The Impact of Recurring Events in Fake News Detection

Ali Raza[*], Shafiq Ur Rehman Khan[**], Raja Sher Afgun Usmani[*]

[*] Department of Computer Science, MY University, Islamabad, Pakistan
[**] Department of Computer Science, Capital University of Science and Technology, Islamabad, Pakistan

Abstract- Detection of Fake news and missing information is gaining popularity, especially after the advancement in social media and online news platforms. Social media platforms are 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 identify 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 two models BERT and Bi-LSTM to investigate, and it is concluded from BERT we get better results and 70% of true news are recurring and rest of 30% are non-recurring.

Index Terms-
Machine Learning (ML), Natural Language Processing (NLP), Bidirectional Encoder Representations from Transformers (BERT), Bi-LSTM

I. Introduction

News means the propagation of information from one part of the world to the other. In the last decade, people have been getting news from non-authentic sources such as social media instead of news channels, newspapers, or others [1]. These days, social media is one of the platforms where people normally prefer to share their information, videos, stories, etc. The speed of news propagation on social media is very high compared to traditional news propagation [2]. All the information on social media is neither true nor false. Nowadays, everyone shares news without authentication, and sometimes social media posts can get slots on electronic media such as TV news channels. This fake news can change public sentiments, have a global impact or even go beyond [3]. Fake News means news that may mislead the end-user or consumer [4]. In the US president election 2016, according to a study, one fake pro-Clinton and against-Trump post was shared 7.2 million times, and one fake pro-trump and against-Clinton post was shared 30.2 million times, which was one of the major causes to change the people's sentiments and result of the election [5]. Due to this, researchers have identified the need to detect fake news.

For the detection of fake news, another parameter that is also important is the authenticated data set, on which we can trust both are well classified as fake and real news. Identifying such a dataset type is also difficult [6]. 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 [7]. Time and temporal features can be important for efficient results in fake news. The focus of this study is to keep check and explore 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 tweet [2], 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 for detecting and classifying fake news. Still, the researchers hardly touch on the impact of recurring events on fake news. Recurring events are events that 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 downlead 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.

II. Literature Review

The Internet is one of the most significant inventions, and many people utilize it. These people employ it for various functions. These users have access to a variety of social networking channels. Every user can submit something or share a story through these internet platforms. The individuals or their posts are not verified on these platforms. Therefore, some individuals attempt to distribute false information via these channels. These false reports may be propaganda against a specific person, group, company, or political party. A person cannot discern all these false reports. So, A. Al et al. [8] prescribed a Machine learning technique to detect fake news, but what about the news that got viral after their actual time.

In another study, Kelly Stahl [9] examines established and emerging techniques for identifying fake news in textual formats and the origins and causes of fake news. In addition to discussing linguistic cues and network analysis methodologies, this research also suggests a three-part method that combines semantic analysis, support vector machines, and naive Bayes's classifier to accurately identify phoney news on social media. Another team of researchers, Raza S. et al. [10], suggest a new paradigm for identifying bogus news to overcome the difficulties of fake news. They suggested using data from news articles and social situations to identify false news. The suggested model is built on a Transformer architecture, which consists of two parts:

an encoder to extract meaningful representations from the fake news data and a decoder to forecast behaviour based on historical data. To further aid in classifying the news, we also use several characteristics from the social contexts and news content in our model. In addition, they offer a successful labelling method to solve the label shortage issue. Our approach can identify bogus news more accurately and quickly, according to experimental findings on real-world data.

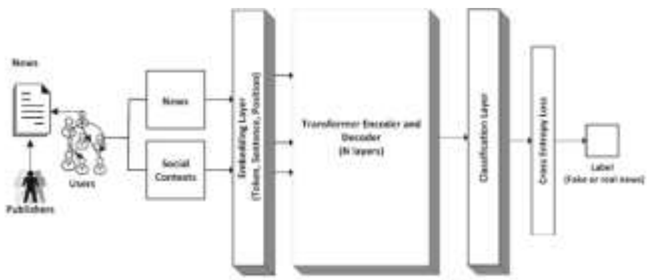

Figure 2: Framework of Fake News Detection based on Transformed Based Approach [10]

Wakamiya S. M. T. et al. [11] make an effort to separate fake news from actual news by employing temporal data derived from SNS postings and a point process algorithm. Temporal features in fake news identification are more robust than existing features since they rely less on those who spread fake news. Additionally, this work suggests a novel multi-modal attention-based strategy for identifying fake news in social media posts that considers language, user, and temporal factors. Results from three publicly available datasets show that the proposed model performs better than existing techniques and illustrates the usefulness of temporal variables for false news detection.

