International Journal of Engineering Trends and Technology
ISSN: 2231–5381 / https://doi.org/10.14445/22315381/IJETT-V72I9P139

Volume 72 Issue 9, 419-427, September 2024

Original Article

Fake News Detection Using Recurrent Neural Network in Somali Language

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Received: 27 March 2024 Revised: 16 July 2024 Accepted: 17 September 2024 Published: 28 September 2024

***Abstract* - *The proliferation of fake news in the digital domain poses a significant threat to public discourse, necessitating the development of effective detection mechanisms. Therefore, this paper presents an empirical analysis of a Recurrent Neural Network (RNN) model tailored for the detection of fake news, offering an in-depth examination of its performance on a testing dataset. The RNN model demonstrated exceptional accuracy, achieving a 98.94% success rate in accurately distinguishing between fake and real news articles, with a low loss value of 0.0372, indicating high precision in classification tasks. Key performance metrics further elucidate the model's capabilities: a precision rate of approximately 98.73% underscores the model's accuracy in identifying fake news. In comparison, a recall rate of about 99.07% highlights its proficiency in correctly classifying a majority of fake news instances within the dataset. The synthesis of these results—accuracy, precision, and recall—attests to the robustness of the RNN model as a highly reliable tool for discriminating between genuine and fabricated news content. These findings not only reinforce the model's applicability in real-world scenarios, crucial for filtering misinformation but also underscore its potential in maintaining informational integrity. This study paves the way for future research and application in misinformation detection, signifying a substantial contribution to the field.*

***Keywords* - *Fake News Detection, Recurrent Neural Network (RNN), Machine Learning, Natural Language Processing (NLP), Adaptive Algorithms, Real-time Analysis.*

1. Introduction

In the contemporary digital scene, the Internet has seamlessly integrated into the fabric of our daily existence, serving as an essential component of our lifestyle. This ubiquitous presence affords unparalleled accessibility to global news, rendering the dissemination of information more facile and congenial. The transformative impact of social platforms, exemplified by Twitter, Facebook, and Instagram, is unmistakably discernible, as explained by the author [1], both in terms of heightened consumer engagement and the technological paradigms employed. The beginning of social media platforms primarily revolved around the sharing of personal information, utilizing posts and images to foster connections among individuals, mostly friends and family. However, the evolution of these platforms has created a paradigm shift wherein they now assume a crucial role in the origination and dissemination of news and information, as emphasized by the author [2]. The expanding popularity of social platforms can be attributed to different factors, encompassing personalized recommendations aligned with user interests, facile accessibility, the ubiquity of web and application-based platforms, and an intuitively designed user interface. Consequently, traditional information mediums like television, radio, magazines, and newspapers are experiencing a diminish in popularity, eclipsed by the growing preference for social platforms as the primary channel for staying up-to-date on global events and occurrences [3]. In today's world, marked by rapid technological growth, we face increasing challenges, particularly in how mass media impacts society. There is a notable issue with how certain entities or organizations misuse the power of media to spread misinformation, a problem that's especially tricky on social media platforms where sifting through fake news is highly challenging [4]. The widespread dissemination of such misinformation—aimed at inciting hostility, skewing perceptions, and fostering biased views, collectively referred to as "fake news"—has significantly diminished public confidence in media sources. This type of misinformation, whether spread by special interest groups or automated bots, is quickly shared and discussed among people, thereby boosting the spread of deceptive news and viewpoints. Before implementing machine learning or deep learning techniques to detect and highlight misinformation on social media, it is crucial to conduct a comprehensive analysis of the sources of fake news. Fake news involves the intentional spread of false information under the guise of legitimate news across both mainstream and social media platforms [5]. The motivations behind spreading such misinformation vary, from damaging individuals' reputations with unfounded stories to generating revenue through ads or clickbait. On SM, the presence of FN is evident in made-up posts, fake profiles, and bogus articles. Manually pinpointing fake news is an exhaustive task that requires considerable resources. The damage caused by these falsehoods is profound because, once they have reached a broad audience, the lasting impact on people's perceptions can be significantly negative [6]. In the context of Somali media, the landscape is uniquely challenged by the proliferation of fake news, exacerbated by the country's complex socio-political dynamics and the significant role of social media as a news source. Its resilience and rapid growth mark Somalia's media environment amidst ongoing conflicts and political instability [7]. However, this growth comes with the increased vulnerability of the public to misinformation, as the lines between genuine journalism and fabricated news become blurred. The swift spread of FN within Somali media outlets and on SM platforms poses a substantial threat to public understanding and trust, influencing public opinion and potentially swaying political and social outcomes. The critical need for effective fake news detection in Somalia is underscored by the country's ongoing efforts to rebuild and stabilize, where ensuring access to accurate and reliable information is paramount. This paper aims to develop a system for DFN using a variety of ML and DL RNN models, aiming to improve the precision and efficiency of identifying false reports.

