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A gated recurrent unit-based model for fake news detection in online social networks

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Abstract

Fake news and online rumors can mislead information, disrupt order, and destabilize society. This misleading information is propagated through online social media and other digital platforms, which results in loss of public confidence, stimulation of social unrest, and a threat to national security. In this work, we present a Gated Recurrent Unit-based fake news recognition approach to reduce the impact of misinformation. Since we want to build an effective model, we pre-process a fake-news-detection dataset having real and fake news by performing effective natural language processing (NLP) tasks such as news text cleaning, tokenization, word embedding, etc. The Gated Recurrent Unit (GRU) architecture is used based on its ability to execute sequential data, which allows the model to find patterns and the semantic relations within news content. The model proposed attained an accuracy of 99.55% and proved to be effective for detecting fake information. Our recommendation is to continue the fight against misinformation and other such cybercrimes.

Subject Classification: *68T50, 68T07, 68U35.*

Keywords: *Fake news, Cybercrime, Gated recurrent units, Deep learning, Misinformation, Disinformation.*

1. Introduction

The widespread problem of misinformation and fake news has been evident in various situations, such as civil wars and cybercrime. [1].There is a growing need to reveal these deceptive practices because they still harm individuals, and communities, and lower public trust. They also damage professional honesty and have a significant impact on public perception [2]. In politics, false information can affect elections and thus widen divisions while promoting extreme beliefs. False information in public health can lead to dangerous actions and increased expenses. The dissemination of misleading news on online forums is causing societal instability and endangering national security. Recognizing false information is important for keeping our information environment clear, which helps protect democracy and public safety from the harmful effects of fake news and rumors [3]. We need automated and scalable solutions because traditional fact-checking methods and traditional machine learning algorithms aren't efficient. The GRUmodels captures long-period connections and efficiently calculates, making it suitable for text classification tasks. Compared to LSTMs, GRUs have simpler designs with fewer parameters, which makes them faster to train. They also handle the vanishing gradient problems as well. GRUs excel in identifying patterns and context in news articles [4].

This study presents a GRU-based model for identifying fake news, addressing the growing issue of misinformation and cybercrime. The process involves data cleaning, pre-processing tasks, one-hot-encoding, and GRU-based model training. Performance is measured using standard metrics and visual tools.

The rest of the text is planned into following sections. Section 2 highlights the review of related research, Section 3 presents the methodology and Section 4 represents the experiment and results, Section 5 provides the concluding remarks of the work by highlighting the future scope.

2. Literature Review

The proliferation of social media channels has rendered fake news an important concern. Studies on detecting false news initially relied on traditional models such as Support Vector Classifiers (SVCs), Naive Bayesian (NB) classifier, Random Forest (RF) and Logistic Regression (LogR), which are limited to handcrafted features [9]. Mohammad, Shitharth, and Kumar [9] developed a cooperative user feedback-based model to categorize fake or real news inspired by transformer learning. The model achieved a 98% accuracy, outperforming other existing baseline models. The study [5] compared SVM, NB, RF, and LogR classifiers for fake news detection on different datasets. SVM classifiers achieve the highest accuracy of 61% in LIAR dataset, 97% in Fake Job posts, and 96% in Fake News dataset. BERT and RoBERT was proposed by [6] have shown potential in detecting textual patterns. Author in [7] tested and implemented several ML models and claimed that LSTM had the highest accuracy 92.34%. Author in [8] offer substantial insights into misinformation related to the COVID-19 pandemic in Georgia. In [9], Mohammad, Shitharth, and Kumar developed an improved LSTM model using a Salp swarm algorithm (SSA) to distinguish real and fake news on social media. This model performed high accuracy levels on three different datasets: 97.89% on the LIAR dataset, 86.49% on the ISOT dataset, and 99.71% on news related to COVID-19. BiLSTM model that performed the best [10], accurately spotting misinformation in 94% of short English texts news. Author in [11] implemented BiLSTM with GloVe embedding ISOT dataset and obtained an accuracy of 98.41% in detection fake news. Author in [12] introduced model named FakeBERT that achieved an impressive accuracy of 98.90%, outperforming others.

3. Proposed Methodology

The research uses a dataset containing news articles from reliable sources. It includes text content, labels, publisher details, and topics, which help in effective classification. The entire process follows these steps. The schematic architecture of this suggested work is presented in figure 1.

3.1 *Dataset*

The study used a publicly accessible dataset called the "ISOT Fake News Dataset," which was provided by [13].

3.2 *Data Cleaning*

The text corpus is analysed by converting it to lowercase letters, removing special characters, punctuation, symbols, numbers, URLs, and email addresses for consistency and model training.