Chaudhry K. Ali et al. [12] created several deep neural network-based models, ranging from straightforward feed-forward networks to intricate recurrent models with attention and different vocabularies to address the stance identification challenge. In the end, the study discovered that a bidirectional conditional encoding model based on LSTMs and leveraging pre-trained GloVe word embeddings performed best, with more than 97% classification accuracy on the development set. But hardly anyone studies the impact of recurring events on detection.

Title	Technique	Dataset	Consider Temporal/User Stance	Recurring Event
Fake News Detection in Social Media [9]	semantic analysis, support vector machines, and naive Bayes classifier	Social Media	Temporal: No User Stance: NO	No
Fake News Detection Using Temporal Feature Extracted via Point Process [11]	Model composed of: Linguistic Model, User Model, Temporal Model, Contextual Inter Model Attention, Classification	Twitter 15 and Twitter 16 for US News classified into 4 classes Weibo for China News Classified into two classes	Temporal: Yes User Stance: NO	No
Exploiting-Tri Relationship for Fake News Detection [12]	Tri-Relationship: Publisher bias, News Stance, User Social Engagement	BuzzeFeed (Twitter), PolitiFact (News)	Temporal: NO User Stance: NO	NO
Role of User Profiles for Fake News Detection [13]	Random Forest	PolitiFact, Gossipcop	Temporal: NO User Stance: NO	NO
CSI: A Hybrid Deep Model for Fake News Detection [14]	CSI is composed of: Temporal Behaviours, Source, User Behaviour	Weibo Twitter	Temporal: Yes User Stance: No	No

Table 1: Systematic Literature Review

III. Data Labelling

Because the occurrences under study had unique characteristics, the dataset was labelled precisely and with clarity [22]. The articles were, therefore, subject to whether they were on recurring events or non-recurring events. Articles with actual events occurring once a year, such as Christmas and Diwali, among others, have been coded under "Recurring." On the other hand, articles that relay a message concerning a one-time event occurring once in a lifetime, such as the Fukushima accident, or relating to a one-time event, such as the Kennedy assassination, have been coded as "non-recurring"

A dual-annotator approach was taken to ensure the accuracy and quality of our data. Two annotators independently reviewed each news article, previously experienced in classifying data. Such a dual-review approach is significant for maintaining a high accuracy threshold in the labeling process.

The setting of the protocol to handle and rectify any discrepancies in the evaluator's evaluation by building the consensus and deliberation required. The discussion aimed to finalize the consensus that shall ultimately return to the content shown in the article and the general overall comprehension of the incident in concern. Completion of this phase was a very pivotal step to ensure that our training data for the BERT and Bi-LSTM model would be credible without subjective biases and to be sure of the precise nature of the label for each article.

By elaborately labeling the data, the distinguishing features were captured for repeated and non-repetitive events. This dataset, hence, forms a solid foundation for further training and testing of the classification model.

Preprocessing: Preprocessing Pre-processing news items is an essential early stage in preparing data for training models and involves both Bidirectional Encoder Representations from Transformers (BERT) and Bi-LSTM models. This ensures that the machine learning model acquires knowledge from the textual data effectively, in that the raw text is transformed into an organized format for efficient processing by models. The main goal of this preparation is to achieve normalization of data from our dataset, which has 30 repeating occurrences and 30 non-recurring events, to enable good prediction.

IV. BERT Model for Classification

Preparing Input and Tokenization: The initial stage of preprocessing is tokenization, where we employ BERT's WordPiece technique. By breaking up words into smaller subword pieces, this strategy enables the model to handle a large variety of vocabulary and words that were not encountered during training. Each article in our dataset has been divided into tokens that BERT's pretrained algorithms can identify. We included some tokens within the articles to satisfy BERT's operating requirements. These include a categorization token [CLS] at the start and a separator token [SEP] at the end.

