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A recurrent neural network model for detecting fake news on social media

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ABSTRACT

The growing popularity of social media platforms for sharing news and videos has made it easier for users to access and share information instantly. However, verifying the credibility of such content remains a significant challenge. These platforms enable the rapid spread of fake news, which often leads to the distribution of inaccurate information. Since social media content is largely unrestricted, users frequently share news without verifying its source or accuracy, causing fake news to spread quickly and sometimes go viral. This can have harmful effects on society. Therefore, it is essential to ensure that the news shared on social media is accurate to prevent users from being misinformed, which is crucial for positive social development. This study proposes a recurrent neural network model using artificial intelligence and machine learning to detect and verify fake news on social media. The framework includes steps such as defining the problem, using datasets labeled as "fake" and "true," and applying natural language processing techniques. The authors conducted data cleaning, feature engineering, and visualization of real and fake news before converting text into tokens. The proposed model achieved a high accuracy of 99.96% with a minimal loss of 0.0083 after processing over 14 million tokens using 128 layers.

1. Introduction

Platforms for social networking have grown at an exponential rate. Any message or news (confirmed or unverified) may be disseminated on the social media network by anyone, and it can be spread or viral without official verification. We live in a world full of disinformation and fake news. Because of its long-term ramifications and implications, detecting fake news has been challenging since 1640 AD, which is famous for fake propaganda in France. With the increasing evolution of social media, fake news issues have become serious in recent years. In this 21st century, we live in what is classified as the 'post-truth era,' which evolved from misinformation campaigns during the Cold War. Social media platforms such as Facebook, Twitter, and Instagram have recently arisen as venues for rapid information broadcast and retrieval. According to Ashraf et al. (2021), about half the population of developed regions gets their news via social media. The significance of social media cannot be taken for granted, and it has proven to be an effective medium during times of crisis through its involvement in breaking news (Bhogade et al., 2021). However, one disadvantage of social media's convenience is the rapid dissemination of fake news. The propagation of this misinformation using social media is a huge concern. The DeepFake films have turned into a source of false information, yet studies have demonstrated the effectiveness of deep learning for identification.

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Artificial Intelligence (AI) and Machine Learning (ML) combined with natural language processing are proving to be effective models for detecting fake news. As online social media users increase, automated fake news detection is the only way to detect fake news. However, using text-based AI and ML models to detect fake news only sometimes provides accurate results. These models must embed the manually crafted features extracted from the text content. Some models detect specific news types, e.g., based on religion, sports, or politics, while some research models use limited datasets per their focus. These methodologies perform poorly on specific news or some topics and perform well on some specific datasets to validate fake or true content. This research focuses on detecting fake news using Recurrent Neural Networks (RNN). AI and ML news detection are crucial for social media organizations and enterprises to detect and predict the circulating news on various social media platforms is fake or true.

Some recent examples of fake news on social media in recent times are presented below:

- "Donald Trump sent his plane to transport 200 stranded marines" - this was a fake news story picked up by a major media talk show host.
- "FBI director received millions from Clinton Foundation, his brother's law firm does Clinton's taxes" – Here, an unreliable and biased news site generated over 538,000 engagements on Facebook by using a fake headline.
- "Pope Francis shocks the world, endorses Donald Trump for president" - was a fake news site that fools world media and generated 960,000 Facebook engagements.
- "Three Reasons Why You Should Stop Eating Peanut Butter Cups" - was shared over 207,500 times on Facebook.
- "Israeli Defense Minister: If Pakistan sends ground troops into Syria on any pretext, we will destroy this country with a nuclear attack" - was yet another fake news that fools world leaders with potentially tragic results.
- "Obama Signs Executive Order Banning the Pledge of Allegiance in Schools Nationwide" - generated over 2 million interactions on Facebook.

This research gap motivated the authors to analyze news texts and data content on social media using natural language processing (NLP) that converts words into numbers, which are used to train the AI and ML model for making predictions.

The highlights of this research are as follows:

- Use AI, machine learning and Recurrent neural models, to detect and assess fake social media news validity.
- The proposed framework involves six steps, from understanding the problem to the results.
- Used two dataset files as fake and true to deploy the natural language processing.
- Feature engineering and data cleansing were performed to visualize the real and fake news.
- Results display an accuracy of 99.96% and a loss of only 0.0083 for 14,210,305 using 128 layers.

This paper is divided into the following sections. Section 1 is the overview, which is the introductory section about the impact of fake news on social media and the detection issues faced by investigators. Section 2 presents the closely matching, relevant research papers by other authors in a similar domain. The authors reviewed and classified the research work and presented the process. Section 3 presents the proposed recurrent neural network framework and the steps. This has been designed to consider the temporal dimension by having memory as a feedback loop. Section 4 illustrates the implemented framework steps, starting with the setup, dataset files and python libraries are imported, and feature engineering and data cleansing are performed. Then the cleaned dataset is visualized. The dataset is divided into training and testing and prepared by tokenizing and padding. Section 5 illustrates the results obtained for the trainable parameters for 128 layers. The output presented an accuracy of 98.36%, higher than any other known RNN model. Finally, the research is concluded with a summary and suggestions for future research.

2. Literature survey

The authors performed a systematic literature survey per keyword, metadata, and results to identify 428 research papers published after 2018 from highly referred journals such as MDPI, IEEE, ACM, and Elsevier. The same work was removed using the selection process presented in Table 1; this helped shortlist only the matching and relevant research. In the first stage, 428 articles were identified, of which 321 were screened in the second stage. The unrelated and duplicate research was excluded, and only 39 records were finalized for quality synthesis, as presented in Table 1. This section presents the abstract of a few of the closely matching research which has been referenced in this research.

Table 1: Research classification and review

Research literatures	Stage: 1	Stage: 2	Stage: 3	Stage: 4	Final breakup
Fake news	112	84	50	10	26.17%
Recurrent neural network	56	42	25	5	13.08%
Social media news detection	83	62	37	7	19.39%
Fake video content	103	77	46	9	24.07%
Machine learning prediction	74	56	33	7	17.29%
Total	428	321	193	39	100%

The literature on fake news detection is vast and multidisciplinary, reflecting the complexity of the challenge at hand. For instance, Guefrechi et al. (2022) and Ishfaq et al. (2022) have explored the use of deep learning models like InceptionResnetV2 for DeepFake video detection and machine learning algorithms for multiclass prediction, respectively. These studies underscore the rapid advancements in AI and ML technologies that hold the potential to revolutionize how fake news is identified and mitigated. Furthermore, the work of Selvanarayanan et al. (2024) on using RNN-driven IoT integrated systems for coffee farming illustrates the versatile application of recurrent neural networks in processing and analyzing temporal data. This is particularly relevant for detecting fake news, where the temporal dynamics of news spread can offer critical insights. The empirical analysis by Ishfaq et al. (2022) of various machine learning algorithms for multiclass prediction also provides a foundation for understanding how different AI models can be tailored to identify the nuanced characteristics of fake news effectively.

The advent and broad acceptance of the social networking (Nasir et al., 2021) sites idea, which coincided with the rise of the Internet, has altered how news is created and disseminated. Social media has made news more accessible, quicker, and less expensive. This shift has brought with it several drawbacks. Because of the high content on social media, the fake news issue, while being presented just lately, has become a significant study subject. It is simple for individuals to create false remarks and news on social media. The most difficult task is to distinguish between true and false news. A two-step strategy for spotting false news on social media is suggested in this research (Ozbay and Alatas, 2020), with an emphasis on fake news.

Due to the rapidity and cheap cost of news transmission on social media (Raza and Ding, 2022), it has become one of the primary routes for individuals to obtain and consume news. However, social media's characteristics make it a hotspot for the spread of false news, which has harmful consequences for people and society. As a result, identifying fake news has emerged as a critical issue that has sparked many studies. Most current approaches for detecting false news are supervised (Reis et al., 2019), which necessitates a significant amount of time and effort to create a consistently annotated dataset. In quest of a solution, this research identified fake news in an unsupervised approach in this study (Yang et al., 2019). The authors regard news facts and users' trustworthiness as a hidden stochastic process and leveraged users' social media interactions to determine how they feel about news authenticity. The conditional relationships among news facts, users' views, and trustworthiness are captured using a Bayesian network model.

