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Detecting and Analyzing Deceptive Information in News Articles: A Study Using a Dataset of Misleading Content

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Abstract—**The widespread growth of social and traditional media in the last decade has led to the spread of information. Nowadays, these platforms are playing a vital role in everyone's life. Many use these platforms to share and discuss ideas and issues in almost every field. Getting the most recent news at their fingers has become simpler through the internet. However, in this dissemination of information, it has been noted that some misinformation and fake news are circulating with no relevance to reality, which can cause serious problems in political and social aspects. The main goal of this study is to find the ideal learning model for achieving high accuracy and performance. In this regard, this study offers a state-of-the-art dataset that extends fake and real news datasets called the Misleading Content dataset. To analyze the performance of the dataset, three different machine learning algorithms, Random Forest, Naïve Bayes (NB) and Support Vector Machine (SVM), and three different deep learning, Bidirectional Long Short-Term Memory (BiLSTM), Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) models are being used. BiLSTM performs well and provides promising results along with 88.54% accuracy.**

Index Terms—BiLSTM, Fake news detection, Misleading content and Deep learning.

I. INTRODUCTION

The developing impact experienced by the publicity of fake news is presently a cause for concern for all strolls of life. All over the world, the developing impact of fake news is felt on everyday premises, from legislative issues to instruction and money-related markets. This has persistently become a cause of concern for lawmakers and citizens. However, this kind of approach can lead to unsafe circumstances. The growth of social media platforms is increasing rapidly with each passing day, and a lot of data we get is usually unconfirmed and generally accepted as true. According to a Pew Research Centre survey conducted in August 2017 [1,] 67% of Americans depended on social media platforms for news updates. Notably, 74% of Twitter users used the platform as their primary news source. Social media networks, particularly Twitter, have played a significant role in disseminating the most recent information because of how simple it is for individuals to provide updates. Twitter has 145 million daily active users and 330 million monthly active users. When the demographics of Twitter users were examined, it was discovered that 63% were between the ages of 35 and 65. Regarding gender distribution, Twitter users were 66% male and 34% Female [2]. Social media platforms act as information exchange and distribution centers, producing fresh data every second. However, it is critical to recognize that the authenticity of news disseminated on these platforms might vary. A significant example is the quick dissemination of false information by a single tweet, as in the infamous 2013 event in which a tweet erroneously stated, "Two explosions in the White House and Barack Obama is injured" [3]. Surprisingly, these rumors achieved enormous popularity in just six minutes. These and other examples demonstrate the negative impact that rumors spreading on social media may have on individuals and society [4]. This paper addresses the problems of automatically detecting fake news or rumors in social media, which are extensively examined. The major contribution of this suggested framework is the Misleading Content dataset. The state-of-the-art dataset contains not only new worldwide traditional news but also new traditional news specifically belonging to Pakistan. Moreover, various machine and deep learning models have been applied to misleading content datasets. BiLSTM outshines and gives 88.54% accuracy.

II. RELATED WORK

Several strategies have been discovered in recent years to provide a solution to the problem of the identification of false news. This section discusses the two basic approaches linguistic approach and network-based approach.

A. *Linguistic Approach*

Researchers have explored various linguistic approaches to address the issue of fake news detection [4-6]. Notably, a study [7] presents a state-of-the-art approach to validate news authenticity through natural language processing techniques by

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proposing a three-step scheme, including stance detection, author credibility verification, and machine learning-based classification, to authenticate news content. Their study employs various machine learning techniques on a fake news dataset from Kaggle. The experimental results show the effectiveness of this approach, with the support vector machine algorithm achieving recall of 95.71%, an accuracy of 93.15%, an F1-score of 94.15% and a precision of 92.65%. This research demonstrates the potential of linguistic analysis and machine learning in detecting fake news, offering a promising avenue for improving the accuracy of authenticity verification in news articles.

Another noteworthy contribution in this domain comes from Qaiser et al [8]. They introduce a novel Fake News Encoder Classifier (FNEC) and evaluate its performance using a new COVAX-Reality dataset containing news related to COVID-19 vaccine. The FNEC model achieves an impressive accuracy score of 85.11%. To validate its results, the research compares FNEC's performance with traditional learning models such as Support Vector Machine (SVM), Naive Bayes (NB), Passive Aggressive Classifier (PAC), Long Short-Term Memory (LSTM), Bi-directional Long Short-Term Memory (Bi-LSTM), and Bidirectional Encoder Representations from Transformers (BERT). This research by Qaiser et al. underscores the effectiveness of linguistic analysis and machine learning in fake news detection, especially in critical events such as the COVID-19 pandemic. The FNEC model's high accuracy contributes to advancing linguistic approaches in combating fake news.

