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# A Hybrid Deep Learning Based Fake News Detection System Using Temporal Features

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### Chronicle

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### Abstract

Detecting fake news and missing information is gaining popularity, especially after social media and online news platforms advancements. Social media is the main and speediest source of fake news propagation, whereas online news websites contribute to fake news dissipation. In this study, we propose a framework to detect fake news using the temporal features of text and consider user feedback to determine whether the news is fake or not. In recent studies, the temporal features in text documents gain valuable consideration from Natural Language Processing and user feedback and only try to classify the textual data as fake or true. This research article indicates the impact of recurring and non-recurring events on fake and true news. We use different models such as LSTM, BERT, and CNN- BiLSTM to investigate, and it is concluded that from BERT, we get better results, and 70% of true news is recurring, and the rest of 30% is non-recurring.

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## INTRODUCTION

With the inauguration of the World Wide Web and the consequent propagation of social networks (Facebook, Twitter and so on), humanity has witnessed an era of information sharing that has not been seen before. Other use cases, such as news outlets, capitalize on the ordinary usage of social media platforms and afford to update their subscribers on time (News n.d.). The news media changed from print media, including newspapers, tabloids, and magazines, to digital media, including blogging sites, social media sites, and other online news and articles. The consumer also had difficulty getting the latest news at their fingertips. Social media sources show that of the total traffic towards news websites, 70% originates from Facebook referrals (Raza et al. 2020). These social media platforms are compelling and beneficial for providing users with ideas and debates about democracy, education, and health. However, specific individuals offer such platforms with a negative outlook, mainly for steering commercial gains and often for developing attitudes for building prejudice, establishing polarized opinions for shaping mindsets, and applying satire and illogicalities. The phenomenon that we are going to discuss is known as synthetic news or fake news (Cai et al. 2024). In the last decade, the incidence of fake news has also risen, and the most apparent of such actions was during the early stages of the 2016 US elections. Because of this regrettable situation, which has seen esoteric articles flood the internet, ignoring facts as discussed earlier, many issues have emanated, and they are not only restricted to the political realm alone; they span

through the various fields, including sports, health and even science among others. This theme is illustrated in the case of the financial markets, which means that an unsubstantiated rumour may lead to disaster and bring the market to a standstill (SOCIAL MEDIA AND FAKE NEWS IN THE 2016 ELECTION 2017). Traditionally, fake news detection relies on machine learning algorithms and data mining techniques that classify content based on textual features (Rohera et al. 2022). One crucial but often overlooked dimension of textual documents is their temporal aspects. Time is associated with text documents in several ways, i.e., creation time, publication time, focus time, update time, and temporal expression reside within the text (Cai et al. 2024). Despite the importance of such rich information, the NLP research community neglected the importance of temporal features for fake news detection. This study aims to identify and exploit the effectiveness of temporal features as standalone (only temporal) and combined with textual features for fake news classification tasks using social media post datasets such as Twitter.

For the detection of fake news, another important parameter is the authenticated data set, on which we can trust that both are well classified as fake and real news. Identifying such a dataset type is also difficult (Ulizia, Caschera, and Ferri 2021). On the other hand, time is also one of the important factors in fake news detection. Time is a continuous entity normally measured as century, decade, year, month, days, hours, and so on, and its dimensions are future, present, and past (Ur et al. 2018). Time and temporal features can be important for efficient results in fake news. The focus of this study is to keep checking and exploring the impact of recurring events on fake news.

Temporal features can also have a scientific impact on detecting fake news. Different research studies identify different temporal features, such as when it propagates, the birthday of the tweet (Raza et al. 2020), the time it propagates most, and others. In the other studies, it is noted that researchers only use classification techniques using machine learning and artificial intelligence algorithms to detect and classify fake news. Still, the researchers hardly touch on the impact of recurring events on fake news. Recurring events happen again after some specific or not specific time, such as Eid, Christmas, Ester etc. This study first identifies the recurring events from the publicly available data set downloaded from Kaggle.com. Then, by analysis, the relationship between recurring events and fake news is explored, and we identify the impact of recurring events on fake news.

