrawal (2023)	Ensemble mechanism combining prediction probabilities of ML and DL models	Accuracy and F1-score up to 0.98	Ensemble learning improves robustness and overall prediction reliability	Increased system complexity; future work may focus on optimization and real-time inference
Bonny et al. (2022)	ML-based fake news detection using TF-IDF and Count Vectorizer with multiple classifiers	Logistic Regression achieved 93.86% accuracy	Simpler ML models with effective feature extraction remain strong baselines	Performance constrained by traditional features; future work can explore contextual embeddings and DL models

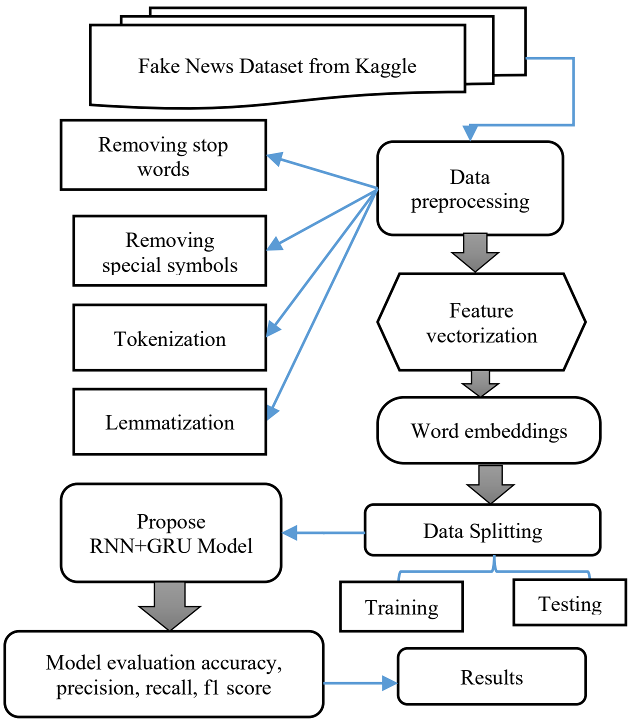

Fig. 1. Proposed flowchart for False News Classification and Identification using Deep learning

III. RESEARCH METHODOLOGY

This paper uses a deep learning methodology to classify fake news based on a Kaggle dataset, which was preprocessed by removing stop-words, special characters, lemmatizing, and tokenizing of text to improve the quality of text. The Count Vectorizer and the GloVe word representations are used to obtain feature representation and present semantic information, respectively. It has been divided into training and testing data in the proportion of 70:30 and the classification is done by a hybrid RNN+GRU model. A confusion matrix and other standard measures, such as accuracy, precision, recall, and F1-score, are used to evaluate model performance. The proposed flowchart of false news classification and Identification related to machine learning is presented in Fig. 1.

The following section presents a comprehensive explanation of each step involved in the proposed methodology:

A. Data Gathering and Analysis

An open-source fake news dataset from Kaggle is used in this work. The dataset contains 26,000 distinct sample documents and has been used in several articles to detect fake news. The dataset is classified into two categories that are fake news and original news shows in Fig. 2. The first category is true news category represented by class '1' and second category is fake news category represented by class '0'.

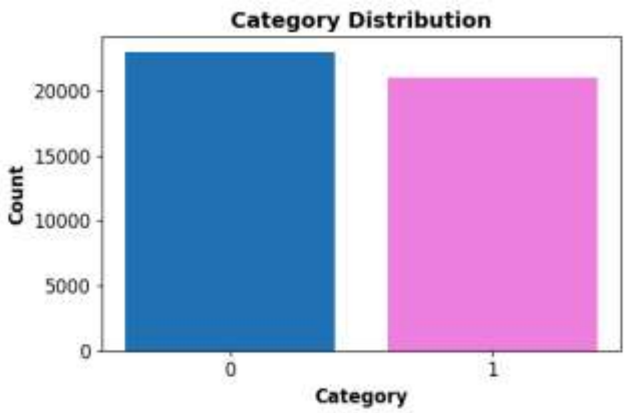

Fig. 2. Bar graph of class distribution with fake and real category

Fig. 2 illustrates the class distribution of the Fake News Dataset using a bar graph, showing the number of instances in the fake and real news categories. The graph indicates that the proportions of the two classes are similar, but category 0 has fewer samples than category 1. It is relatively an equal distribution to minimize the bias of classes when training a model and make learning and assessment more reliable. In general, the number indicates that the dataset is well distributed for effective experiments in false news detection.