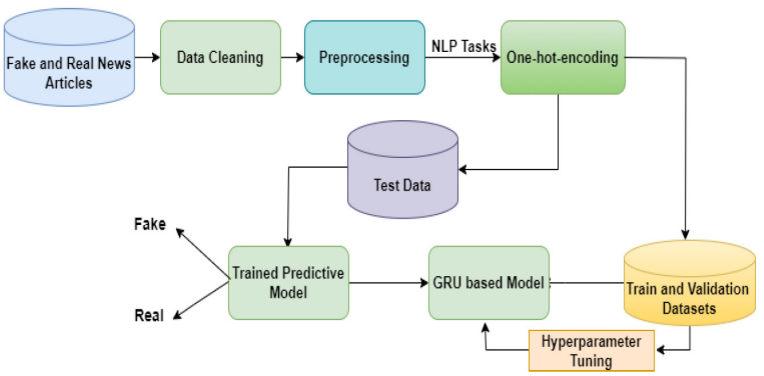


Figure 1

The architecture of the suggested work

3.3 *Preprocessing*

The main step in this step is tokenization, that is used to break down text into individual words, preparing it for analysis and model training in machine learning models.

3.4 *One-hot Encoding*

The text data was converted into a one-hot encoded format, allowing easier input into machine learning models. This process transforms each

word into a binary vector, with only one "1" representing its presence, but can create high-dimensional and sparse vectors, particularly with large vocabulary.

3.5 *Architecture of Gated Recurrent Units (GRU) Cell*

The GRU model is effective for fake text news detection due to its ability to understand and remember important text patterns, making it faster than LSTM. The GRU structure consists of multiple parts as shown in figure 2 and explained as follows [8].

Reset gate (r_t): This component regulates the degree to which the prior hidden state (h_{t-1}) is forgotten when calculating the new hidden state for the current time step. The reset gate is calculated utilizing the sigmoid function (σ), which produces values ranging from 0 to 1. The mathematical representation of the reset gate (r_t) is in Eqn. 1.

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

The update gate (z_t): It determines the amount to which the preceding hidden state is retained for the subsequent time step. It regulates the extent of data from the preceding hidden state (h_{t-1}) is propagated to the current hidden state(h_t). Similar to the reset gate, the update gate is controlled by a sigmoid activation(σ). The mathematical representation of the update gate (r_t) is in Eqn. 2.

$$z_t = \sigma(W_z * [h_{t-1}, x_t]) \tag{2}$$

Candidate hidden state ($\tilde{h}_t$): This signifies the prospective new information that the GRU contemplatesincorporating into the hidden state. This value is calculated utilizing the current input (x_t), the reset gate (r_t), and the preceding hidden state (h_{t-1}). It is processed through a *tanh* activation function, which constrains the values in the interval (-1, 1). The mathematical form is presented in Eqn. 3.

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

Final hidden state (h[t]): This state is derived from a synthesis of the candidate hidden state and the preceding hidden state, regulated by the update gate (z_t). A higher value of the update gate, approaching 1, results in greater incorporation of the new candidate information into the final hidden state. The mathematical form is in Eqn. 4.

$$h_t = (1 - z_t) * h_{t-1} + z_t * h_t \tag{4}$$

These parts enable the GRU cell to effectively handle long sequences, which makes it helpful for tasks like classifying fake and real news.

3.6 *The Proposed Model*

The classification model was built using a sequential structure, which allows layers to be stacked one after another. It uses the strong feature of GRUs for classifying news articles. The design of this model is shown in Figure 3. The model goes through the following layers of for its implementations.

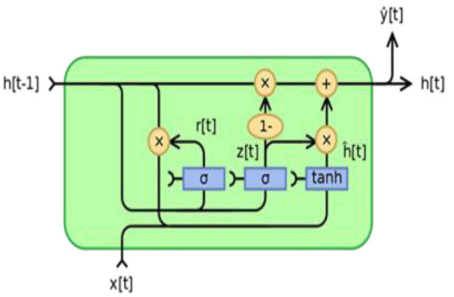


Figure 2
The architecture GRU cell

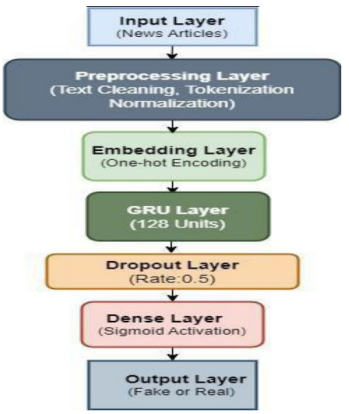


Figure 3
Proposed architecture

The embedding layer creates detailed word representations during training, transforming words into smaller, detailed vectors. The GRU layer uses 128 units and the "tanh" function to find complex connections in the data. The model uses a dropout layer to prevent overfitting with a 0.5 dropout rate. It uses the Adam optimizer and binary cross-entropy loss function. The model uses a dense layer with a sigmoidal activation function for binary classification, determining if input text is "fake" or "real." Table 1 provides a list of the hyperparameters used in the designed model.