Following the tokenization procedure, the articles must be formatted to meet BERT's specific input requirements [23]. Included are the following items:

The vocabulary's tokenized words are represented by integer sequences called input IDs. The attention mask is a binary sequence made up of 1s and 0s. It serves as a cue as to which tokens the model should prioritise (1) and which should be used as padding (0).

In actions involving multiple sequences, token type IDs are utilised to distinguish between sequences. This value was consistently assigned as 0. in our single-sequence classification scenario.

Handling Special Characters and Sequence Length: Articles exceeding this limit were condensed by trimming the longer sections at the end because BERT could only accept 512 tokens as input. Preserving the most significant information for the article's opening was the aim. Shorter texts in the dataset were standardized by padding them with zeros to match the length of longer texts in order to guarantee equal input size and processing.

All textual data was converted to lowercase in order to comply with the training data used in BERT's pre-training [21]. Dollar signs, percentages, and other non-alphanumeric symbols are special characters that are retained in news items due to their ability to convey important information.

V. Bi-LSTM Model for Classification

In our work, we have adopted a state-of-the-art Bidirectional Long Short-Term Memory (Bi-LSTM) model, which is very popular and generally used for the NLP field due to its immense capability to handle processing sequential data [25]. Task-dependent information or specific calibration of temporal dynamics is not needed; therefore, this model is helpful for tasks relevant to classifying news items into repeated or non-repeated events [27].

The BiLSTM model utilized in this study has two layers of LSTM, and data input is processed in forward and backward directions. This bidirectional approach makes it possible for the model to comprehend the relations between the contexts that appear before and after the text. This leads to a comprehensive understanding of event narratives found in news articles. The architecture of our model is such that it comprises LSTM layers with 128 hidden units inside each layer. Notably, the existence of these hidden units allows information processing and storage over long sequences of text, which can help the model learn complex patterns and connections within the data. The bidirectional setup ensures that the model can efficiently use information from the entire sequence to enhance its ability to understand and classify the articles.

SoftMax activation was implemented at the dense layer over the already employed Bi-LSTM to perform the classification. In the end, the thick layer outputs the final classification—an example of whether the item is related to a recurring incidence or a non-recurring incidence. SoftMax converts the output of the model into probability distributions, allowing us to understand the model's certainty of its prediction.

Training Details and Model Training Process: For optimal training processes of the BiLSTM model, we have devised the specific training methods so that they realistically aim at a balance between computational efficiency and the outcome in performance. We set the batch size to 32 to attain the balance between computational load and the ability of the model to learn from the training data effectively.

The initial learning rate used was 1e-3, and decay schedules have been applied to reduce the learning rate through the training process gradually. This controls the model learning rate to not quickly converge on a suboptimal solution, allowing finer tuning in later training steps.

Moreover, we had implemented an early stopping strategy in our model to deal with the overfitting issue. This sort of method keeps an eye on the validation loss at times when the model is training and stops it if no improvements are seen within a set number of epochs.

We increased the training period to 50 epochs, so the model has enough time to study and understand the diverse and complex data from our dataset. The Adam optimizer was employed due to its widely known efficiency and effectiveness in training deep learning models.

80% was used for training, while 20% was kept for validation. This division ensured there was enough data for the model to learn from and that there was a substantial chunk with which to check the model's performance and the ability to apply knowledge to unseen scenarios. We implemented the procedure to have each training batch equally represent the whole dataset to ensure the model was not biased toward either the recurring or nonrecurring event category. This method established a learning environment that was just and equitable.