2. Related Work

The detection of FN has emerged as a critical industry in the contemporary landscape inundated with misinformation. Researchers have undertaken extensive investigations into developing robust methodologies, with a substantial focus on leveraging machine learning algorithms for enhanced accuracy. A study conducted by [8] explores the development of novel approaches and algorithms specifically designed for detecting fake news. Their work highlights the prevalence of machine-learning techniques as a foundation for understanding and perceiving the distinct characteristics of fake news from authentic content. Similarly, [9] contributes to this discourse by emphasizing the significance of advanced algorithms, especially within the framework of deep learning techniques, in scrutinizing and comprehending the complicated patterns associated with fake news. These studies collectively underscore the growing reliance on machine learning as a pivotal tool in addressing the challenges posed by fake news, given its ability to analyse massive datasets and discern subtle nuances that may elude manual detection.

2.1. Fake News Detection

To tackle the increase of misinformation and lessen the bad impacts of FN, it's important to vet and set aside such information before accepting or circulating it. A fundamental approach to this challenge is the implementation of fact-checking, a methodical process designed to ensure the reliability and accuracy of news stories. Fact-checking can be done through two main methods: MFC and AFC. MFC involves two approaches: Expert-Based and Crowd-Sourced. The Expert-Based method relies on specialists with subject matter expertise to review and validate news accuracy. While this approach is highly reliable, it is often limited by high costs and challenges in scaling to handle large volumes of information [10]. Presently, Expert-Based fact-checking is facilitated through dedicated websites like PolitiFact, FactCheck, TruthOrFiction, Gossip Cop, and Haoxslayer. These platforms not only label news items but also provide a scorecard offering in-depth analyses of news authenticity, enhancing the granularity of reliability assessment [8]. Particularly, websites such as PolitiFact and Gossip Cop have contributed to the public domain by making datasets containing fake news available at no additional cost. Datasets such as FakeNewsNet [11] are examples. Moreover, the detailed analyses presented on these platforms, elucidating the specific aspects of news that are false and the rationale behind labelling them as fake, offer valuable insights for diverse research endeavours related to fake news.

In the field of Crowd-Sourced Fact-Checking, the public steps in as fact-checkers, offering insights and verdicts on digital forums to collaboratively determine the veracity of news via collective wisdom. Insights from the MIT Sloan School of Management have shown that this form of fact-checking matches the effectiveness of its professional counterparts. This success is mirrored in platforms like Stack Overflow, Wikipedia, and Quora, which harness collective contributions to amass extensive knowledge bases. Despite its utility in handling complex tasks, Crowd-Sourced Fact-Checking is not without its drawbacks, notably in terms of speed. An example of a resource in this field is CREDBANK, a dataset made available by [11], encompassing 60 million tweets related to 1049 actual events over three months, with annotations from 30 fact-checkers. This dataset is invaluable for exploring public perceptions and stances on various events, serving as a rich resource for further study on misinformation. While Crowd-Sourced Fact-Checking continues to develop, platforms like Fiskkit invite participants to debate, verify articles' truths, rate comments, and tag content according to its fidelity. Meanwhile, Automatic Fact-Checking operates through two phases: Fact Extraction and Fact Verification. The initial phase involves harvesting data from the internet, which might be imprecise, conflicting, or outdated. This raw data is then refined and organized into a structured format, often through the creation of a knowledge graph, a process known as Knowledge Base Construction. The verification phase then assesses the credibility of news by juxtaposing extracted facts against those in the established knowledge base, a step known as Knowledge Comparison. Data scientists employ a variety of computational techniques to sift authentic news from falsehoods, equipping journalists with powerful verification tools [10]. Furthermore, FC portals like Factcheck and Politifact utilize a team of esteemed fact-checkers to deliver trustworthy results. Nonetheless, manual fact-checking faces hurdles, especially with the growing tide of misinformation and the substantial manpower required to counter it. These challenges highlight the critical need for automated systems to efficiently detect and curb the spread of FN [7].