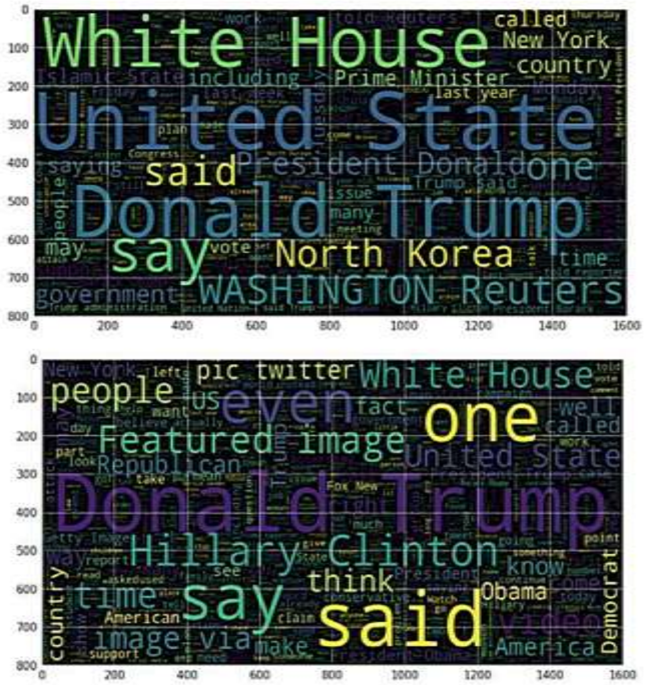

Fig. 3. Word cloud for original and Fake news dataset

Fig. 3 shows word clouds of the original (top) and fake (bottom) news datasets, revealing the most common words in each dataset. The use of key words like the white house, United State, and Donald Trump in the original news data is as well eminent, which is the formal coverage of significant political entities, and events. The fake news word cloud, by contrast, presents a combination of political leaders and informal words such as one, even, people, and so on, implying a more sensationalized and less organized style of language. The comparison shows that fake news frequently is based on easily repeated and eye catching words, where true news focuses on words that are contextually relevant and informational.

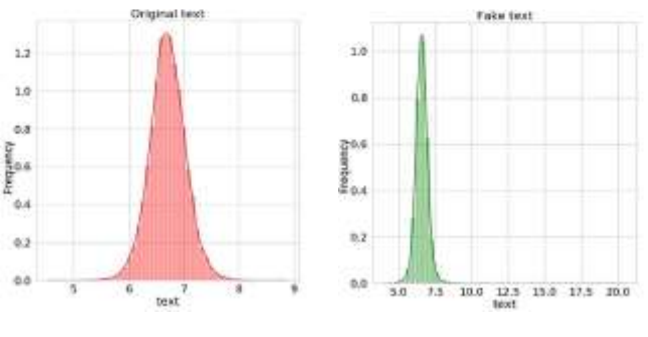

Fig. 4. Length classification of real and fake words in news

Fig. 4 displays the data distribution of word lengths in original and fake news articles. The histogram reveals that original news texts (left, red) have a relatively few and more evenly distributed word length range, the most common one being 6- 7 characters. Meanwhile, texts that contain fake news (right, green) have a more narrow distribution with shorter terms with the main ones being 5-7 characters. This implies that the fake news has the tendency of using less and shorter words and this could also be one of the reasons it gets read instantly and becomes viral unlike genuine news material.