The authors introduced a deep convolutional neural network for detecting fake news in this paper (Kaliyar et al., 2020). Rather than depend on hand-crafted characteristics, our model uses many hidden layers in a deep neural network to automatically discover the discriminating features for false news categorization. To extract many characteristics at each layer, we develop a deep Convolutional Neural Network. The authors evaluated the suggested method's performance compared to other baseline models.

da Silva et al. (2019) used a systematic literature strategy to scan traditional electronic libraries for the most current works on false news identification on social media. The goal was to describe the status of false news identification, define fake news, and determine the best effective machine learning approach (Ahmad et al., 2020) for doing so. The authors concluded that the most widely utilized approach for automated false news identification is a combination of conventional machine learning methods managed by a neural network rather than a single methodology.

Due to the obvious open and simple spread of information in social media (Sahoo and Gupta, 2021; Mridha et al., 2021), there is an urgent demand for online false news detection and verification. To assure news spreaders' legitimacy on social networking sites, the scientific community must contribute to developing automated algorithms for detecting false claims, misinformation, and inaccuracy. The goal of automatic fake news detection is to save time and human resources by detecting false news and spewers from a stream of constantly produced data (Ashraf et al., 2021).

Fake news can influence public perception and, consequently, may harm society. As a result, it's crucial to check the news stories' trustworthiness and originality before sharing them on social networking sites. The subject of false news has recently gotten much attention from the scientific community, and it desperately needs efficient and effective solutions (Kaliyar et al., 2021; Zhang et al., 2023). Conventional usage approaches are based on user-based attributes and ethical news or social context. To detect false news, the substance of the news story, and the presence of echo chambers in the social media network, are considered.

A discussion of how to identify false news on social media, covering various sorts of news platforms, fake news generalizations obtained from different for fake news, and current algorithms from a data mining approach are covered in this article. Rehman et al. (2023) discussed how influential users can be identified in online discussion networks. To solve the difficulty, Yuan et al. (2021) suggested a domain-adversarial and graph-attention neural network architecture, also known as domain-adversarial and graph-attention (Song et al., 2021) neural network prototype." Its main benefit is that in a text environment with various events/domains (Qi et al., 2019), only incomplete website specimen data is required to train a model for precise cross-domain fake news detection (Zhou et al., 2020; Chauhan and Palivela, 2021) in domains with few samples, which needs to compensate for the boundaries of conventional machine learning is based on deep learning (Wani et al., 2021) tasks due to news and information evolvement or cross-domain identifiers.

Reshmi et al. (2021) examined several strategies for detecting and preventing false news. The Bayes classifier, a machine learning stochastic classifier, is suggested here as a tool for identifying false news. For detecting fake news, the origin of the news is also considered in addition to the Bayes classifier. Fake news pieces contaminate social media news if they are not accurately detected and eliminated periodically. It is a difficult issue to solve. Many current algorithms (Singhal et al., 2019; Cao et al., 2020) for detecting bogus news performed well. To take advantage of the current state of the art, powerful AI in the form of deep learning is required. In study of Madhubala et al. (2021), an algorithm is developed to provide a false news detection system. Deep Convolutional Neural Network (CNN) based Fake New Detection is the name of the method, which combines NLP with a Deep CNN and a revolutionary pre-processing technique (Kaur et al., 2022).

Various strategies for detecting false news have recently been developed. Existing efforts do not generate a precise statistical assessment for a specific piece of news. Media category and input limits cause less variation. Divya and Banik (2021) looked at computerized fake news detection approaches and devised a system for recognizing different types of news. In addition, researchers looked at the effectiveness of a system for predicting false news derived from data resources. Fake or misleading news may have a significant influence on individuals who become targeted. Kumar et al. (2021) examined documents from 2017 through 2021, as well as several fake news detecting tools. This study provides a comprehensive overview of current and previous studies on fake news detection using various machine learning methods.

To combat false news, scientists are using AI-powered techniques such as computer vision and natural language processing. Karwa and Gupta (2021) provided a thorough summary of previous detection strategies and a computational formalism and technique for improving the outcome. Fake news may be used to spread propaganda against a person, a group, an organization, or a political group. All this bogus news is impossible to detect by a person. As a result, machine learning techniques that can automatically identify bogus news are required. This comprehensive literature review discussed the use of machine learning classifiers for identifying false news.

Khanam et al. (2021) examined the research on fake news detection and examined conventional ML procedures to determine which is the finest, to develop a prototype with supervised machine learning that can categorize fake news as true or false, utilizing tools such as Python Scikit-Learn and NLP for text analysis (Alonso et al., 2021). Bhogade et al. (2021) wanted to do a parallel categorization of diverse news pieces available online using AI, ML, and NLP. The project's outcome determines the identification of false news for social networking sites using deep learning (Kaliyar et al., 2020) and verifies the legitimacy of the news website that is being published.

3. Fake news prediction framework

Regarding the interpretability of the proposed model, the authors propose the following items:

- Input Analysis: Analyze the input features used by the model to make predictions. Identify the important features that contribute to distinguishing between fake and genuine news on social media. For example, you can explore the significance of textual content, user profiles, timestamps, engagement metrics, or any other relevant information.
- Feature Importance: Employ techniques such as feature importance scores or attention mechanisms to highlight the most influential features in the model's decision-making process. This can help understand which aspects the model focuses on when differentiating between fake and genuine news.
- Visualization: Utilize visualization methods to illustrate the inner workings of the model. For instance, you can generate word clouds, saliency maps, or activation heatmaps to visualize the regions of interest and the attention distribution across the text. These visualizations can provide insights into how the model processes and interprets social media news data.
- Model Explainability: Apply explainable AI techniques to shed light on the model's decision-making process. This can include methods such as LIME (Local Interpretable Model-agnostic Explanations) or SHAP (SHapley Additive exPlanations) to explain individual predictions. These techniques can help identify the key factors driving the model's classification decisions for specific instances.
- Error Analysis: Perform an error analysis to understand the model's limitations and potential biases. Examine cases where the model misclassifies news articles or fails to detect fake news correctly. Investigate whether there are any patterns or specific types of news that the model struggles with and discuss the potential implications of these limitations.
- Comparison with Baselines: Compare the interpretability of your proposed model with other baseline models or existing approaches for fake news detection. Highlight the advantages and disadvantages of your model's interpretability techniques in comparison to alternative methods.

The authors propose employing Recurrent Neural Networks, or RNN, which are a sort of artificial neural network with a memory (internal state) as a feedback loop that considers the time dimension. The hidden layer of an RNN has a temporal loop in which it not only creates an output but also feeds itself. Time is also introduced as an extra dimension, and the RNN can recall earlier time stamps (Sharma et al., 2022) occurrences and deal with text sequences. Due to fixed input and output, feedforward ANNs are restricted. The derivatives of the network are calculated by shifting from the outermost layer (near the output) back to the beginning layer during backpropagation [26-30], which calculates ANN gradients (close to the inputs). The weights and biases are no longer updated when the gradients decline exponentially. Each layer is reliant on the output of the one before it.

$$y = b + (m * x) \quad (1)$$

$$\text{Cost Function: } f\,(m, b) = \frac{1}{N}\sum_{i=1}^{n}(error)^2 = \frac{1}{N}\sum_{i=1}^{n}(\hat{y}i - yi)^2 \quad (2)$$

$$\text{Gradient Descent Loss function: } f(m, b) = \sum_{i=1}^{n}(\hat{y} - yi)^2 \quad (3)$$

The long short-term memory (LSTM) network outperforms the vanilla RNN because it avoids vanishing gradient difficulties, whereas RNNs fail to develop long-term dependencies. By default, LSTM remembers long-term dependencies and recalls information for a long time. This study follows the stages in Fig. 1 for training the model, making predictions, and evaluating the performance of the proposed model.