We have developed a system that utilizes hybrid deep-learning techniques to identify fake news. The first step is to acquire the data, and temporal features are extracted from the dataset. Different deep-learning techniques have been employed to detect fake news. The experimental results demonstrated that the proposed hybrid deep learning system outperformed the state-of-the-art techniques. The main contributions of our work are given below:

- A hybrid deep learning approach for fake news detection using temporal and textual features was developed.
- Explored the impact of recurring events on fake news and identified their relationship.
- Proposed a system that utilizes different deep learning algorithms with temporal features to generate effective fake news detection.

- Improved performance comparable to state-of-the-art techniques.

The remainder of this paper follows: The second section discusses literature and previous studies, in which time is discussed. The third and fourth sections outline detailed methodology and results, respectively. Finally, the research study is completed in the last section.

## LITERATURE REVIEW

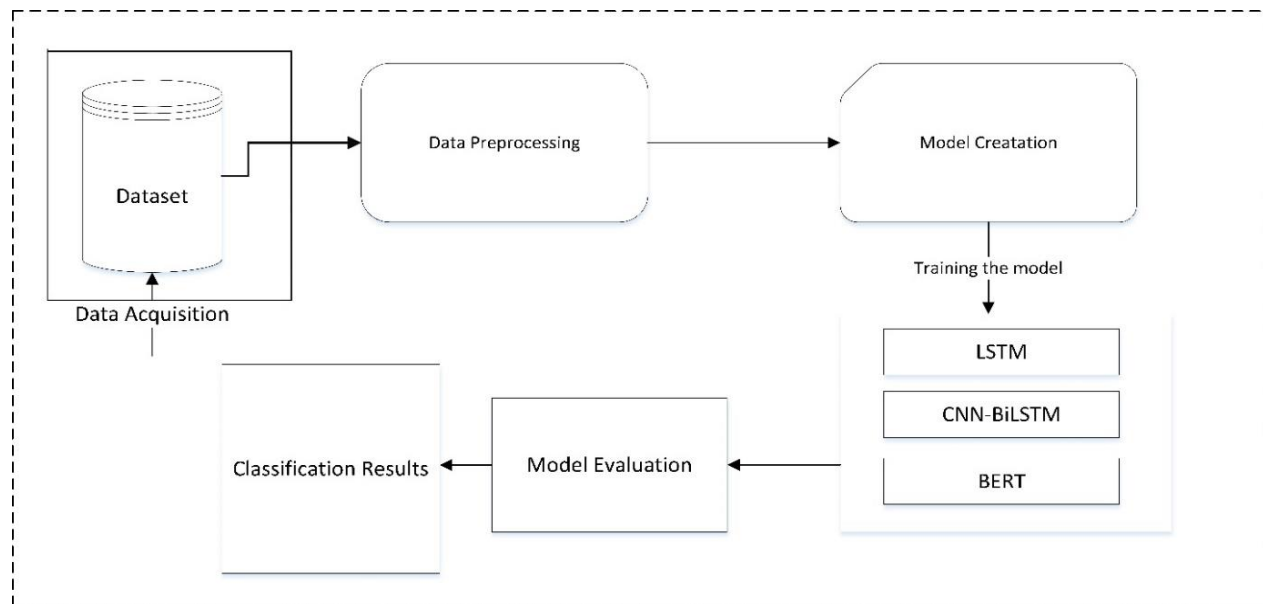
This section examines prior research regarding the identification of false information. Fake news refers to deliberately created information that resembles the format of news media content but lacks the same organizational process and goal (Lazer et al. 2018). Recently, numerous automated methods for detecting fake news have been implemented. For instance, Shu, Kai, et al. (Shu et al. 2017) provided a variety of approaches to address the issue of fake news categorization, including user-based, knowledge-based, social network-based, and style-based methods. Julio and his colleagues introduced a novel collection of characteristics and evaluated the predictive value of existing processes and characteristics in automatically identifying false information (Reis et al. 2019). Daniel and his colleagues (Castillo, Mendoza, and Poblete 2013) conducted a study demonstrating the reliability of Twitter information. Heejung, et al. Heejung, et al. The data used in the Bidirectional Encoder Representations from Transformers model (BERT) are pre-processing data: Wikipedia data and the Book Corpus Data. In the same way, all these data encompass a multitude of information, but general information on individual domains remains limited.