2.2. Models for Fake News Detection

In the dynamic world of information sharing, honing models to detect FN is a critical research focus. Researchers have delved into numerous methods, especially harnessing machine learning to spot the distinctive patterns and traits of misinformation. A key strategy has been the use of NLP to sift through text, pinpointing language cues that signal false information. Various SL techniques, such as SVM and LR, have been put to use, training on datasets with known outcomes to automate the identification of fake news via linguistic indicators. Furthermore, combined approaches like random forests and gradient boosting have been applied, aiming to improve the detection models' reliability and precision by integrating the capabilities of several algorithms [12]. Graph-based models, rooted in network graph theory, have also gained importance in the quest to unveil the intricate relationships and propagation patterns of fake news across social networks. These models represent information dissemination as a network, where nodes signify entities such as users or news articles, and edges represent connections or interactions. By analysing the topology and dynamics of these networks, researchers aim to identify anomalies and misinformation cascades, contributing to a more nuanced understanding of the spread of FN. Moreover, DL techniques, particularly RNNs and CNNs, have demonstrated efficacy in capturing complex shapes and progressive dependencies within textual data, enabling enhanced detection capabilities. The literature on models for detecting fake news showcases a dynamic and multidisciplinary exploration, continuously adapting to the evolving nature of misinformation and the technological landscape [13].

2.2.1. Natural Language Processing

The drive to integrate Natural Language Processing (NLP) into systems and algorithms stems from the desire to enhance their functionality, particularly in understanding and generating speech across different languages. This facet of NLP is crucial for algorithms that need to interpret actions from linguistic inputs. A pioneering approach highlighted by [14] showcases a system capable of action extraction from English, Italian, and Dutch speeches. This system integrates a variety of NLP tools, including NER and POS tagging, demonstrating NLP's flexibility and effectiveness across multiple linguistic settings. Further, sentiment analysis is highlighted by [15] as a key component in evaluating emotional responses to specific subjects. This process identifies terms linked to a subject, extracts sentiments, and performs a relational analysis. Utilizing bilingual resources, such as a lexicon and a database of sentiment models, sentiment analysis can distinguish between positive and negative connotations, categorizing them on a scale from -5 to 5. The extension of part-of-speech tagging tools to encompass European languages and efforts to adapt these tools for languages such as Sanskrit, Hindi, and Arabic are ongoing. While European languages have seen success with these techniques, adapting them to Asian and Arabic languages presents unique challenges. For example, Sanskrit uses a tree-bank method for POS tagging. Arabic relies on the Support Vector Machine (SVM) method to identify symbols and parts of speech, thus uncovering essential sentence structures in Arabic texts. This exploration into NLP and sentiment analysis emphasises the important role of linguistic diversity in the domain of computational linguistics [16].

2.2.2. Machine Learning Classifications

ML constitutes a category of algorithms that enhance the accuracy of software systems without necessitating direct reprogramming. Data scientists play an important role in this process by identifying alterations or features essential for the model to analyse and generate predictions. Upon completing the training phase, the algorithm extrapolates the acquired knowledge to process new data [17]. In the context of detecting fake news, six specific algorithms are employed for classification within the scope of this study. To elaborate further, the core of ML is its capacity to enable systems to learn from previous data and refine their performance over time, eliminating the need for manual reprogramming. Data scientists engage in a thoughtful characterization of relevant features or changes that the model should recognize during training. This process involves exposing the algorithm to a substantial amount of data, allowing it to discern patterns, correlations, and nuances that contribute to more accurate predictions when faced with new information. In the realm of FN classification, the choice of six specific algorithms reflects a strategic approach to addressing the complexities of misinformation detection. These algorithms, selected based on their suitability for the task at hand, play an important role in analysing and categorizing news content as authentic or deceptive [18].

2.2.3. Decision Tree

The DT is a fundamental tool that operates using a structured, flowchart-like approach, mainly utilized for tackling classification challenges. Within this framework, each node internally of the decision tree stands a test or condition applied to an attribute, leading to branches that are formed based on the outcomes of these tests. The endpoint, or leaf node, carries a class label, which is assigned after all attributes have been evaluated. The journey from the tree's root to its leaf forms the basis of the classification rule. Decision trees are celebrated for their adaptability, capable of handling both categorical and continuous variables with ease.

```
    Decision Tree Pseudo-code
    GenerateDecisionTree(Sample s, features F)
1.  If stop _conditions(S,F) = true then
    a.  leaf = create_Node()
    b.  Leaf.lable= classify(s)
    c.    Return leaf
2.  root = create_Node()
3.  root.testcondition = find_bestSplit(s,f)
4.  v = { v l v a possible outcome of root.testconditions)
5.  for each value v∈ V:
6.  sv: = {s | root.testcondition(s) = v and s ∈ S};
7.  child = Tree_Growth(Sv ,F) ;
8.  Grow child as a descent of roof and label the edge (root→child) as
    v
        Return root
```