B. Data Pre-processing

Data pre-processing is a crucial step that involves manipulating data before it is executed, to boost efficiency. It involves data cleaning and data transformation which is seen in the next section after this. The important preprocessing processes are as follows:

- **Removing stop words:** To eliminate stop words from a sentence, the text is divided into words and then it is checked to see if the word is in the NLTK list of stop words. If the particular word exists in the collection of a corpus, the word is then eliminated.
- **Removing special symbols:** Dealing with special symbols like punctuation marks, emoticons, and non-alphanumeric signs in the text. This step will minimize noise in the data and help the model focus on the most relevant words, enhancing feature extraction and overall performance.
- **Lemmatization:** Lemmatization is used to transform the words into root words. We can resolve data ambiguity and inflection with lemmatization.
- **Tokenization:** The representation of every word as a number is called tokenization. To make use of textual data to predictive model, the text is first broken down to eliminate certain words and this process is referred to as tokenization.

C. Feature vectorization

The process of transforming textual data into numeric features that can be used to train machine learning models is known as feature vectorization. Because majority of the algorithms do not handle text but instead handle numeric vectors of fixed length, so the text is then tokenized, word occurrences counted, and the data normalized. CountVectorizer is used in this research to create a vocabulary of unique words and to represent each document as a vector based on word frequency. This is a straightforward but powerful method that converts word sequences into structured numerical feature vectors that can be classified and recognized with great efficiency by machine learning and deep learning models.

D. Word embeddings

GloVe (Global Vectors) is an unsupervised algorithm that produces dense word vector representations using global word co-occurrence statistics from a corpus. Unlike Word2Vec, which relies mostly on local context, GloVe captures both local and global semantic relationships, enabling the vectors to model finer syntactic and semantic patterns. It does this by using a log-linear regression model that integrates the effectiveness of global matrix factorization and local context-based approaches, yielding embeddings useful for a wide range of natural language processing tasks.

E. Data Splitting

The data was separated into training and test set at a ratio of 70:30. The model can learn well using most of the data and is also capable of reliable assessment using unseen samples.

F. Proposed RNN+GRU Model

The suggested model combines Recurrent Neural Network (RNN) with Gated Recurrent Unit (GRU) to successfully address both long-term and short-term dependencies in text. The architecture is started with an embedding layer based on

GloVe vectors to translate words to dense semantic representations. This is followed by a two-way RNN layer that takes contextual information of both forward and backward sequence and transfers it to a GRU layer to accommodate long-term dependencies and overcome the problem of a vanishing gradient.

It has a fully connected dense layer whose output is connected to a sigmoid activation function to help classify the output as either fake or real news. The model parameters during training are a batch size of 64, a learning rate of 0.001, and Adam optimizer. The loss function is binary cross-entropy and the model is trained in 10 epochs. Between layers, dropout of 0.3 is used to minimize overfitting and early stopping is used to stop training once the validation loss ceases to improve. The arrangement of this model allows it to be highly accurate and robust with a strong ability of training and generalizing on unknown data.

G. Evaluation metrics

The suitability of the proposed model was assessed in the light of some standard performance measures. The first step was the creation of a confusion matrix to provide the overall picture of the outcomes of classifications, showing the number of correctly and incorrectly classified instances per class. Based on this matrix, several important elements were obtained which are the True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN). The evaluation metrics of interest (use of accuracy, precision, recall, and F1-score) were calculated using formula presented in Equations (1) to (4):

$$Accuracy = \frac{\mathrm{TP+TN}}{\mathrm{TP+Fp+TN+FN}} \tag{1}$$

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

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

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

Accuracy is the ratio of the number of instances correctly predicted by the trained model to the total number of instances in the dataset (input samples). Precision is the proportion of positive instances successfully predicted to all positive instances predicted by the model. Recall is ratio of events that were accurately predicted as positive to all instances that should have proved positive. F1 score is a combination of the harmonic mean of precision and recall, that is, it helps to balance recall and precision. Its range is [0, 1].