(Jwa et al. 2019) employed an automatic approach towards fake news detection. This was done using the BERT model, which was trained to detect fake news by considering the relation between the fake news headline and the body of the text news. Their result outperforms other state-of-the-art models with an F-score of over 14. Mohammad Hadi and his colleagues (Goldani, Momtazi, and Safabakhsh 2021) employed n-grams of various levels in this dataset of false news designated as ISOT. Saqib et al. (Hakak et al. 2021) applied an ensemble classification approach to detect fake news that provides better accuracy than the current standards for detection in the ISOT fake news dataset. Sebastian and his colleagues (Kula et al. 2020) applied a neural network-based text analysis approach to detecting fake news using the ISOT fake news set to evaluate the need for CI.

Zeng et al. (Zeng, Sun, and Li 2023) have done a study on fake news detection in which the authors have employed textual content of the news to detect fake news. They also adopted language features that include the hashtag '?'; 'Happy/Sad' faces; positive and negative sentiment words; and 'I' and 'We' pronouns to rate the credibility of information posted on the social media platform –Twitter. The first and foremost reason for identifying fake news is to feed deep neural networks where historical new data is used to determine the factors of fake news with the help of DL methods. The issue of identifying and mitigating fake online reviews has become particularly relevant in the last several years. Customers believe that information found in reviews is credible, and for this reason, many establishments may opt to employ the services of spammers to give them an advantage over other competitors. In this regard, several machine-learning techniques have been proposed to detect fake reviews with the assistance of an

artificially intelligent system. In another study, Raza A et al. (2021) aspired to compare machine-learning approaches to identifying fake reviews. In this work, Logistic Regression and Support Vector Machines were compared to the performance for classification of hotels based on the review dataset. The authors concluded that using Deep Learning approaches, such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM), overperformed the traditional machine learning algorithms while meeting relatively low computational complexity. Previous studies suggest that machine learning, such as deep learning, has increased researcher's attention in detecting false reviews and misleading content. This trend highlights the need for researchers to enhance the ML models employed to enhance fake review identification (Raza, S., & Ding, C. (2022).

Although numerous investigations have been conducted on fake news detection, current solutions still have limitations, such as low precision, high computational complexity, or lack of temporal aspect. This research presents a proposed privacy-preserving hybrid deep learning approach that effectively utilizes temporal features and textual content to screen fake news. Unlike other methods, the proposed system achieves higher accuracy, providing an all-encompassing framework for fake news surveillance. The results obtained with the proposed system are evaluated against benchmark methods, indicating the ability of the new system to overcome the shortcomings mentioned in the literature.



**Figure 1.**  
**Proposed Method**

## METHODOLOGY

An overview of the proposed method is depicted in Figure 1. Fake news detection can be classified into four stages: data-cleaning, data-processing, word2vec, models, and transferring.

## Data Collection (Dataset)

Data collection is the first step in research, and it was affected by two datasets: 'True.csv' and 'Fake.csv.' In this method, datasets prepared are collections from news articles that are either true or confirmed to be fake. The two datasets were obtained from various sources on the internet. The sources used include websites, among other internet sources, such as fact-checked and news websites. This dataset contains a comprehensive collection of several thousand Fake news and Real articles sourced from reliable news websites and websites that are not trustworthy by Politifact.com. This is after filtering out chosen articles deemed relevant to the topic and using precise language. Table 1 shows the information about the dataset used in this work.

**Table 1.**  
**Dataset.**

News	Size (Number of articles)	Subjects	
Real-News	21417	<b>Type</b>	<b>Article Size</b>
		World-News	10145
		Politics-News	11272
Fake-News	23481	<b>Type</b>	<b>Article Size</b>
		Government News	1570
		Middle east	778
		US News	783
		Left-news	4459
		politics	6841
		News	9050

## Data Preprocessing

The main purpose of this stage is to employ Natural Language Processing (NLP) methods to preprocess the incoming data and prepare it for the subsequent phase of extracting the appropriate characteristics. The dataset we employ comprises news headlines and articles. The maximum length of each title is approximately 12.45 words, but the maximum size of each text is approximately 405.28 words. Our project relies solely on the headlines to identify false news due to the impractical use of extensive texts. Additionally, the content is too intricate and laden with information for a news article, potentially causing a delay for the models during their training process.