The setup involves using Rhyme as the online platform, with Jupyter Notebook and Python for this research. Rhyme is configured and set up as a cloud desktop with all the software preinstalled. The setup is configured to perform fake news classifications between fake and true classes from the dataset.

4. Implemented framework

This research is divided into a series of tasks as the authors reviewed the problem statement to build a business case for predicting true and fake news accurately. Python libraries are imported along with datasets to ensure task numbers, after which initial exploration data analysis is performed. Then the basic level of data cleaning and feature engineering is implemented, and then visualize the cleaned-up dataset is visualized. The next step involves preparing the cleaned data using token organization and padding. The next step is to validate and then perform an intuition behind recurrent neural networks. Finally, the required dataset is built and trained for the proposed framework. The authors also determined the accuracy and performance of the proposed model. The research steps are performed in the following steps as a proposed framework to detect fake news, and illustrated in Fig. 2.

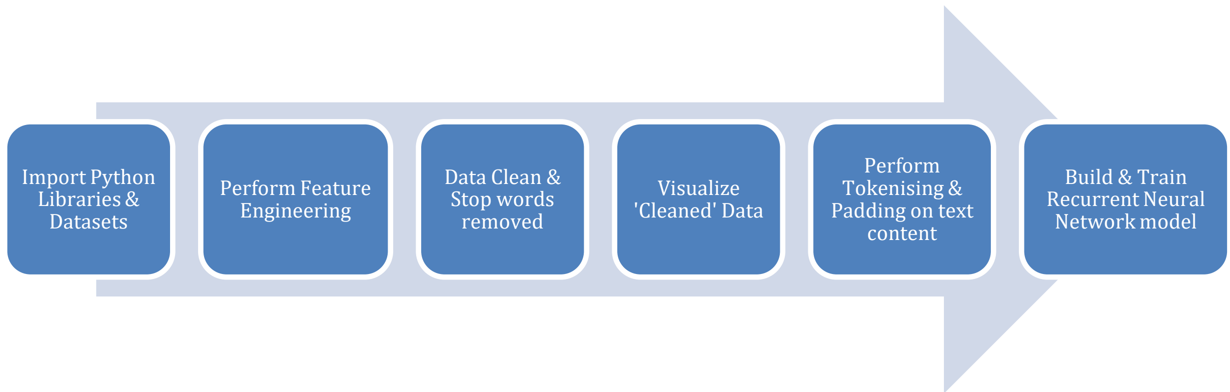

Fig. 1: Proposed setup steps

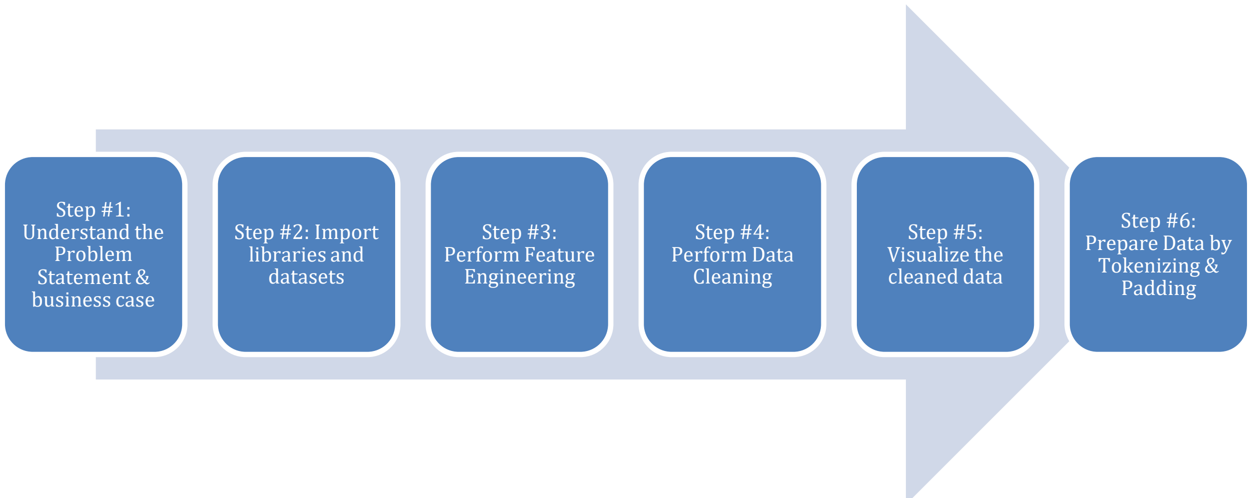

Fig. 2: Steps for the fake news detection framework

4.1. Step #1: Understand the problem statement and business case

The research uses the Jupyter Notebook entitled 'FakeNewsClassification' and two CSV classes of files, as true and fake. LSTM is trained, which essentially classifies the news. The dataset has challenges, including all the information that can be found on a typical social media platform. This will be trained and tested to predict fake news. Fig. 3 illustrates the Jupyter notebook and Rhyme desktop.

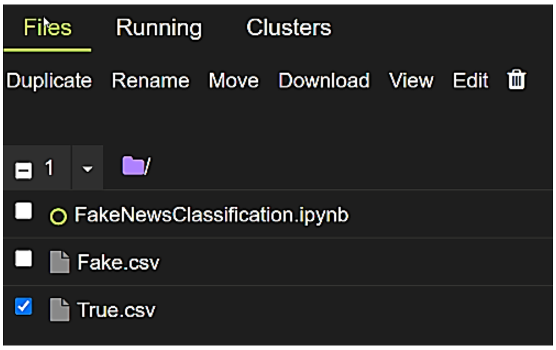

Fig. 3: Jupyter notebook files

4.2. Step #2: Import libraries and datasets

This step involves upgrading the setup to use the latest Python libraries, shown in Fig. 4, and installing Tensorflow as 'pip install --upgrade TensorFlow-gpu==2.0.' TensorFlow is a Google framework for building, training, and deploying AI and ML models, as illustrated in Fig. 4 to build our proposed prediction network. This research installed Plotly to perform data visualization and natural language libraries such as 'Jensen' and Work Cloud. In addition to these, Pandas is also installed for data frame manipulation, NumPy for numerical analysis, matplotlib, and Seaborn for advanced data visualization. The authors used Pandas to read the CSV files into data frames as 'pd_true'=pd.read_csv("true.csv") for True news and 'pd_false'=pd.read_csv("false.csv") for Fake news.

4.3. Step #3: Perform feature engineering

After importing the data, a feature engineering process is performed. In this step, a new column is added to each data frame to label the data. The column named isfake is assigned the value 1 for the true news data frame using df_true['isfake'] = 1, and its structure is checked using df_true.head(). The true news data frame contains the columns title, text, subject, date, and isfake.

The authors loaded the data as df_true and df_fake and validated the entries for any missing or null elements and determined the size as 'df_true.info()' at 669.4KB and 'df_false.info()' at 733.9KB, as illustrated in Fig. 5.

Similarly, for the fake news data frame, the isfake column is assigned the value 0 using df_fake['isfake'] = 0, and its structure is viewed using df_fake.head(), as shown in Fig. 6. This labeling process prepares the data for training the LSD model.

```
import tensorflow as tf
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud, STOPWORDS
import nltk
import re
from nltk.stem import PorterStemmer, WordNetLemmatizer
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize, sent_tokenize
import gensim
from gensim.utils import simple_preprocess
```

Fig. 4: Updating and installing the required libraries

```
# Load the data
df_true = pd.read_csv("True.csv")
df_fake = pd.read_csv("Fake.csv")

df_true.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21417 entries, 0 to 21416
Data columns (total 4 columns):
 #  Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0  title    21417 non-null  object
 1  text     21417 non-null  object
 2  subject  21417 non-null  object
 3  date     21417 non-null  object
dtypes: object(4)
memory usage: 669.4+ KB

df_fake.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23481 entries, 0 to 23480
Data columns (total 4 columns):
 #  Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0  title    23481 non-null  object
 1  text     23481 non-null  object
 2  subject  23481 non-null  object
 3  date     23481 non-null  object
dtypes: object(4)
memory usage: 733.9+ KB
```

Fig. 5: Data loading and validation

These fake and true data frames are combined and concatenated to have the harmonized fake and real news in one single data frame as 'df['original'] = df['title'] + ' ' + df['text']' and 'df.head().' This provides an index starting from zero to the total number of combined samples as 44,898, with five columns from 21,417 for True and 23,481 for Fake, as performed in Fig. 7.