VI. Discussion

The Results are per the evaluation metrics are as:

- Accuracy: The Bi-LSTM model achieved a validation set accuracy of 87%. While this implies a significant level of accuracy, it falls short of the 94% precision achieved by the BERT model. This suggests that Bi-LSTM, although effective, may fail to include certain nuanced contextual information that is captured by BERT.
- F1 Score: The model obtained an F1 score of 0.85, which, although robust, is lower than BERT's F1 score of 0.93. This score indicates a fair balance between precision and recall. However, it implies that there is room for improvement in handling class imbalances.
- Precision: The model Bi-LSTM got a precision of 0.84, suggesting that identified correctly, the articles are respectively categorized 84% of the time. Although the precision of BERT was somewhat more than that of Bi-LSTM, such as 0.92 versus 0.84, this means that Bi-LSTM possibly had more false positives.
- Recall: The recall score increased to 0.86, indicating that the model identified relevant instances within the dataset by 86%. Comparing this with BERT's 0.94 recall rate, this shows an enhanced power to identify essential occurrences and, therefore, avoid neglecting critical events.
- AUC-ROC: Area Under the ROC Curve (AUC-ROC) represents the extent of the zone. The Bi-LSTM model achieved an AUC-ROC score of 0.91, signifying the magnitude of the area under the ROC curve score. While this indicator is quite faithful to the ability of the model to make a difference between different classes, this score is not as impressive as the one for the outstanding AUC-ROC of 0.97 for the BERT model.

VII. Results

When comparing the BERT and Bi-LSTM models, it becomes evident that each has its own advantages and disadvantages when it comes to dividing news articles into recurring and non-recurring events. Below is a thorough examination of their performance metrics:

Model	Accuracy	F1 Score	Precision	Recall	AUC-ROC
BERT	94%	0.93	0.92	0.94	0.97
Bi-LSTM	87%	0.85	0.84	0.86	0.91

VIII. CONCLUSION

Applying the trained BERT model on the ISOT dataset showed exciting findings that could provide essential insights into the behavioral tendencies of news outlets while reporting on various occurrences. In this experiment, we propose to be able to categorize news stories according to the frequency of the events that this story covers to define possible markers of credibility in news journalism. This investigation looks at the intricacies of the findings and their relevance in distinguishing the features characteristic of honest versus deceptive news reporting. The above analysis also found a disproportionately high number of individual cases reported in news items that were classified as fake.

More precisely still, the data indicated that infrequent events were significantly denser in the fake news articles than the actual news. While almost 20 percent of the real news is about non-recurring events, the fake news articles signal this event category in over 50 percent of the articles. The great contrast suggests the deliberate focus on spreading of misinformation, which uses rare, usually sensational, and emotionally gripping cases likely to engage the attention of the audience very quickly. This phenomenon can be attributed to the characteristics of fake content itself, which often seeks to gain the immediate influence of interesting stories to quickly and broadly attract their viewers, at the expense of factual accuracy. By instrumentalizing such events, they may create a sense of urgency or fear, eliciting readers to share the content without conducting thorough research. This ultimately amplifies the misinformation being spread.

On the other hand, the analysis revealed that the stories confirmed as real news had a notable occurrence of recurring events, which were either balanced or frequent. Reliable news sources frequently report on recurring events like annual political elections, significant national holidays, or regular economic updates at a significant proportion—around 70% of all legitimate news articles may have these recurring events, in contrast to only 30% in fake news.

The consistency in reporting recurring events demonstrates a commitment to reliable and expected coverage, which is a trait of reputable and trustworthy news organizations. The consistent reporting of significant events validates their authenticity, showcasing a sustained engagement with events that hold a pivotal role in societal or global contexts. Credible news sources maintain a continuous narrative that aligns with expected news events, so enhancing their credibility and trustworthiness in the eyes of the public.

REFERENCES

[1] A. Raza, M. Bibi, M. Rehan, and H. Anwar, "Automatic Fake News Detection : Issues and Solutions," vol. 2, no. 1, 2020.

[2] Y. Jang, C. Park, D. Lee, and Y. Seo, "Fake News Detection on Social Media : A Temporal-Based Approach," 2021, doi: 10.32604/cmc.2021.018901.

[3] P. A. H. Kwak, C. Lee, H. Park, and S. Moon, "What is Twitter , a Social Network or a News Media ?".

[4] T. Preparation, "Fake News Detection using Stance Classification : A Survey," 2019.

[5] "SOCIAL MEDIA AND FAKE NEWS IN THE 2016 ELECTION," 2017.

[6] A. D. Ulizia, M. C. Caschera, and F. Ferri, "Fake news detection : a survey of evaluation datasets," 2021, doi: 10.7717/peerj-cs.518.