## Word Embedding

This section is crucial since it requires the conversion of the dataset into a format that models can process. We employ several word embedding techniques for the different models we have constructed. The first and foremost measure is the tokenization tokenizer before applying LSTM, Bidirectional LSTM, and CNN. Combining and rearranging sequential words is one of the most common methods of tokenization that creates what we refer to as tokenized words. Using terminal padding, we moved on to ensure that each sequence had a fixed size of 42 by applying zero padding. For the instance of the embedding layer, we used it as it turns out that the weights used for it should be initialized randomly to enable the embedding of every word in the training set. The Embedding layer (Akbik et al. 2019) The sequence changes into a vector representation of continuous voltage float point numbers. First, we used a BERT tokenizer for the downstream tasks of BERT, in which we tokenized the dataset's news titles. BERT employs Google NMT's WordPiece Tokenization (Wu et al. 2016) to break down words into

fragments so that they can still be understood even when they have no record of the terms in their vocabulary.

## MODELS

This study consisted of two machine learning models: (1) **LSTM** with temporal features and (2) **CNN-BiLSTM**, both with temporal features. It chose to use the LSTM model since it can learn with sequence data and has performed well in text classification applications. This model was selected because the **CNN-BiLSTM** model can address text classification processes effectively and extract relevant local and global features from the text data.

### LSTM

Long-short-term memory (LSTM) is an enhanced enhancement of Recurrent Neural Network (RNN) that facilitates the retention of previous data in memory. The LSTM model is particularly suitable for processing sequential data, particularly in the context of difficulties with NLP. Therefore, we utilized LSTM to identify counterfeit information. The architecture includes input, LSTM, and output layers. The input layer considers the input for pre-processed text data and the temporal features. LSTM layer size: 100 Pass through an Activation: passed through the sigmoid function with output layer (one-dimensional unit with an activation passed through the sigmoid function). Equation (1) determines the input gate, which determines the amount of new information added to the cell system.

$$i_t = \sigma(W_i \cdot [x_t, T] + b_i) \quad (1)$$

where  $x_t$  be the input text sequence at time step  $t$ .  $T$  is the temporal characteristics (year, month, day, day of week),  $W$  is the learned weights, and  $b$  is the learned bias. The forget gate is given in Eq (2).

$$f_t = \sigma(W_f \cdot [x_t, T] + b_f) \quad (2)$$

This equation (3) computes the forget gate, which determines the amount of information that is discarded from the cell.

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tanh(W_c \cdot [x_t, T] + b_c) \quad (3)$$

$f_t$  is the forget gate at time step  $t$ .  $W_f$  is the learnable weight for the forget gate,  $x_t$  is the input text sequence at time step  $t$ ,  $b_f$  is the learnable bias for the forget gate, and  $\sigma$  is the sigmoid activation function.

$$o_t = \sigma(W_o \cdot [x_t, T] + b_o) \quad (4)$$

Equation (4) computes the output gate, which determines the final output of the LSTM. Where  $o_t$  is the output gate given in eq (4) at time step  $t$ ,  $W_o$  is the learnable weight for the output gate,  $b_o$  is the learnable bias for the output gate.

$$h_t = o_t \cdot \tanh(c_t) \quad (5)$$

Eq (6) computes the hidden states, where  $h_t$  be the hidden state of the LSTM at time step  $t$ ,  $C_t$  be the cell state of the LSTM at time step  $t$ . The output layer is given by Eq (6).

$$y = f(W_y \cdot h_t + b_y) \quad (6)$$

Where  $y$  is the output label (0 or 1). This equation computes the final output of the LSTM, which is the predicted probability distribution over the classes.

### CNN-BiLSTM

In this part, we utilised a CNN to the higher-level component of Bidirectional LSTM. Therefore, taking the CNN output removes one layer of complexity from the sequence labelling problem and becomes the input to BiLSTM (Graves and Schmidhuber 2005). Convolution layers are also applied to extract features and information from the input text. Furthermore, it utilizes BiLSTM for efficiency, allowing a forward and backward pass to provide results depending on the full-text input. The CNN-BiLSTM model with temporal features consisted of a convolutional layer, a max pooling layer, a bidirectional LSTM layer, and an output layer. The convolutional layer consisted of 32 filters of 5 sizes and used the ReLU activation function. The max pooling layer used a pool size of 2. The bidirectional LSTM layer comprised 100 units and used the sigmoid activation function. The output layer consisted of a single unit and utilized the sigmoid activation function. The Convolutional Layer is provided by Eq (7).