The authors decided not to use data as an accurate measure of news, so the data column was dropped. For better clarity, title and text columns are leveraged into a new column called 'original' by having them in one massive text as 'df['original'] = = df['title'] + ' ' + df['text'] and df.head() as presented in Fig. 8. Next, to validate and view the new column data, we check this as 'df['original'][0] as presented in Fig. 9. This has the contents from the title and text columns into one single column.

4.4. Step #4: Perform data cleaning

Now, stop words, which are common words that do not add meaningful information (such as a, we, if, by, to, and as), are removed. First, the stop words package is downloaded, as illustrated in Fig. 10. The list of stop words is then imported and extended by adding several additional words, including from, subject, re, edu, and use. After that, all stop words are removed using the Gensim library for natural language processing. This is done by iterating through the text, identifying any stop words, and removing them one by one.

```
df_fake['isfake'] = 1
df_true.head()
```

	title	text	subject	date	isf
0	As U.S. budget fight looms, Republicans flip t...	WASHINGTON (Reuters) - The head of a conservat...	politicsNews	December 31, 2017	1
1	U.S. military to accept transgender recruits o...	WASHINGTON (Reuters) - Transgender people will...	politicsNews	December 29, 2017	1
2	Senior U.S. Republican senator: Let Mr. Muell...	WASHINGTON (Reuters) - The special counsel inv...	politicsNews	December 31, 2017	1
3	FBI Russia probe helped by Australian diplomat...	WASHINGTON (Reuters) - Trump campaign adviser ...	politicsNews	December 30, 2017	1
4	Trump wants Postal Service to charge 'much mor...	SEATTLE/WASHINGTON (Reuters) - President Donal...	politicsNews	December 29, 2017	1

```
df_fake['isfake'] = 0
df_fake.head()
```

	title	text	subject	date	isf
0	Donald Trump Sends Out Embarrassing New Year ...	Donald Trump just couldn't wish all Americans ...	News	December 31, 2017	0
1	Drunk Bragging Trump Staffer Started Russian ...	House Intelligence Committee Chairman Devin Nu...	News	December 31, 2017	0
2	Sheriff David Clarke Becomes An Internet Joke...	On Friday, it was revealed that former Milwauk...	News	December 30, 2017	0
3	Trump Is So Obsessed He Even Has Obama's Name...	On Christmas day, Donald Trump announced that ...	News	December 29, 2017	0
4	Pope Francis Just Called Out Donald Trump Dur...	Pope Francis used his annual Christmas Day mes...	News	December 25, 2017	0

Fig. 6: Feature engineering

```
df['original'] = df['title'] + ' ' + df['text']
df.head()
```

	title	text	subject	isfake	orig
0	As U.S. budget fight looms, Republicans flip t...	WASHINGTON (Reuters) - The head of a conservat...	politicsNews	1	As U.S. budget fight looms, Republicans flip t...
1	U.S. military to accept transgender recruits o...	WASHINGTON (Reuters) - Transgender people will...	politicsNews	1	U.S. military to accept transgender recruits o...
2	Senior U.S. Republican senator: 'Let Mr. Muell...	WASHINGTON (Reuters) - The special counsel inv...	politicsNews	1	Senior U.S. Republican senator: Mr. Muell...
3	FBI Russia probe helped by Australian diplomat...	WASHINGTON (Reuters) - Trump campaign adviser ...	politicsNews	1	FBI Russia probe helped by Australian diplomat...
4	Trump wants Postal Service to charge 'much mor...	SEATTLE/WASHINGTON (Reuters) - President Donal...	politicsNews	1	Trump wants Postal Service to charge 'much mor...

Fig. 7: Concatenation of fake and true data frames

```
df['original'] = df['title'] + ' ' + df['text']
df.head()
```

	title	text	subject	orig
0	As U.S. budget fight looms, Republicans flip t...	WASHINGTON (Reuters) - The head of a conservat...	politicsNews	As U.S. budget fight looms, Republicans flip t...
1	U.S. military to accept transgender recruits o...	WASHINGTON (Reuters) - Transgender people will...	politicsNews	U.S. military to accept transgender recruits o...
2	Senior U.S. Republican senator: 'Let Mr. Muell...	WASHINGTON (Reuters) - The special counsel inv...	politicsNews	Senior U.S. Republican senator: Mr. Muell...
3	FBI Russia probe helped by Australian diplomat...	WASHINGTON (Reuters) - Trump campaign adviser ...	politicsNews	FBI Russia probe helped by Australian diplomat...
4	Trump wants Postal Service to charge 'much mor...	SEATTLE/WASHINGTON (Reuters) - President Donal...	politicsNews	Trump wants Postal Service to charge 'much mor...

Fig. 8: Adding new column 'Original'

```
df['original'][e]

As U.S. budget fight looms, Republicans flip their fiscal script WASHINGTON (Reuters) - The head of a conservative Republican facti
the U.S. Congress, who voted this month for a huge expansion of the national debt to pay for tax cuts, called himself a "fiscal cons
ve" on Sunday and urged budget restraint in 2018. In keeping with a sharp pivot under way among Republicans U.S. Representative Mark
Meadows, speaking on CBS's 'Face the Nation,' drew a hard line on federal spending, which lawmakers are bracing to do battle over
in January. When they return from the holidays on Wednesday, lawmakers will begin trying to pass a federal budget in a fight likely
to be linked to other issues, such as immigration policy, even as the November congressional election campaigns approach in which
Republicans will seek to keep control of Congress. President Donald Trump and his Republicans want a big budget increase in military
spending, while Democrats want proportional increases for non-defense 'discretionary' spending on programs that support education,
scientific research, infrastructure, public health and environmental protection. 'The (Trump) administration has already been willing
to say: "We're going to increase defense discretionary spending ... by about 7 percent,"' Meadows, chairman of the small but
influential House Freedom Caucus, said on the program. 'Now, Democrats are saying that's not enough, we need to give the government
a pay raise of 10 to 11 percent. For a fiscal conservative, I don't see where the rationale is. ... Eventually you run out of other
people's money,' he said. Meadows was among Republicans who voted in late December for their party's debt-financed tax overhaul,
which is expected to balloon the federal budget deficit and add $1.5 trillion over 10 years to the $20 trillion national debt. 'It's
interesting to hear Mark talk about fiscal responsibility,' Democratic U.S. Representative Joseph Crowley said on CBS. Crowley said
the Republican tax bill would require the United States to borrow $1 trillion, to be paid off by future generations, to finance tax
cuts for corporations and the rich. 'This is one of the least fiscally responsible bills we've ever seen passed in the history of
the House of Representatives. I think we're going to be paying for this for many years to come,' Crowley said. Republicans insist
the tax package, the biggest U.S. tax overhaul in more than 30 years, will boost the economy and job growth. House Speaker Paul
Ryan, who also supported the tax bill, recently went further than Meadows, making clear in a radio interview that welfare or
'entitlement reform,' as the party often calls it, would be a top Republican priority in 2018. In Republican parlance, 'entitlement'
programs mean Social Security, housing assistance, Medicare and Medicaid health insurance for the elderly.
```

Fig. 9: Contents of the 'Original' column

```
        nltk.download("stopwords")

        [nltk_data] Downloading package stopwords to
        [nltk_data] C:\Users\Administrator\AppData\Roaming\nltk_data...
        [nltk_data] Unzipping corpora\stopwords.zip.

        True

def preprocess(text):
    result = []
    for token in gensim.utils.simple_preprocess(text):
        if token not in gensim.parsing.preprocessing.STOPWORDS and len(token) > 3 and token not in stop:
            result.append(token)
    return result

# Apply the function to the dataframe
df['clean'] = df['original'].apply(preprocess)
```