Fig. 1 Decision tree pseudo code

```
F[0..N-1]: a feature set with N features that is sorted by information gain in decreasing order accuracy(i):
accuracy of a prediction model based on SVM with F[0...i] gone set
  low = 0
  high = N-1
  value = accuracy(N-1)
  IG_RFE_SVM(F[0...N-1], value, low, high) {
      If (high }≤ low)
        Return F[0...N-1] and value
    mid = (low + high ) / 2
    value_2 = accuracy(mid)
    if (value_2 ≥  value)
        return IG_RFE_SVM(F[0...mid], value_2, low, mid)
    else (value_2 < value)
```

Fig. 2 SVM Pseudo Code

Their strength lies in pinpointing essential variables and clearly mapping out the interconnections among different variables. Furthermore, decision trees are invaluable for creating new variables and features, which significantly aids in data exploration and boosts the accuracy of predicting the target variable, as can be seen from Figure 1 [19]. The remarkable capability of decision trees extends to their utility in predictive modelling using supervised learning techniques, contributing to the establishment of high-accuracy models. Notably, they excel in capturing non-linear relationships, proving adept at solving classification or regression problems, often referred to as Classification and Regression Trees (CART) [20]. The robustness and interpretability of decision trees make them valuable in various domains, providing insights into complex relationships within datasets and facilitating effective decision-making processes.

2.2.4. Random Forest

Random Forests rely on the ensemble approach, creating a multitude of decision tree predictors, each delivering its verdict. These individual verdicts from the various decision trees are then compiled in the Random Forest algorithm to produce a final outcome. This method boosts diversity among the trees through a mechanism of randomly picking a subset of features for each tree [21]. The utility of Random Forests is significantly enhanced with the incorporation of decision trees that show little correlation with one another. When trees that are too similar are used, the aggregated output tends to mirror the prediction of a single decision tree. Random Forests circumvent this by employing bootstrapping—a resampling technique—to generate different sets of data for training each tree and by injecting randomness into the selection of features at each split. This dual strategy not only ensures the production of diverse, uncorrelated trees but also amplifies the Random Forest's capacity to deal with a variety of data types, enriching its capability to uncover a wider array of patterns and connections in the dataset [22].

2.2.5. Support Vector Machine

The SVM algorithm treats each piece of data as a point in an n-dimensional space, with "n" reflecting the total number of features or attributes present. In this setup, each attribute's value is represented by its coordinate in the n-dimensional space. Given a dataset with n attributes, the SVM algorithm plots each data point in this multidimensional space, where every coordinate corresponds to the value of a specific feature. The core objective of the SVM algorithm is to identify an optimal hyperplane that divides the data points into separate categories, leveraging the attributes provided [23]. This process facilitates the classification of data into distinct groups, enhancing the algorithm's ability to distinguish between different classes effectively, as can be seen in Figure 2. To elaborate further, envision a scenario where the SVM algorithm is applied to a dataset with numerous features. The algorithm constructs an n-dimensional space, effectively creating a coordinate system where each feature contributes to the position of a data point. The objective of SVM is to get a hyperplane within this space that maximally separates instances belonging to different classes. This hyperplane serves as the decision boundary, enabling the SVM algorithm to classify new data points based on their coordinates in the n-dimensional space [24].

2.2.6. Naïve Bayes

The Naive Bayes algorithm is grounded in Bayes' theorem, operating under the assumption that predictors within the model are independent of each other. It's a staple in various machine learning tasks due to its simplicity and effectiveness [25]. Essentially, Naive Bayes treats each feature of a category as if it has no relationship with any other feature. For example, it would classify a fruit as an apple based on characteristics like its red color, particular texture, and a diameter of around 3 inches without considering potential relationships between these features. Naive Bayes works on the assumption that each attribute independently provides evidence that the fruit is an apple, even though, in reality, some features might interact or be affected by external factors [26]. Comparing Random Forest (RF) and Naive Bayes reveals significant differences, notably in the size and adaptability of their models. Naive Bayes models, given their foundational assumption of feature independence, tend to be more compact and excel with data where this assumption holds true, making them less prone to capturing complex behaviour patterns. This compactness can be advantageous for consistent datasets.