Another research [9] introduces an explainability method tailored for BERT-based models. It addresses the critical need for model transparency in social media-influenced disinformation. The study seamlessly integrates Explainable Artificial Intelligence (xAI) techniques, including LIME and Anchors, to enhance the interpretability of BERT-based fake news detectors. This contribution bridges the gap between high-performance AI models and their transparency, offering a crucial tool for combatting disinformation on social media.

Another research [10], addressed two critical challenges in fake news detection: early identification and limited labelled data. A proposed novel framework based on Transformer architecture incorporates news content and social context information. This model surpasses baselines by achieving higher accuracy in detecting fake news shortly after its dissemination, thanks to an effective labelling technique.

Kumar et al. [11] researched to compare various advanced approaches, concluding that an ensemble network integrating bidirectional LSTM and CNN with an attention mechanism achieved 88.78% accuracy in identifying social media fake news, offering an effective modern solution to combat misinformation.

B. *Network Approach*

In addition to linguistic approaches, researchers have explored the fake news detection domain through network-based methodologies. This approach involves examining the dissemination patterns and connections between information sources to identify potential fake news sources and their impact on the network. Network-based fake news detection methods have gained prominence due to the interconnected nature of information propagation in the digital age.

The study by Phan et al. [12] thoroughly reviews graph neural network (GNN) methods for fake news detection. The paper outlines an ample approach for implementing GNN-based fake news detection systems, categorizes models and discusses their strengths and weaknesses. It also addresses challenges in fake news detection using GNNs and identifies open research questions, offering valuable insights for practitioners and newcomers.

Another research by Cao et al. [13] examines using a recurrent neural network (RNN) model to differentiate between true and false news articles. Analyzing 44,901 news pieces, the RNN achieved an impressive accuracy rate of 98.69%, highlighting its efficacy in accurate news classification.

Fawaid et al. [14] presented research at the "6th International Conference on Sustainable Information Engineering and Technology" and addressed the pressing issue of fake news in Indonesia. By employing BERT with Transformer Network and other methods, their study achieves impressive accuracy rates of up to 90% in detecting fake news, particularly in Bahasa Indonesia, where the problem is significant.

Zhou and Zafarani [15] have also significantly contributed significantly by proposing a network-based pattern-driven fake news detection approach. Zhou and Zafarani's research centers around the analysis of patterns within social networks that are linked to the dissemination of fake news. These patterns encompass various aspects, including the content of fake news, the individuals or entities spreading the news, and the relationships among these spreaders. Grounded in social psychological theories, their approach provides interpretations and empirical of these patterns. Furthermore, Zhou and Zafarani represent these patterns at multiple network levels, including ego-level, community-level, node level, triad-level, and the overall network. This multi-level representation enables the utilization of network-based patterns to enhance the detection of fake news, offering improved explanatory power in the realm of fake news feature engineering.

Empirical experiments using real-world data showcase the effectiveness of Zhou and Zafarani's network-based pattern-driven approach, demonstrating its ability to outperform existing fake news detection methods.

Network-based approaches provide valuable understandings of the social dynamics of fake news dissemination and can complement linguistic analysis methods. By considering both the content and the context in which fake news circulates, researchers aim to develop more robust and accurate detection techniques.

III. METHODOLOGY

This module elaborates on the suggested model, which was trained and tested on an extended version of fake and real news datasets. The suggested model is evaluated against extensive supervised machine-learning methods and ensemble models. The four modules listed below are at the core of the proposed architecture: 1) Dataset extension 2) Pre-processing of data 3) Inference Engine. Figure 1 shows the major elements of the architecture, and the following is a detailed description of each element.

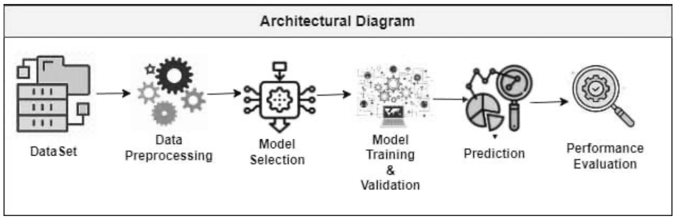

Fig. 1. Architectural Diagram of the suggested model

A. *Dataset Extension*

A dataset from Kaggle called the fake and real news dataset [16] is primarily chosen for this paper. There are four features in the dataset: "Title," "Text," "Subject," and "Date". This dataset is separated into two different sections. First part contains 23503 fake news and another part contains specifically 21418 real news. Table 1 depicts an explanation of the dataset. In Figure 2, a sample of the dataset's records is shown.