Fig. 10: Processing stop words

Then we validate to check the stop words dropped from the original as 'print(df['clean'][0]),' the contents are presented in Fig. 11. The content now has unique words only which are separated as required for the ML model processing. To determine the list of entire words, present in the cleaned-up dataset without stop words, as illustrated in Fig. 12, which is 92,76,947 words.

```
print(df['clean'][0])

['budget', 'fight', 'looms', 'republicans', 'flip', 'fiscal', 'script', 'washington', 'reuters', 'head', 'conservative', 'republican',
ction', 'congress', 'voted', 'month', 'huge', 'expansion', 'national', 'debt', 'cuts', 'called', 'fiscal', 'conservative', 'sunday',
d', 'budget', 'restraint', 'keeping', 'sharp', 'pivot', 'republicans', 'representative', 'mark', 'meadows', 'speaking', 'face', 'nat,
'drew', 'hard', 'line', 'federal', 'spending', 'lawmakers', 'bracing', 'battle', 'january', 'return', 'holidays', 'wednesday', 'lawm
s', 'begin', 'trying', 'pass', 'federal', 'budget', 'fight', 'likely', 'linked', 'issues', 'immigration', 'policy', 'november',
'con onal', 'election', 'campaigns', 'approach', 'republican', 'seek', 'control', 'congress', 'president', 'donald', 'trump', 'republica,
'want', 'budget', 'increase', 'military', 'spending', 'democrats', 'want', 'proportional', 'increase', 'defense', 'discretionary',
ing', 'programs', 'support', 'education', 'scientific', 'research', 'infrastructure', 'public', 'health', 'environmental', 'protecti',
'trump', 'administration', 'willing', 'going', 'increase', 'defense', 'discretionary', 'spending', 'percent', 'meadows', 'chairman',
l', 'influential', 'house', 'freedom', 'caucus', 'said', 'program', 'democrats', 'saying', 'need', 'government', 'raise', 'percent',
al', 'conservative', 'rationale', 'eventually', 'people', 'money', 'said', 'meadows', 'republicans', 'voted', 'late', 'december',
di', 'debt', 'financed', 'overhaul', 'expected', 'balloon', 'federal', 'budget', 'deficit', 'trillion', 'years', 'trillion', 'national',
t', 'interesting', 'hear', 'mark', 'talk', 'fiscal', 'responsibility', 'democratic', 'representative', 'joseph', 'crowley',
'said', ey', 'said', 'republican', 'require', 'united', 'states', 'borrow', 'trillion', 'paid', 'future', 'generations', 'finance',
tations', 'rich', 'fiscally', 'responsible', 'bills', 'seen', 'passed', 'history', 'house', 'years', 'come', 'crowley',
'said', 'republicans', 'insist', 'package', 'biggest', 'overhaul', 'years', 'boost', 'economy', 'growth', 'sc', 'speaker',
'paul', 'ryan', 'supported', 'recently', 'went', 'meadows', 'making', 'clear', 'radio', 'interview', 'welfare', 'cnt', 'nt', 'reform',
'party', 'calls', 'republican', 'priority', 'republican', 'parlance', 'entitlement', 'programs', 'mean', 'food', 'stan', 'housing',
'assistance', 'medicare', 'medicaid', 'health', 'insurance', 'elderly', 'poor', 'assistan', 'assist', 'needy', 'democrats', 'seized',
ryan', 'early', 'december', 'remarks','saying', 'spending', 'cuts', 'social', 'programs','goals','house','republicans','seat', 'budget',
'prevent', 'government', 'shutdown', 'democrats', 'leverage', 'senate', 'republicans', 'narrowly', 'control', 'defend', 'discretionary',
'defense', 'programs', 'social', 'spending', 'tackling', 'issue', 'dreamers', 'people', 'brought', 'illegally', 'country']
```

Fig. 11: Stop words removed from the 'Original' column

```
# Obtain the total words present in the dataset
list_of_words = []

for i in df.clean:
    for j in i:
        list_of_words.append(j)
```

```
list_of_words

'downer',
'london',
'factor',
'decision',
'open',
'counter',
'intelligence',
'investigation',
'moscow',
'contacts',
'trump',
'campaign',
'times',
'reported',
'effort',
'loomed',
'white',
'house',
'trump',
'took',
'office',
'january',
'shows',
'receding',
'trump',
'prepares',
'second',
'year',
'power',
'despite',
'intensified',
'rhetoric',
'trump',
```

```
'carrier',
'probe',
'launched',
'federal',
'bureau',
'investigation',
'members',
'trump',
'campaign',
'administration',
'convicted',
'indicted',
'investigation',
'trump',
'allies',
'deny',
'somebody',
'look',
'department',
'justice',
'dossier',
'bothers',
'greatly',
'want',
'somebody',
'look',
'graham',
'said',
'said',
'russia',
'investigation',
'continue',
'matter',
'fact',
'hurt',
'contacts',
'trump',
'campaign',
'times',
'reported',
'months',
'meeting',
'australian',
'officials',
'passed',
'information',
'came',
'papadopoulos',

len(list_of_words)

9276947
```

Fig. 12: Total number of words after removing stop words

Next, we create one massive string by joining together all the unique words as df.clean_joined, Fig. 13 illustrates the 'clean_joined' data frame.

4.5. Step #5: Visualize the cleaned data

Here we use Seabourn and Countplot to determine the number of similar subject news as per the count, which is samples belonging to any of the classes such as 'politicsnews,' 'worldnews,' or just 'news' and 'politics.' The visual representation is presented in Fig. 14. Next, we plot the word cloud for real and fake texts. This is a powerful visualization for text data from the clean joined only when isfake equals to one (i.e., True news) or isfake equals to zero (i.e., Fake news). This visualization provides deep insights into the texts, answering questions such as what the customers are posting on social media or what is the top trending news. This visualization is an important word. Fig. 15 and Fig. 16 illustrate the fake and real news.

```
df['clean_joined'] = df['clean'].apply(lambda x: " ".join(x))
```

	title	text	subject	original	clean	clean_joined
0	As U.S. budget fight looms, Republicans flip t...	WASHINGTON (Reuters) - The head of a conservat...	politicsNews	As U.S. budget fight looms, Republicans flip...	[budget, fight, looms, republicans, flip, fiscal...]	budget fight looms republicans flip fiscal scr...
1	U.S. military to accept transgender recruits o...	WASHINGTON (Reuters) - Transgender people will...	politicsNews	U.S. military to accept transgender recruits o...	[military, accept, transgender, recruits, monday, pentagon...]	military accept transgender recruits monday pe...
2	Senior U.S. Republican senator: 'Let Mr. Muell...	WASHINGTON (Reuters) - The special counsel inv...	politicsNews	Senior U.S. Republican senator: 'Let Mr. Mueller...	[senior, republican, senator, mueller, washington...]	senior republican senator mueller washington...
3	FBI Russia probe helped by Australian diplomat...	WASHINGTON (Reuters) - Trump campaign adviser ...	politicsNews	FBI Russia probe helped by Australian diplomat...	[russia, probe, helped, australian, diplomat, washington...]	russia probe helped australian diplomat washi...
4	Trump wants Postal Service to charge 'much mor...	SEATTLE/WASHINGTON (Reuters) - President Donal...	politicsNews	Trump wants Postal Service to charge 'much mor...	[trump, wants, postal, service, charge, amazon...]	trump wants postal service charge amazon ship...
...	...	...	...	...	...	...
44893	McPain: John McCain Furious That Iran Treated	21st Century Wire says As 21WIRE reported earl...	Middle-east	McPain: John McCain Furious That Iran Treated	[mcpain, john, mccain, furious, iran, treated...]	mcpain john mccain furious iran treated

```
df['clean_joined'][0]
```