In contrast, Random Forest models are generally larger due to their construction from numerous decision trees, which increases their risk of overfitting. However, Random Forests are adept at handling complex datasets with intertwined variables. While Naive Bayes models can be quickly updated with new information, making them highly flexible, Random Forests might require a complete rebuild to incorporate changes, highlighting their distinct applications depending on the data's complexity and variability [27].

2.2.7. K-nearest Neighbours

The KNN algorithm assigns a new data point to a specific category based on the predominant class among its 'k' closest neighbors. The classification of the data point into a particular category largely depends on a democratic vote of these neighboring points, with proximity playing a crucial role in the decision-making process [28]. As a method within the supervised learning domain, KNN finds its use in various applications like detecting unauthorized network intrusions and recognizing patterns within datasets. Unlike parametric models that assume a fixed form for the data distribution, KNN is characterized by its nonparametric nature [30]. This means it doesn't make any prior assumptions about the shape of the data distribution, setting it apart from models such as Gaussian Mixture Models (GMM) that presuppose a Gaussian distribution for the data. This attribute of KNN lends it the flexibility to adeptly manage a wide array of datasets, accommodating those with unknown or variable distributions, thereby highlighting its utility in situations where the precise nature of the data distribution is uncertain or not uniform [30].

3. Methodology

The primary goal of this proposed study is to develop an ML capable of accurately categorising news articles as either fake or real. To achieve this, we utilized a comprehensive approach involving dataset preparation, text vectorization, model development with Recurrent Neural Networks (RNNs), and performance evaluation. The methodology was implemented using Python, with libraries such as Pandas for data handling, TensorFlow for model building, and Matplotlib, along with Seaborn for visualization, as can be seen in Figure 3.

3.1. Text Vectorization and Word Embedding

Text vectorization is a critical pre-processing step in NLP tasks, converting data that is text format into a numerical way that ML models can understand. In our study, we used word embeddings, a sophisticated method of text vectorization that gets the semantic correlations between words. This method allows words with similar meanings to have similar vector representations, enriching the model's input with contextual information. To implement word embeddings, we utilized the Tokenizer class provided by TensorFlow. This class facilitated the conversion of our textual dataset into sequences of integers. This step is crucial for managing computational resources and model complexity effectively while ensuring that the vast majority of the textual information is retained. The choice of vocabulary size is a balance between covering a wide range of common words and excluding rare words that might lead to overfitting or distract the model from learning general patterns. Following tokenization, the sequences of integers were transformed into fixed-length vectors using padding. This process ensures that all text inputs to the model have a uniform length, a requirement for batch processing in neural networks. With the textual data thus vectorized, each article is represented by a sequence of vectors, with each vector encoding the semantic properties of a word in the context of our dataset. This representation serves as the input to our RNN model. Through this approach, we leverage the power of word embeddings to provide a nuanced and powerful feature set for distinguishing between fake and real news.

3.2. Recurrent Neural Network Architecture

The development of our model is centered around the use of RNNs, a class of neural networks explicitly intended to handle sequential data. RNNs are uniquely capable of processing sequences of varying lengths, making them ideal for text analysis where inputs can range from short sentences to lengthy articles. Unlike traditional neural networks that assume independence between inputs, RNNs can maintain a 'memory' of previous inputs in the sequence, letting them make predictions based on both current and past information. This feature is particularly valuable in our context for identifying patterns and nuances in news articles that differentiate fake news from real news.

Our model architecture uses a layered approach to maximize the RNN's capabilities. Layer 1 is an Embedding which transforms the integer-encoded text into dense-vector representations. These word embeddings will be pre-trained text corpora and serve as a nuanced input feature set that captures semantic similarities between words. Following the Embedding layer, we utilize Bidirectional LSTM layers. LSTMs are an advanced variant of RNNs capable of learning long-term dependencies in data, addressing the vanishing gradient problem inherent in traditional RNNs.

The bidirectional aspect allows the model to process information in either direction, ensuring a comprehensive understanding of context and improving the model's ability to capture linguistic patterns. To construct a model that is both powerful and generalizable, we incorporate several techniques to manage complexity and prevent overfitting. Dropout layers are strategically placed throughout the network, where a certain percentage of neurons are randomly deactivated during training. This process prevents the model from becoming overly reliant on any specific neuron, thereby promoting the learning of more generalized and robust features. By reducing the co-adaptation of neurons, the model is less likely to overfit and more capable of handling unseen data. In addition, the model incorporates Dense layers with ReLU activation functions.