4. Experiment and Results

The text details the training and testing process for a GRU-based model for fake news detection, including model training and measuring performance using defined metrics to determine its ability.

Table 1
List of hyperparameters utilized in the proposed model

Hyperparameter	Description	Value
Vocabulary Size	Limit of unique words in the embedding layer.	20000
Embedding Dimension	Dense vector representation dimensionality for each embedding layer word.	100
Input Length	Input sequence length after padding.	1000
Number of Units	Number of GRU layer units, determining model pattern learning capacity.	128
Activation Function	Non-linearity-introducing GRU layer activation function.	"tanh"
Dropout Rate	The GRU layer dropout rate reduces training overfitting.	0.5
Loss Function	The objective function that is being used to evaluate model performance.	Binary Cross-Entropy
Batch Size	Number of samples processed before updating model parameters.	32

4.1 *Model Training and Validation*

The model is built using an embedding, GRU, and dense output layers. The dense layer uses a sigmoidal activation and the Adam optimizer for optimal classification results. Early stopping during training helps prevent overtraining. The model is trained for 10 epochs and validated on validation data after each round. The GRU learning curves in Figures 4 and 5 provide a visual summary of how well the model learns to detect fake news over time. The evaluation of the model's performance involves metrics such as accuracy, precision, recall and F1-Scores are shown in Table 2, which showcasing its capability.

4.2 *Performance Evaluation*

The proposed model demonstrated excellent performance in identifying fake news and real news as represented in Figure 6 and 7. The Receiver Operating Characteristic (ROC) curve showed nearly perfect model, with an AUC score of 0.996 as shown in Figure 8.

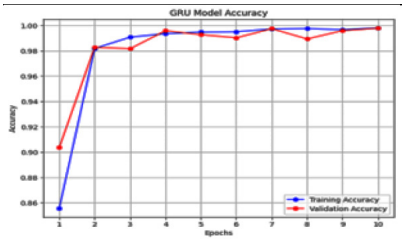


Figure 4

GRU model accuracy curve

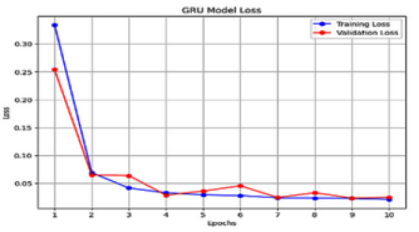


Figure 5

GRU model loss curve

Table 2

Performance of the suggested model

Class Label	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Support
FAKE	99.55	99.92	99.16	99.54	6541
REAL	99.55	99.21	99.93	99.57	6929

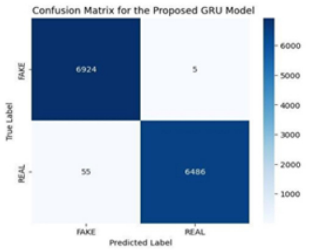


Figure 6

Confusion matrix

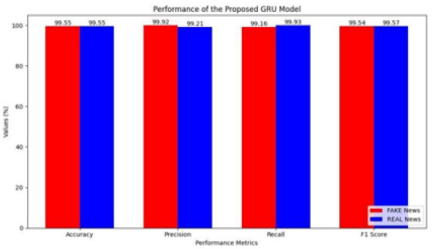


Figure 7

Performances of the suggested model

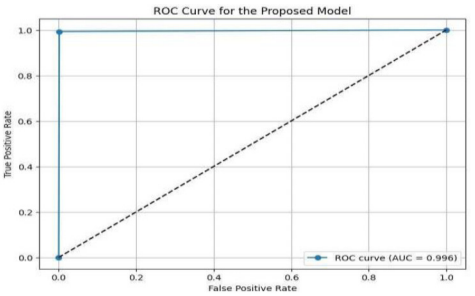


Figure 8

ROC Curve for the suggested model

5. Conclusions

The research presents a GRU-based model for identifying fake news, achieving high accuracy and perfect precision, recall, and F1 scores. The model's robust performance and well-designed nature make it a potential solution for large-scale information combat.Future studies could incorporate external knowledge graphs, context data, transformer learning, reinforcement learning, and adversarial training to enhance its understanding of complex ideas and contexts, and improve its ability to detect disinformation in diverse media and datasets of diverse domains.

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