'budget fight looms republicans flip fiscal script washington reuters head conservative republican faction congress voted month huge tension national debt cuts called fiscal conservative sunday urged budget restraint keeping sharp pivot republicans representative mark ws speaking face nation drew hard line federal spending lawmakers bracing battle january return lawmakers begin pass federal budget fight likely linked issues immigration policy november congressional election campaigns approach republicans seek roll congress president donald trump republicans want budget increase military spending democrats want proportional increases defense entitlements education spending programs support education scientific research infrastructure public health environmental protection trump administration willing going increase defense discretionary spending percent meadows chairman small influential house freedom caucus said programs cuts saying need government raise percent fiscal conservative rationale eventually people money said meadows republicans voted block earlier party debt financed overhaul expected balloon federal budget deficit trillion years trillion national debt interesting mark new fiscal responsibility democratic representative joseph crowley said crowley said republican require united states borrow trillion pain generations finance cuts corporation risk fiscally responsible bills seen passed history house representatives think going painful time crowley said republicans insist package biggest overhaul years boost economy growth house speaker paul ryan supported recentl interview welfare entitlement reform party calls republican priority republican parlance entitlement reform can food stamps housing assistance medicare medicaid health insurance elderly poor disabled programs created washington assist needy ryan said ryan early december remarks saying showed republicans overall seeking spending social programs goals house republicans senate votes democrats need prevent government shutdown democrats leverage senate republicans narrow control democrats threatened blocking republican spending plans children immigrants illegally country children trump september...

Fig. 13: Cleaned and joined data frame

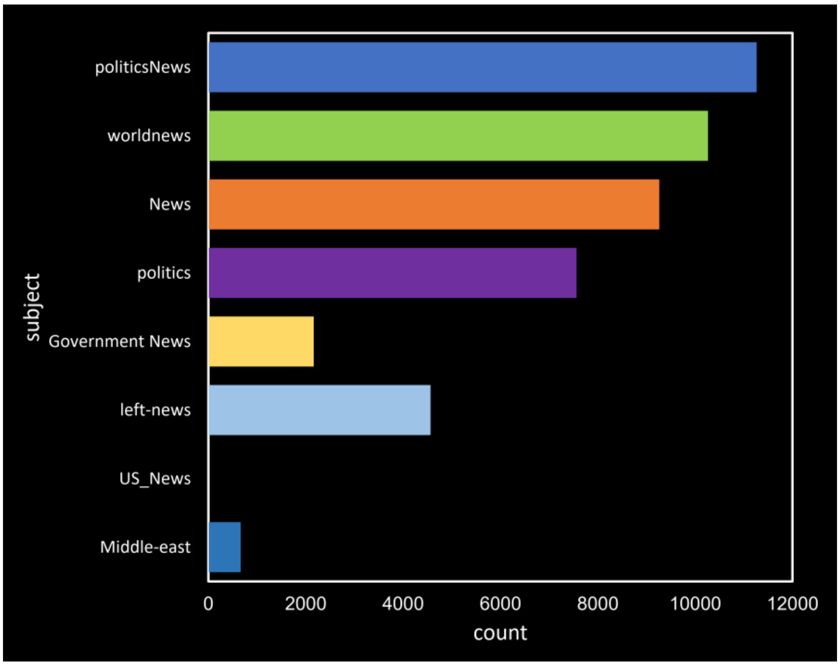

Fig. 14: Visualizing similar subject news

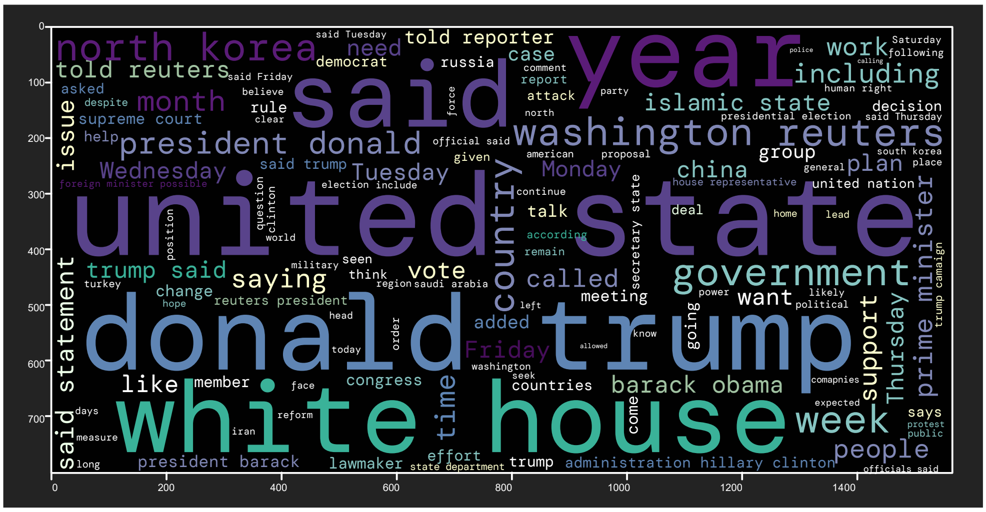

Fig. 15: Fake news visualization

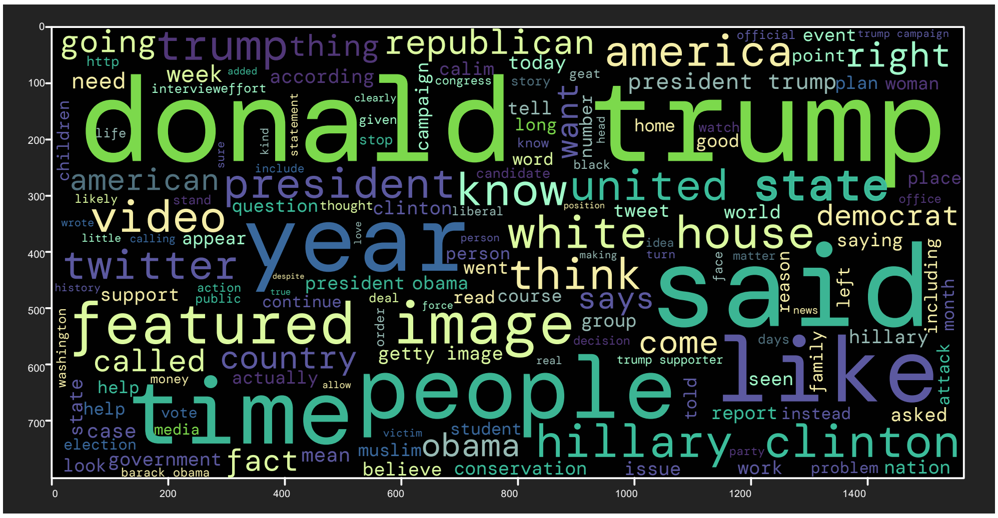

Fig. 16: Real news visualization

Next, we prepare the dataset by calculating the maximum length of the words. This is performed by defining a variable 'maxlen' set to minus one initially and going over the entire data frame to pick sample by sample, and taking the greater length as the new maximum length count. The code executed is presented in Fig. 17. Using Plotly. An interactive histogram is displayed for the count and values.

```
maxlen = -1
for doc in df.clean_joined:
    tokens = nltk.word_tokenize(doc)
    if(maxlen < len(tokens)):
        maxlen = len(tokens)
print("The maximum number of words in any document is =", maxlen)

The maximum number of words in any document is = 4405

import plotly.express as px
fig = px.histogram(x = [len(nltk.word_tokenize(x)) for x in df.clean_joined], nbins = 100)
fig.show()
```

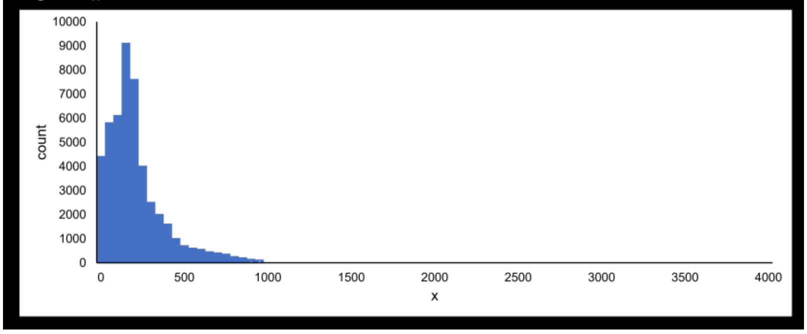

Fig. 17: Code for calculating maximum length and Plotly histogram

4.6. Step #6: Prepare data by tokenizing and padding

Here we train our dataset, so we divide it into training and testing, and perform tokenization. This division vectorizes the text corpus by turning every text into numbers (integers) with input and output for the model using the 'nltk' library. Here, we allocate 0.2 or 20% data for testing and the remaining 80% for training. The idea is to ensure the framework generalizes and does not memorize the data as presented in Fig. 18. Every bunch of news is transformed into numbers, such as train data 35,913 and test data 8980.