IV. Results And Discussion

This part explains the experimental design and assesses the effectiveness of the proposed model in terms of both training and testing, and proves its effectiveness and computational efficiency. The tests were held on a computer that is of a high performance with the Intel Core i3 processor and 32 GB RAM. The programming language was Python 3.7, the operating system was Windows 11 (64-bit), and machine-learning libraries, such as Scikit-learn to select a model and evaluate its performance and Seaborn to visualize it. The development platforms were Jupyter Notebook 7.0 and Anaconda 3 (5.2.0) platforms. It was demonstrated that the proposed RNN+GRU model was trained on the Fake News Dataset, which was provided by Kaggle and evaluated by the conventional performance measures (including accuracy, precision, recall, and F1-score) as shown in Table II. The findings show excellent classification accuracy, its model has 99.8% accuracy, precision, recall, and F1-score. These consistent high measures in the metrics indicate the balanced and reliable detection capacity of the model and an effective mechanism to reduce false positives and false negatives.

TABLE II. Classification results of proposed model for False News Detection

Performance Matrix	RNN+GRU	
	Testing	Training
Accuracy	99.8	100
Precision	99.8	100
Recall	99.8	100
F1-score	99.8	100

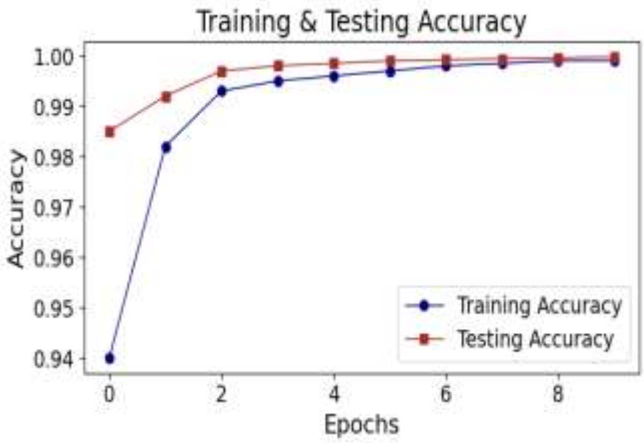

Fig. 5. Testing and training accuracy for RNN+GRU model

Fig. 5 shows the trends of accuracy of training and testing of the RNN+GRU model in various epochs. Its accuracy on training steadily increases with the first few epochs and then begins to level off, whereas its accuracy on testing is always high and remains very close to the training curve. Such behaviour denotes successful learning, proper convergence, and a minimum overfitting which shows that the proposed model is robust.

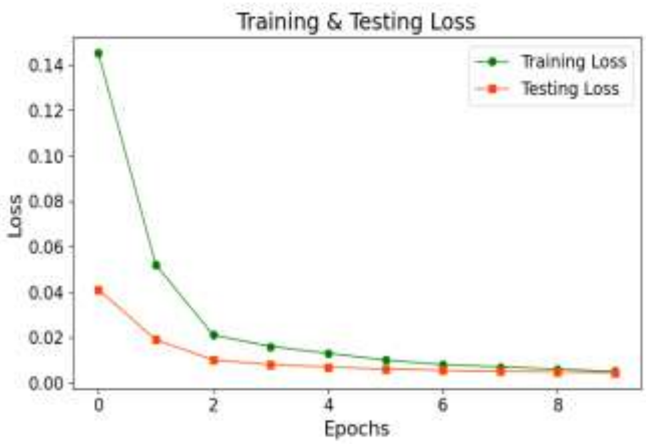

Fig. 6. Testing and training loss curve for the RNN+GRU model

Fig. 6 presents the training and testing loss curves of the RNN+GRU model over successive epochs. Both training and testing loss reduce drastically during the first epochs and tend to converge towards small values as training continued. This steady decrease denotes that there is optimization, good learning, and good generalization without excessive overfitting.