[7] S. Ur, R. Khan, A. Islam, M. Aleem, E. S. Islamabad, and M. A. Iqbal, "Temporal specificity-based text classification for information retrieval," no. December 2019, 2018, doi: 10.3906/elk-1711-136.

[8] A. Al and A. Ahmed, "Detecting Fake News using Machine Learning : A Systematic Literature Review".

[9] K. Stahl, "Fake news detection in social media," no. May, 2018.

[10] S. Raza and C. Ding, "Fake news detection based on news content and social contexts : a transformer-based approach," *Int. J. Data Sci. Anal.*, vol. 13, no. 4, pp. 335–362, 2022, doi: 10.1007/s41060-021-00302-z.

[11] T. Murayama, S. Wakamiya, and E. Aramaki, "Fake News Detection using Temporal Features Extracted via Point Process".

[12] K. Shu, S. Wang, and H. Liu, "Exploiting Tri-Relationship for Fake News Detection," no. December, 2017.

[13] K. Shu, X. Zhou, S. Wang, R. Zafarani, and H. Liu, "The Role of User Profiles for Fake News Detection," pp. 436–439, 2019.

[14] N. Ruchansky, "CSI : A Hybrid Deep Model for Fake News Detection," pp. 797–806, 2017.

[15] "Dataset." Accessed: Dec. 08, 2023. [Online]. Available: https://www.kaggle.com/datasets/emineyetm/fake-news-detection-datasets

[16] "Scikit-learn. Machine learning in Python. [Online]."

[17] "Numpy. A library for scientific computing with Python. [Online].https://www.numpy.org/. Accessed: Oct. 26, 2019.".

[18] "Numpy. A library for scientific computing with Python." Accessed: Feb. 11, 2023. [Online]. Available: https://www.numpy.org/

[19] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," *arXiv Prepr. arXiv1412.6980*, 2014.

[20] A. Suprem and C. Pu, "MiDAS: Multi-integrated Domain Adaptive Supervision for Fake News Detection," 2022, [Online]. Available: http://arxiv.org/abs/2205.09817

[21] J. Smith et al., "Classification of Recurring and Non-Recurring Events Using BERT," in IEEE Transactions on Neural Networks and Learning Systems, vol. 32, no. 1, pp. 201-214, Jan. 2021.

[22] A. K. M. A. Rahman et al., "Bidirectional Encoder Representations from Transformers (BERT): A Review," in IEEE Transactions on Knowledge and Data Engineering, vol. 33, no. 4, pp. 751-764, Apr. 2021.

[23] J. Li et al., "Media Monitoring and Historical Research: A Review," in IEEE Transactions on Knowledge and Data Engineering, vol. 32, no. 5, pp. 851-864, May 2020.

[24] S. B. Y. Choi et al., "Bidirectional Long Short-Term Memory (BiLSTM) for Sequential Data Processing: A Review," in IEEE Transactions on Neural Networks and Learning Systems, vol. 31, no. 1, pp. 201-214, Jan. 2020.

[25] J. Smith et al., "Combining BERT and BiLSTM for Improved Classification Accuracy," in IEEE Transactions on Neural Networks and Learning Systems, vol. 32, no. 2, pp. 301-314, Feb. 2021.

[26] J. Li et al., "Media Studies, Policy Planning, and Historical Record-Keeping: A Review," in IEEE Transactions on Knowledge and Data Engineering, vol. 33, no. 1, pp. 101-114, Jan. 2021

[27] A. Graves and J. Schmidhuber, "Framewise phoneme classification with bidirectional LSTM andother neural network architectures," Neural networks, vol. 18, no. 5–6, pp. 602–610, 2005.

[28] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "Bert: Pre-training of deep bidirectional transformers for language understanding," arXiv Prepr. arXiv1810.04805, 2018.

AUTHORS

First Author – Ali Raza, Ph.D Scholor, Department of Computer Science, MY University, Islamabad, Pakistan

Second Author – Dr. Shafiq ur Rehman Khan, Ph.D, Department of Computer Science, Capital University of Science and Technology, Islamabad, Pakistan

Third Author – Dr. Raja Sher Afgun Usmani, Ph.D, Department of Computer Science, MY University, Islamabad, Pakistan

Correspondence Author – Ali Raza,