The clean joined data sample is taken for the train sequence. Then, a tokenizer is created for tokenizing the words and for creating the sequence of tokenized words. This converts words to numbers marked in BLUE, which the computer will essentially learn for the proposed LSTM model from the news dataset as presented in Fig. 19.

```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(df.clean_joined, df.isfake, test_size = 0.2)
from nltk import word_tokenize
---------------------------------------------------------------------------
AttributeError                    Traceback (most recent call last)
<ipython-input-38-223c38996980> in <module>
    1 # split data into test and train
    2 from sklearn.model_selection import train_test_split
---- > 3 x_train, x_test, y_train, y_test = train_test_split(df.clean_joined, df.isfake, test_size = 0.2)

~\anaconda31\lib\site-packages\pandas\core\generic.py in _getattr_(self, name)
    5272     if self_info axis.__can_hold_identifiers_and_holds_name(name):
    5273     return self[name]
-> 5274     return object.__getattribute__(self, name)
    5275
    5276     def __setattr__(self, name: str, value) -> None:

AttributeError: 'DataFrame' object has no attribute 'isfake'
```

```
len(train_sequences)
35913
```

```
len(test_sequences)
8980
```

Fig. 18: Splitting data into test and train

```
tokenizer = Tokenizer(num_words = total_words)
tokenizer.fit_on_texts(x_train)
train_sequences = tokenizer.texts_to_sequences(x_train)
test_sequences = tokenizer.texts_to_sequences(x_test)
print("The encoding for document\n",df.clean_jointed[0],"\n is : ",train_sequences[0])

The encoding for document
budget fight loons republicans flip fiscal script washington routers head conservative republican faction congress voted month huge
sion national debt cuts called fiscal conservative sunday urged budget restraint keeping sharp pivot republicans representative mark
us speaking face nation drew hard line federal spending lawmakers bracing battle january return holidays wednesday lawmakers begin tt
pass federal budget fight likely linked issues immigration policy november congressional election campaigns approach republicans seei
rol congress president donald trump republicans want budget increase military spending democrats want proportional increases defense
etionary spending programs support education scientific research infrastructure public health environmental protection trump adminsi
n willing going increase defense discretionary spending percent meadows chairman small influential house freedom caucus said program
rats saying need government raise percent fiscal conservative nationale eventually people money said meadows republicans voted late c
er party debt financed overhaul expected balloon federal budget deficit trillion years trillion national debt interesting hear mark i
iscal responsibility democratic representative joseph crouley said crouley said republican require united states borrow trillion paic
re generations finance cuts corporations rich fiscally responsible bills seen passed history house representatives think going payin
s come crouley said republicans insist package biggest overhaul years boost economy growth house speaker paul ryan supported recently
meadows making clean radio interview welfare entitlement reform party calls republican priority republican parlance entitlement progi
ean food stamps housing assistance mediocre medical health insurance elderly poor disabled programs created washington assist needy
rats seized ryan early december remarks saying showed republicans overhaul seeking spending cuts social programs goals house republi
ent senate votes democrats needed approve budget prevent government shutdown democrats leverage senate republicans narrowly control c
discretionary defense programs social spending tackling issue dreamers people brought illegally country children trump september mar
ination date deferred action childhood arrivals doca program protects young immigrants deportation provides work permits president si
cent twitter messages wants funding proposed nextcan border wall immigration changes exchange agreeing help dreamers representative c
dinpell told favor linking issue policy objectives will funding need daca clean said wednesday trump aides meet congressional leaders
us issues followed weekend strategy sessions trump republican leaders white house said trump scheduled meet sunday florida republic
ernor rick scott wants emergency house passed billion package hurricanes florida texas puerto rico wildfires california package execu
illion requested trump administration senate voted
 is : [2365, 558, 332, 2311, 2716, 42, 972, 27, 11043, 950, 513, 120, 258, 57, 30, 558, 332, 6402, 972]

 is : [36, 8377, 584, 5148, 12866, 71, 1468, 878, 223, 282, 1321, 584, 1021, 3, 115, 328, 772, 36, 1277, 911, 2287, 743, 511, 54, 1094,
 222, 179, 26, 2611, 301, 223, 227, 1187, 2877, 24172, 1306, 11257, 71, 4, 4322, 362, 234, 188, 254, 67, 1778, 327, 433, 452, 447, 214, 11,
 190, 16, 261, 114, 254, 18242, 152, 198, 50, 2, 71, 1288, 2628, 290, 504, 356, 359, 44, 294, 162, 91, 704, 2421, 6166, 16, 263, 327, 1181
 3, 333, 431, 602, 1768, 4848, 274, 1888, 511, 403, 399, 294, 303, 77, 65, 77, 4806, 2, 31, 390, 1754, 96, 59, 2391, 489, 206, 14957, 967,
 14121, 1559, 209, 261, 469, 16, 679, 2756, 3164, 4096, 2963, 188, 16, 8513, 2879, 4607, 58, 2479, 2, 122, 718, 1132, 1092, 145, 244, 71, 1
 481, 3915, 119, 2629, 36, 65332, 1718, 2683, 1813, 164, 835, 1924, 330, 145, 416, 33, 423, 551, 311, 117, 1109, 254, 1082, 63, 324, 489, 8
 938, 294, 7243, 15983, 11254, 2, 71, 8895, 1535, 1720, 2728, 292, 584, 70, 28, 1114, 7102, 11255, 24173, 190, 70, 4097, 94, 145, 906, 518
 8, 489, 1720, 3720, 65113, 6684, 471, 15429, 3152, 522, 572, 480, 63, 1876, 327, 24173, 2, 212, 71, 1179, 63, 918, 119, 488, 15429, 2816,
 5695, 1114, 1729, 3720, 256, 4454, 71, 5866, 277, 294, 2491, 28792, 773, 73, 117, 483, 584, 381, 367, 2885, 2215, 318, 2293, 2391]
```

Fig. 19: Tokenizing words to integers

We also need to ensure each new data has the same length, so we apply pad sequencing for both test and train data, specifying the maximum length is 4405 for both as illustrated in Fig. 20.

```
padded_train = pad_sequences(train_sequences, maxlen = 4405, padding = 'post', truncating = 'post')
padded_test = pad_sequences(test_sequences, maxlen = 4405, truncating = 'post')

for i,doc in enumerate(padded_train[:2]):
    print("The padded encoding for document",i+1," is : ",doc)

The padded encoding for document 1 is : [  36 8937  584 ...  0  0  0]
The padded encoding for document 2 is : [748 112  24 ...  0  0  0]
```

Fig. 20: Applying padding sequence

5. Results

Instead of having a huge amount of data for performing modeling, this research uses the embedded layer concept, so the layers use low-dimensional continuous input of the discrete variables and specify low-dimensional features to represent the input data. This helps the subsequent layers learn effectively with fewer variables and computing resources. For building the proposed LSTM model, we used Caras and Tensorflow 2.0. Initially, an embedded layer is added with a total number of words and a dense layer of 128 layers, which feed-forward artificial layer having activation 'relu.'