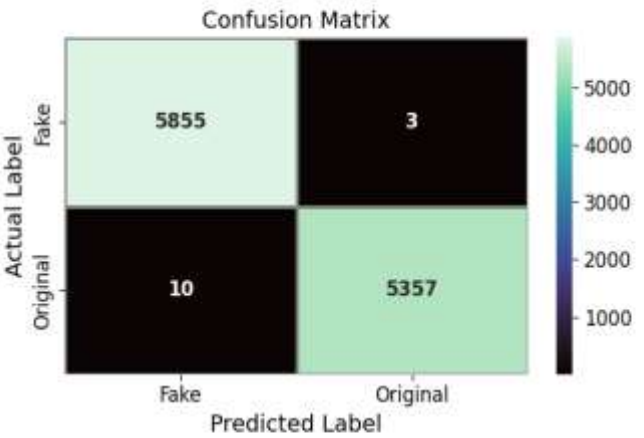

Fig. 7. Confusion Matrix for the **RNN+GRU** Model

Fig. 7 presents the confusion table of the proposed RNN +GRU model whereby fake and original news have a high classification performance. The model properly recognizes 5,855 and 5,357 instances of fake and original news respectively, and few misclassifications occur. It means that the proposed approach has high accuracy, high discriminative capabilities, and reliable generalization.

A. Comparative analysis

Comparative analysis is performed based on conventional evaluation measures, such as accuracy, precision, recall, and F1-score, shows in Table III. CNN model indicates a 85.8% accuracy with a concomitant precision, recall and F1-score of 87.4, 88.6 and 88 respectively showing moderate detection. XGBoost also performs better, with 89.7% meanwhile Random Forest model also improves the method of classification with accuracy of 93. LSTM model has shown good and balanced performance with a score of 95 percent in all the measures of evaluation. It is worth noting that the presented hybrid RNN+GRU model is by far the best, achieving 99.8% accuracy, precision, recall, and F1-score. These results clearly show that the RNN+GRU model is more robust, consistent, and reliable than the other models thus making it the best method to encourage false news detection in comparison to the models that have been evaluated.

TABLE III. COMPARISON OF DIFFERENT MACHINE LEARNING MODELS FOR FALSE NEWS DETECTION

Model	Accuracy	Precision	Recall	F1-score
CNN[21]	85.8	87.4	88.6	88
XGB[22]	89.7	88.9	90.2	89.5
ALBERT[23]	94.8	94.2	94.9	94.5
RF[24]	93	92	94	93
LSTM[25]	95	95	95	95
RNN+GRU	99.8	99.8	99.8	99.8

The proposed RNN +GRU model has a number of strengths worth noting as it has a very high classification performance, which shows high discriminative power, and has balanced false and real news representations. The fact that training and testing accuracy are closely matched and loss curves converge to their final value is a strong indicator of effective training, strong generalization, and low overfitting. Besides, the hybrid architecture can effectively identify both the short and long term contextual dependencies in textual data, which is better than traditional machine learning and single deep learning models. Nonetheless, the model has some weaknesses as it has a relatively high computational complexity and training time, in comparison to more standard classifiers, including Random Forest or XGBoost. In addition, the high performance is confirmed on a single benchmark set, which might not be generalizable to different news sources or languages, suggesting that the performance should be evaluated further on cross-domain and multilingual sets.

V. CONCLUSION AND FUTURE STUDY

The influence of fake news is immense particularly in some areas such as politics and economy within our society. The emergence of the social media use to a certain degree favors the promotion of fake/false news. An effective answer in this regard would mean many benefits to the society at large. This research proposed deep learning methods to address fake news problem. Based on the experimental results, a comparative analysis of various models shows that deep learning strategies consistently outperform traditional machine learning methods in detecting fake news. As CNN, Rand forest, and random forest have decent accuracies of 85.8, 89.7, and 93% respectively, sequence-based models like LSTM score even higher with an accuracy of 95. The hybrid RNN+GRU model proposed has the highest accuracy of 99.8% which shows its better ability to balance short-term and long-term contextual dependency in news information. The findings validate the assertion that the RNN+GRU model offers a better and stronger model to classify fake news more accurately than the current models. Future research will aim at enhancing the generalizability and scalability of the proposed model by testing it on more and more diverse fake news data, such as cross-domain and multilingual news corpora. To counteract the problem of computational complexity, the idea of lightweight architectures and training models optimization may be considered, along with the aim to minimize the training duration and the consumption of resources.

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