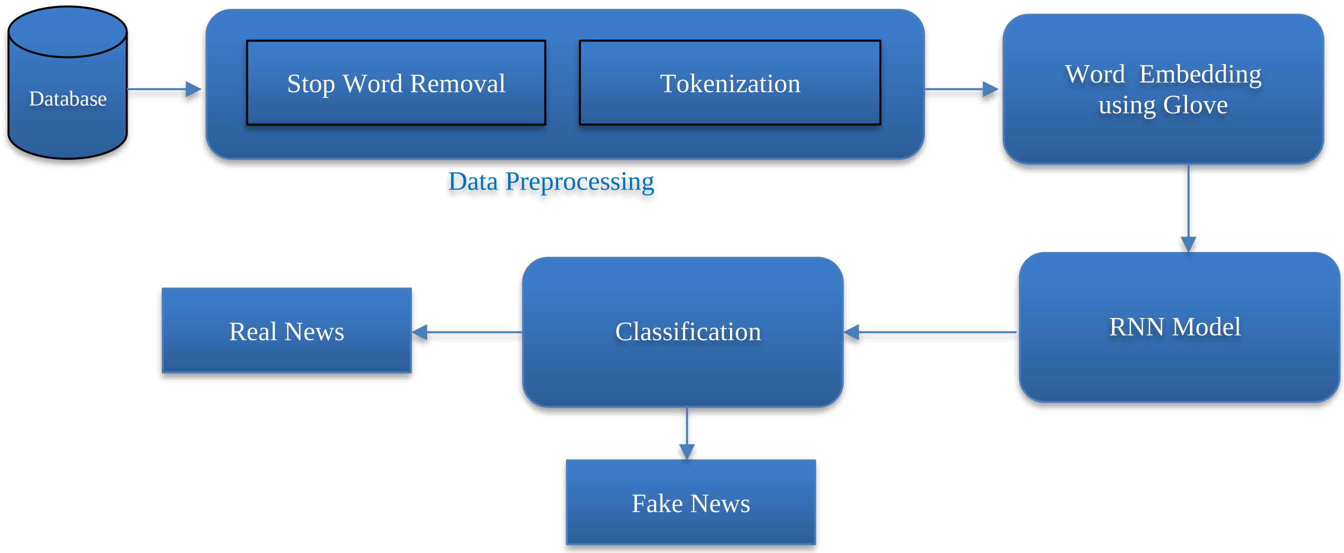

Fig. 3 Proposed methodology

ReLU introduces non-linearity, which is essential for the model to capture complex patterns and relationships within the data. Without this non-linearity, the model would struggle to represent intricate dependencies between features, as linear layers alone are insufficient for complex tasks. The final output layer is designed to match our binary classification task, producing a single score indicating the likelihood of the article being real or fake.

Training the model involves feeding the vectorized text data through this network, using a BCL function suited for BC problems. An Adam optimizer is selected for its efficiency and AL rate capabilities, facilitating faster convergence. To further ensure the model's performance and generalizability, we implement an early stopping mechanism. This technique monitors the validation loss during training, halting the training process if the model begins to overfit by not showing improvement over a specified number of epochs. This strategy ensures we retain the best version of the model, optimized for accuracy on both seen and unseen data.

3.3. Evaluation Metrics

In order to evaluate the performance of the proposed model, we used accuracy, precision, and recall. These metrics ensure that not only overall accuracy is considered but also how well the model identifies each class and manages false positives and false negatives. Furthermore, a confusion matrix is used to provide a visual comparison between the model’s predictions and the actual labels, allowing for a more detailed analysis of its predictive strengths and weaknesses. The model’s training and validation accuracy, as well as the loss, are plotted across epochs to display how the model learns over time. These plots help in understanding whether the model is overfitting the training data or maintaining a good balance between learning from the training data and generalizing to unseen data.

4. Results and Discussions

In this section, we present the experimental results of the proposed framework. We begin by providing a detailed overview of the findings from both the training and testing phases, with a focus on analyzing and interpreting their significance. Subsequently, we conduct an in-depth evaluation of the captured signatures and perform a comparative analysis against other benchmark models to assess the framework's relative performance.

4.1. Dataset Description

Our dataset comprises two sets of news articles labelled as 'fake' and 'real'. The first step involved cleaning the data by removing missing values, standardizing text to lowercase, and eliminating URLs, non-alphabetic characters, and extra spaces. This pre-processing ensures a clean and uniform dataset for model training and testing. The cleaned dataset is then divided into training (80%) and testing (20%), facilitating both the training of the model and the evaluation of its generalization to new, unseen data. The distribution of the dataset is almost the same, as can be seen in Figure 4.