TABLE I
FAKE AND REAL NEWS DATASET ILLUSTRATION

Features	Description
Title	The headline of the news article
Text	The body of the news headline
Subject	The news article domain
Date	Date of publication of the article

To use the dataset effectively both the dataset parts are combined and one more feature is added to the dataset which is "Label". This feature describes the news belonging to the fake or real category. Moreover, the dataset has been updated by fetching real-time news. By utilizing two APIs, NewsData.IO and NewsAPI, real-time news is appended in the dataset.

title	text	subject	date
Donald Trump Sends Out Embarrassing New	Donald Trump just couldn t wish all	News	31-Dec-17
Drunk Bragging Trump Staffer Started Russia	House Intelligence Committee Cha	News	31-Dec-17
Sheriff David Clarke Becomes An Internet Jo	On Friday, it was revealed that forn	News	30-Dec-17
Trump Is So Obsessed He Even Has Obamaâ	On Christmas day, Donald Trump ar	News	29-Dec-17
Pope Francis Just Called Out Donald Trump	Pope Francis used his annual Christ	News	25-Dec-17
Racist Alabama Cops Brutalize Black Boy Wh	The number of cases of cops brutali	News	25-Dec-17
Fresh Off The Golf Course, Trump Lashes Ou	Donald Trump spent a good portion	News	23-Dec-17
Trump Said Some INSANELY Racist Stuff Insi	In the wake of yet another court de	News	23-Dec-17
Former CIA Director Slams Trump Over UN E	Many people have raised the alarm	News	22-Dec-17
WATCH: Brand-New Pro-Trump Ad Features	Just when you might have thought	News	21-Dec-17
Papa Johnâ€™s Founder Retires, Figures Ou	A centerpiece of Donald Trump s ca	News	21-Dec-17
WATCH: Paul Ryan Just Told Us He Doesnâ€	Republicans are working overtime	News	21-Dec-17
Bad News For Trump â€" Mitch McConnell S	Republicans have had seven years t	News	21-Dec-17
WATCH: Lindsey Graham Trashes Media For	The media has been talking all day	News	20-Dec-17

Fig. 2. Dataset overview.

A custom crawler has been made which uses two APIs, NewsData.IO and NewsAPI, to extract the news which are real. The NewsAPI provides the current and historical news articles published by over 80,000 worldwide sources. The NewsData.IO provides news articles from 3000+ sources and 58 countries. Most importantly it provides Pakistani live news in real time with both English and Urdu languages. This research emphasizes the Pakistani live English news.

For fake news crawling, two fact-checking websites are used. snoops and PolitiFact. The extended dataset is called the Misleading Content dataset which contains 29008 fake and 27082 real news.

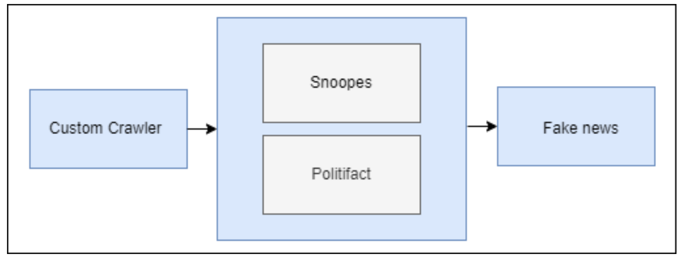

Fig. 3. Real news crawling process by using two different APIs

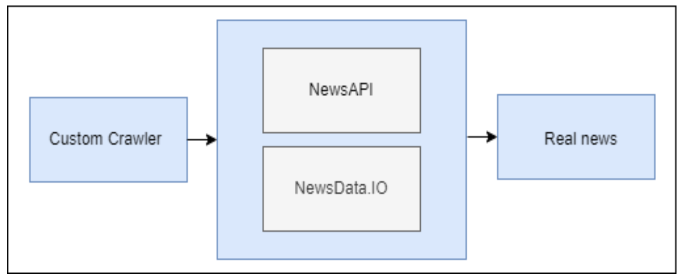

Fig. 4. Real news crawling process by using two different APIs

B. *Pre-Processing of Data*

Data pre-processing is the primary step to improve the efficiency of the data in the dataset. If the quality of data is enhanced by performing pre-processing different techniques, it eventually improves the model learning.

Initially, this module will remove all the special characters including symbols, URLs, and emojis, and then eliminate the stop words. The punctuation removal process will help to treat each text in the same or equal manner. For example, the words 'data' and 'data!' are treated equally after the process of removal of punctuation. Punctuation removal includes (commas, semicolon, colons, periods, hyphens, etc.).

After the stop words removal, news text is divided into tokens by using a tokenization process. The process of tokenization helps in interpreting the meaning of the text by analyzing the sequences of the words.