$$x'_t = \max(W_c \setminus * x_t + b_c) \quad (7)$$

Where  $x_t$  be the input text sequence at time step  $t$ , be the convolution operator, and  $\max$  be the pooling operator. Eq (8) computes the BiLSTM Layer.

$$h_t, c_t = BiLSTM(x'_t + T) \quad (8)$$

Where  $T$  is the temporal features (year, month, day, day of week),  $h_t$  be the hidden state of the BiLSTM at time step  $t$ ,  $c_t$  be the cell state of the BiLSTM at time step  $t$ ,  $y$  be the output label (0 or 1).

$$y = f(W_y \cdot h_t + b_y) \quad (9)$$

The output layer is computed by Eq (9).  $W$  is the learnable weights,  $b$  the learnable bias, and the sigmoid activation function are all necessary.

### BERT

Transformers have been an essential contributor to the field of NLP. BERT is a transformer-based method that has revolutionized the field of NLP with its exceptional performance (Devlin et al. 2018). Two key attributes characterize the model: firstly, it is a sophisticated transformer capable of efficiently handling long phrases by utilizing the 'attention' mechanism, and secondly, it is bidirectional, meaning it considers the complete input sentence while generating its output. We utilized BERT, a powerful language model, to analyze the dataset and create a deep learning system. The numerous parameters involved in constructing a model for NLP require a significant amount of time. We employ pre-trained BERT models that enable us to perform transfer learning effectively. We selected the pre-trained bert-base-uncased model from among numerous models with distinct parameters. A set of criteria determines the selected individual and does not consider variations in the letter case (uppercase and lowercase).

## EXPERIMENTS

### Experimental Setup

The experiments used Python as a programming language and trained scikit-learn using an open-source machine learning library (Scikit-learn. Machine learning in Python. (accessed Jun. 04, 2021).[Online]. Available : n.d.). The TensorFlow library was used to build and train machine learning models (Numpy. A library for scientific computing with Python n.d.). Binary cross-entropy loss function and Adam were used as the optimizer to train the model (Kingma and Ba 2014).

## RESULTS

The use of metrics by many authors led us to use the most utilized metrics to measure the performance of the models we constructed for the fake news detection issue.

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

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 - score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

The following four metrics are widely utilized in machine learning, particularly for classification tasks. It allows us to evaluate the effectiveness of a classifier from several viewpoints. Typically, 'Accuracy' is the most indicative statistic for evaluation as it is entirely based on the classification model. **Error! Reference source not found.** validates these aspects based on the balanced and imbalanced datasets concerning the abovementioned measures of performing the four models we employed in this study. We can conclude that our models trained in imbalanced datasets perform approximately 7% better than models trained in balanced learned datasets for the fake news detection issue. Altogether, the results indicate that all the Transformer-based models are better than the others by a very wide margin. Deep learning models with many attributes can be ranked higher than models with fewer attributes.

The findings in Table 2 are encouraging. Moreover, we must acquire a deeper understanding of the instances where failures occur.

**Table 2.**

**The performance of the different models on imbalanced datasets**

Model	Accuracy	Precision	Recall	F1-Score
LSTM	0.9780	0.98	0.98	0.98
C-BiL	0.9791	0.98	0.98	0.98
BERT	0.9903	0.99	0.99	0.99



## CONCLUSION

For the last few years, it has been servicing the security of national security and the decision-making of political issues. Indeed, this research aimed to classify fake news using deep learning models, such as LSTM, CNN-BiLSTM, and the recently introduced transformer-based models like BERT on the ISOT fake News dataset. As for our datasets, we used balanced and distorted datasets, where word embedding, and feature selection were used to develop word sequences. Furthermore, these sequences were incorporated into the current models. We noticed that the experimental results prove several key points: As we can see from the comparison, the proposed models have similar experimental results while showing the progress from the initial LSTM model to the BERT model. In both datasets, BERT is the better-performing model, and it showcased fast and incredible outcomes throughout the training process.

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**Consent to Participate:** Yes

**Consent for publication and Ethical approval:** Because this study does not include human or animal data, ethical approval is not required for publication. All authors have given their consent.

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