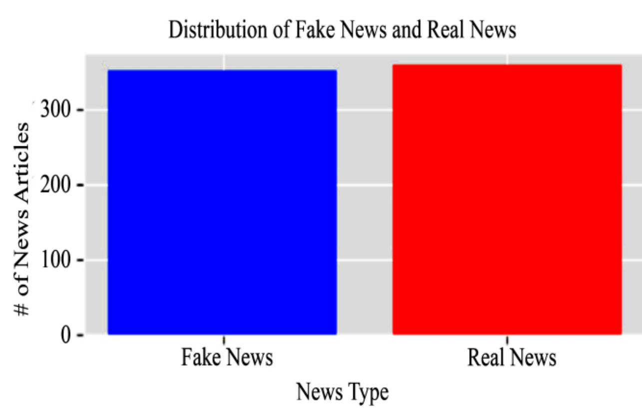

Fig. 4 Dataset distribution

4.2. Results

The performance of our RNN model on the testing offers a comprehensive and promising insight into its ability to distinguish between what is fake and what is real news articles accurately. Based on the output of the model evaluation and the calculated metrics, we can dissect the model's performance as follows:

4.2.1. Model Evaluation Output

The model achieved a loss of 0.0372 and an accuracy of approximately 98.94% on the testing set. The low loss value shows that the model's predictions are very close to the actual labels, signifying a high level of precision in distinguishing between the classes. The accuracy metric, being notably high, demonstrates the model's overall effectiveness in correctly identifying fake and real news articles across the dataset presented to it for testing.

4.2.2. Calculated Performance Metrics

Accuracy: The model achieved an accuracy rate of 98.94% on the testing set. This percentage represents the ratio of correct predictions made by the model, encompassing both fake and real news articles. The exceptionally high accuracy suggests that the model performs its classification tasks with a high degree of reliability and effectiveness, demonstrating a low error rate in its predictions.

4.2.3. Precision

Precision stands at approximately 98.73%. This metric indicates the proportion of positive identifications (in this case, the fake news articles identified by the model) that were actually correct. A high precision rate implies that the model is highly accurate when it asserts an article is fake, with a low rate of false positives (i.e., real news articles wrongly classified as fake).

4.2.4. Recall

The recall rate achieved is about 99.07%. Recall measures the proportion of actual positives (true fake news articles) that were correctly identified. The high recall rate signifies model is exceptionally accomplished in capturing and correctly classifying the majority of fake news articles, with few false negatives (i.e., fake news articles missed and classified as real), which can be seen in Table 1. The impressive performance metrics of the model—high accuracy, precision, and recall—demonstrate its robustness in reliably distinguishing between fake and real news articles, as shown in Figure 5. The high precision means that when the model predicts an article as fake, it is highly likely to be accurate. Additionally, the high recall indicates that the model effectively identifies the majority of fake news articles in the dataset, making it highly efficient in detecting misinformation.