Then we have activation equal to one neuron with activation equal to sigmoid. The output is selected as one since we are looking for binary classification (true=1 or fake=0). Then, using the model optimizer as 'Adam' and a loss of binary cross-entropy, the matrix will be the accuracy of the proposed model. Fig. 21 displays the printed 14,210,305 trainable parameters.

```
model = Sequential()
_____________________________________________________________________________
model.add(Embedding(total_words, output_dim = 128))
model.add(Bidirectional(LSTM(128)))
_____________________________________________________________________________
model.add(Dense(128, activation = 'relu'))
model.add(Dense(1,activation='sigmoid'))
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['acc'])
model.summary()

Model: "sequential"
_____________________________________________________________________________
Layer (type)                 Output Shape                     Param #
-----------------------------------------------------------------------------
embedding (Embedding)        (None, None, 128)                13914112
_____________________________________________________________________________
bidirectional (Bidirectional (None, 256)                      263168
_____________________________________________________________________________
dense (Dense)                (None, 128)                      32896
_____________________________________________________________________________
dense_1 (Dense)              (None, 1)                        129
=============================================================================
Total params: 14,210,305
Trainable params: 14,210,305
Non-trainable params: 0

total_words

108704
_____________________________________________________________________________
```

Fig. 21: LSTM trainable parameters

Now we need to fit the data with our model, so the y_train is taken to feed to the model, having input as padded_train, batch size 64, validation split as 0.1, and epochs 2, and the output as y-train. The authors divided the training data into 10% for cross-validation and 90% for actual training of the model. Fig. 22 illustrates the model to be 99.96% accurate with just 2 epochs, with a validation loss of 0.0083. This means the proposed model worked very well, and the training data was a perfect fit.

```
model.fit(padded_train, y_train, batch_size = 64, validation_split = 0.1, epochs = 2)

Train on 32326 samples, validate on 3592 samples
Epoch 1/2
32326/32326 [==============================] - 3645 ilms/sample - loss: 0.0397 - acc: 0.9836 - val_loss: 0.0052 - val_acc: 0.9983
Epoch 2/2
32326/32326 [==============================] - 3435 ilms/sample - loss: 0.0018 - acc: 0.9996 - val_loss: 0.0083 - val_acc: 0.9972
```

Fig. 22: Accuracy of 99.96% and validation loss of 0.0083

Next, if we change the embedding output dimension from 128 to 240, now we get the model trainable parameters as 26,499,841 as presented in Fig. 23. This indicates that changing one parameter can lead the model to require a lot more time and computing resources to train.

```
model.add(Dense(128, activation = 'relu'))
model.add(Dense(1,activation='sigmoid'))
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['acc'])
model.summary()

Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_1 (Embedding)      (None, None, 240)         26088960
_________________________________________________________________
bidirectional_1 (Bidirection (None, 256)               377856
_________________________________________________________________
dense_2 (Dense)              (None, 128)               32896
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 129
=================================================================
Total params: 26,499,841
Trainable params: 26,499,841
Non-trainable params: 0
_________________________________________________________________
```

Fig. 23: LSTM trainable parameters with 240 embedding output dimensions

The author also assessed the trained LSTM model's performance on the testing data. Here, instead of feeding in the training data, we get the testing data, which is data that never seen by the model during training. Since we are using the sigmoid activation function in the output, the prediction will be an issue. So, we need to set a threshold of 0.5, and essentially, if that number is greater, then the model is fine. If it is less than 0.5 or class zero, then the model is inaccurate. So, we create predictions going through all the samples and then check if the value is greater than 0.5, then we append ones, else we append zeros. Finally, we'll have a vector containing zeros and ones and compare it with the model rules. Fig. 24 displays the misclassified 8 and 51 samples.

```
Accuracy = accuracy_score(list(y_test), prediction)

print("Model Accuracy : ", accuracy)
```

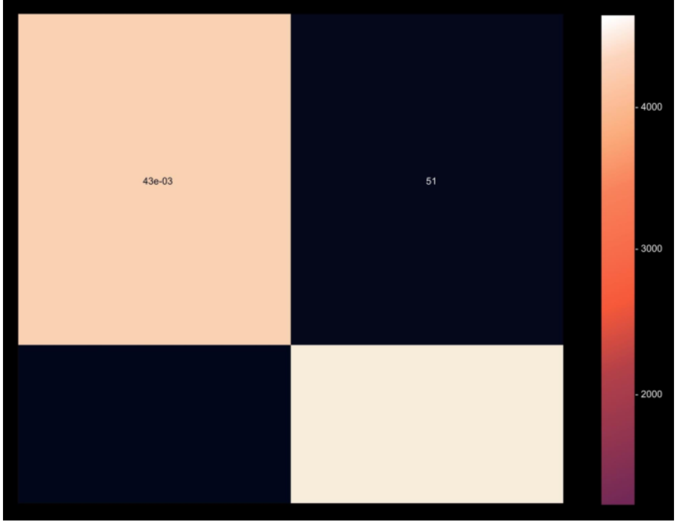

Fig. 24: Confusion matrix

6. Conclusion

Fake news detection on social media platforms involves a wide distribution of the population consuming the news. Information that is inaccurate, deceptive, or whose source cannot be confirmed is referred to as fake news. This information might be created to purposely harm people's reputations, deceive them, or draw attention to themselves. During the 2016 US Presidential Elections, the term gained prominence. Social media platforms wield tremendous influence. On social media platforms, which have become the go-to venue for sharing ideas, feelings, views, and intentions, millions of tweets are expected to be sent and received. This creates perfect conditions for disseminating news with the fewest possible limits and constraints. It is common in today's environment to get news via internet sources such as social media. Readers' perceptions of news are frequently subjective. We frequently opt to consume stuff that appeals to our various emotions. As a result, the most widely disseminated information may not be true or accurate news. Furthermore, true news may be skewed during broadcast. It's possible that a reader will receive many copies of the same news. It's possible that this will result in information overload. This research presents a recurrent neural network-based model for the use of NLP with a real and fake news dataset. The proposed framework displayed an accuracy of 99.96% with just two epochs and a validation loss of 0.0083. This proves the proposed model worked very well, and the training data is a perfect fit. Here are some key implications:

- Fake News Detection: The proposed model contributes to the field of NLP by addressing the critical problem of fake news detection on social media. As social media platforms have become primary sources of news for many users, the ability to automatically identify and filter out fake news is crucial for maintaining information integrity and combating misinformation. The research offers insights into the application of AI and recurrent neural networks for this purpose.
- Interpretability in NLP: The research explores interpretability techniques in the context of fake news detection. Interpretability is a significant concern in machine learning and NLP, as complex models like recurrent neural networks can be difficult to understand. By investigating the interpretability of the proposed model, this research contributes to developing techniques that enhance the transparency and explainability of NLP models.
- Feature Importance and Attention Mechanisms: The research investigates feature importance and attention mechanisms in the model's decision-making process. Understanding the importance of different features and the attention distribution across the text helps researchers gain insights into which aspects of language contribute most to identifying fake news. These findings can be valuable for developing more efficient and accurate NLP models in various applications beyond fake news detection.
- Model Explainability and Trust: By employing explainable AI techniques, the research promotes model transparency and fosters trust in the predictions made by NLP models. Interpretable models are essential, particularly in sensitive domains where the decisions impact individuals or society at large. This research contributes to the broader efforts in machine learning and NLP to develop models that can provide clear and understandable explanations for their decisions.
- Generalization and Transfer Learning: The insights gained from this research can potentially be generalized and applied to other domains within NLP. Techniques and methodologies developed for fake news detection can be extended to address related challenges, such as sentiment analysis, information retrieval, or document classification. The research lays the foundation for future investigations into transfer learning approaches that leverage the knowledge gained from fake news detection to improve performance on other NLP tasks.

This research has implications for advancing the understanding of interpretability in NLP, improving the trustworthiness of NLP models, and applying the findings to other domains and challenges within the field of machine learning.

List of abbreviations

AI	Artificial intelligence
ANN	Artificial neural network
CNN	Convolutional neural network
CSV	Comma-separated values
GPU	Graphics processing unit
IoT	Internet of things.
LIME	Local interpretable model-agnostic explanations
LSTM	Long short-term memory
ML	Machine learning
NLP	Natural language processing
RNN	Recurrent neural network
SHAP	SHapley additive explanations

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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