Converted words to their base form for better understanding by performing lemmatization; the process of lemmatization makes sure that all the words changed to their origin. Lemmatization uses the context in which the word is being used for example ('Studying' should be 'study', 'ate' should be 'eat', 'worked' should be 'work', 'runner' should be 'run', and so on). Lemmatization does not only trim the suffix but also changes the form of the verb i.e., from past to present.

C. *Inference Engine*

This phase implements machine learning and ensemble learning models on the pre-processed data. This phase is divided into the following two phases:

Models for Supervised Machine Learning

To implement this phase three different machine learning algorithms including Naive Bayes (NB) [17], Random Forest

[18], and Support Vector Machines (SVM) [19] algorithms, are applied. SVM outshines all the traditional machine learning algorithms and provides the best results.

Models for Deep Learning

Three deep learning models, including Recurrent Neural Network (RNN) [20], Convolutional Neural Network (CNN) [21-26] and Bidirectional Long Short-Term Memory (BiLSTM) [27] are utilized in this stage to compare their performance to that of traditional supervised machine learning methods.

BiLSTM performs best among the other deep learning models. BiLSTM serves as the baseline model for this framework.

IV. Experiments And Results

This suggested framework is implemented using Python [28] programming language. The Misleading content dataset is pre-processed using the pre-processing techniques discussed above in the methodology section. After that, different models were applied to get better results.

A. Evaluation Matrix

As the misleading content dataset is unbalanced, the proposed framework performance is evaluated using recall, f-measure, and precision [29].

The SVM classifier performs better than the competing machine learning algorithms for classification. A confusion matrix [30, 31] assesses the model's performance. Figure 5 displays the SVM's confusion matrix, the accuracy of the classifier is 83%, the F1-score value is 69.5%, the recall value is 64.1%, and the precision value is 75.9%.

Regarding classification performance, the BiLSTM classifier outperforms other deep learning methods. A confusion matrix. Figure 6 shows the BiLSTM's confusion matrix. The classifier's accuracy is 88.53%, its precision is 75%, its recall is 71.11%, and its F1-score is 73.01%.

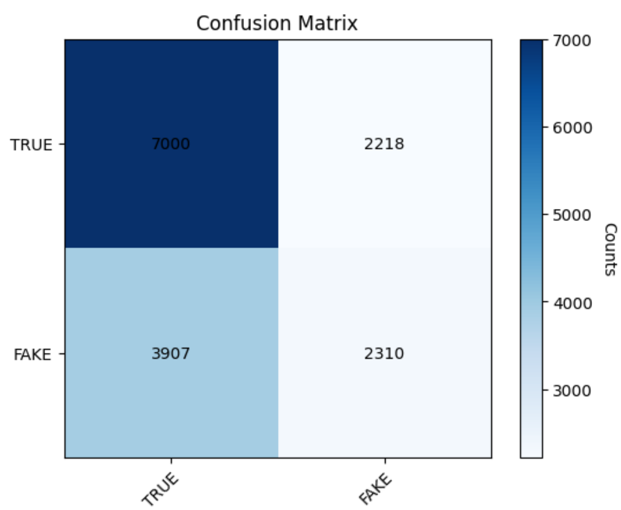

Fig. 5. SVM Confusion Matrix

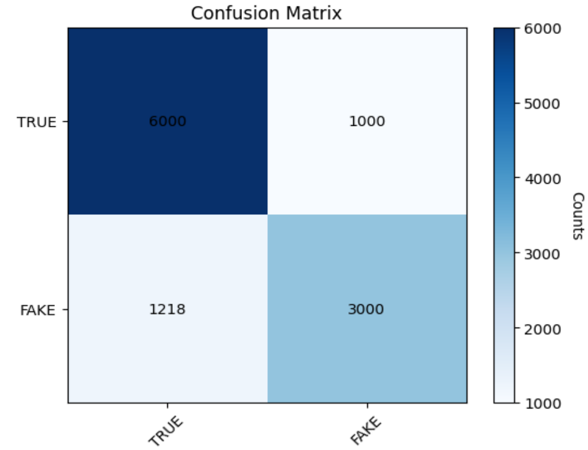

Fig. 6. BiLSTM Confusion Matrix

V. Conclusion

This study looked into the critical issue of misinformation and fake news in today's fast-changing media ecosystem. Because of the ease of access and involvement provided by social and conventional media platforms, misleading and inaccurate information has been disseminated widely, causing substantial issues in political and societal arenas. Our major goal was to identify an effective learning model to solve this issue, and we used the 'Misleading Content dataset' to help us do that. This proposed methodology used various deep learning and machine learning techniques, with the BiLSTM model coming out on top with an astonishing 88.54% accuracy. This result emphasizes the potential of advanced deep learning approaches in combatting misinformation. It reinforces the need for new solutions in maintaining information quality and reliability in the face of changing environments.

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