Table 1. Result

No	Model	Accuracy (%)	Precision	Recall	F1
1	RNN	98.94	98.73	99.07	98.3

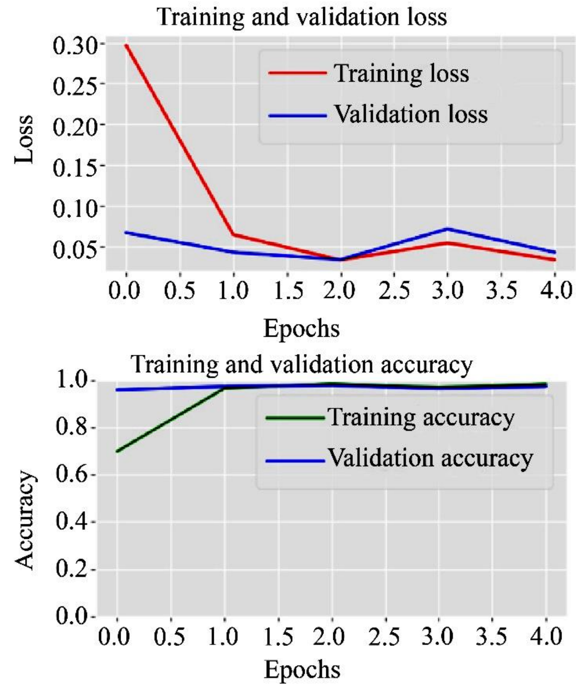

Fig. 5 Loss and accuracy

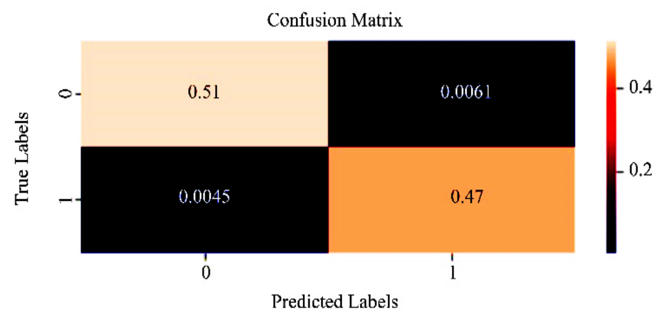

Fig. 6 Confusion matric

In practical terms, these results underscore the potential applicability of the model in real-world scenarios where distinguishing between fake and real information is crucial. The model not only promises to be a reliable tool in identifying misinformation but also ensures minimal wrongful classification of legitimate information as fake. This balance is critical in maintaining the integrity of information while combating the spread of misinformation. The confusion matrix in Figure 6 shows that the RNN model indicates a strong performance in classifying the test data accurately. The majority of predictions fall into the true positives and true negatives categories, with values of 0.47 and 0.51, respectively, demonstrating that the model correctly identifies most of the instances for both classes. The false positives and false negatives have very low values (0.0061 and 0.0045, respectively), which suggests that instances of misclassification by the model are minimal. Overall, these results highlight the RNN model's effectiveness in discerning between the classes, showcasing its reliability in the classification task at hand with a high degree of precision.

Table 2. Comparative analysis

Author, Year and Reference	Proposed Methodology	Accuracy
Mjung Park (2023) [29]	RF with XGBoost	94%
Krishna et al. (2022) [26]	DT Algorithm	97.67%
Rozi (2023) [20]	RF with sentimental Analysis	78%
Xavier Jose (2021) [13]	Attention-Based BiLSTM	93.46%
This Study	RNN with Word Embeddings	**98.94%**

4.3. Comparative Study

In the comparative analysis in Table 2 present the performance of our model against other significant models in the literature. Mjung Park (2023) used a Random Forest (RF) with XGBoost, achieving an accuracy of 94%. While effective for linear separability, SVMs may not capture the sequential and contextual nuances in text data as effectively as neural networks. Rama Krishna et al. (2022) explored the potential of a Decision Tree Algorithm. Their DT model demonstrated improved performance, reaching an accuracy of 97.67% by leveraging sequence data processing capabilities. However, it lacked the additional architectural enhancements found in our model. Fahrur Rozi (2023) introduced a Random Forest for Text Classification, achieving a notable accuracy of 78%. RF excel in capturing local patterns but may not fully grasp the long-range dependencies in sequential data like text. Xavier Jose (2021) introduced an Attention-Based Bidirectional LSTM (BiLSTM), which enabled the model to concentrate dynamically on the most relevant parts of the input data. This approach led to an impressive accuracy of 93.46%. The use of attention mechanisms in this model demonstrates their effectiveness in enhancing model performance by allowing it to better prioritize critical information. Our model, an RNN with Word Embeddings, outperformed these approaches with an accuracy of 98.94%. The model's outstanding performance can be credited to its effective use of the sequential structure of text data, along with the deep linguistic insights enabled by word embeddings. The comparative analysis further emphasizes the model's strength in fake news detection, demonstrating its potential as a leading solution in this field.

5. Conclusion

This paper explores the dynamic realm of ML algorithms for DFN, highlighting the diversity of methodologies ranging from the basic yet effective RNN. It emphasizes the pivotal role of Natural Language Processing (NLP) in augmenting this algorithm's capacity to accurately interpret and analyze textual nuances. The comparative analysis indicates that the effectiveness of this algorithm is influenced by the unique characteristics of each dataset, highlighting that there is no universal solution in the fight against misinformation. This study not only demonstrates the range of tools available to address the spread of fake news but also emphasizes the need for algorithms to adapt and evolve alongside the continuously shifting landscape of digital information and misinformation strategies. For future work, there is a significant opportunity for advancing research in the field of FND through the integration of more sophisticated NLP techniques and the exploration of emerging machine learning models. Additionally, fostering collaborative initiatives between technologists, media practitioners, and policymakers will be crucial in creating a holistic approach to safeguarding the information ecosystem. As misinformation continues to pose a challenge to the integrity of public discourse, the ongoing refinement and development of detection algorithms will play a critical role in maintaining the veracity and reliability of information in the digital age.

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