FactFinder : RNN-LSTM based Fake news detection System

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Abstract—This paper presents an RNN-LSTM based fake news detection system to address the escalating problem of misinformation in the digital age. By leveraging Recurrent Neural Networks (RNNs) with Long Short-Term Memory (LSTM) units, the system effectively analyzes the sequential nature of textual data to distinguish between real and fake news. Through preprocessing, word embedding, and training on a labeled dataset, the model learns to identify patterns that indicate the authenticity of news articles or statements. The proposed system offers a promising solution to combat fake news, contributing to the promotion of reliable information dissemination in today's media landscape.

Keywords—Recurrent Neural networks, Long Short-Term Memory, sequential modeling, preprocessing.

I. Introduction

The emergence of the digital age has fundamentally changed how we access and distribute information. However, it has also contributed to the worrying increase of false information. In order to deceive public opinion, fake news is defined as material that is willfully untrue or misleading yet presented as news. This phenomena offers serious risks to society since it can spread false information, erode confidence in reputable sources, and have a considerable impact on a variety of spheres of daily life, including politics, social discourse, and health.

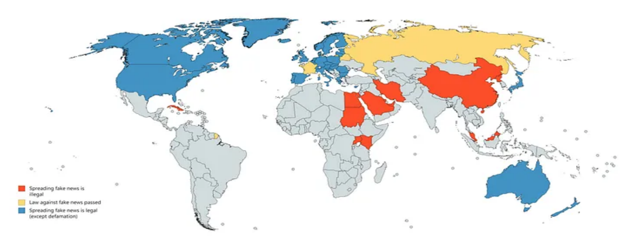


Fig 1.1 Spreading of Fake news all over the world

As you can see the map at fig. 1.1, fake news is a problem all over the world. Fake news detection and elimination are significant difficulties in the current information environment. The rapid dissemination of misleading information on social media platforms and online news sources makes it difficult and time-consuming to use traditional fact-checking and verification techniques. In order to create automated systems that can recognise and flag fake news, researchers and practitioners have resorted to machine learning and natural language processing approaches.

In this paper, we propose a deep learning and sequential modeling-based fake news detection system that uses RNN-LSTM to address the issue of fake news. Recurrent neural networks (RNNs) with long short-term memory (LSTM) units are highly suited for the analysis of news articles and statements because they can capture temporal dependencies and contextual information in textual input. The method seeks to identify true news with high accuracy by using word embeddings and training the model on labelled datasets. The creation of such a system has the potential to stop the spread of false information, protect the reliability of information sources, and promote an informed society.

II. Literature Survey

The false news detection field has generated a wealth of research and methodologies, which are examined in this study's literature review. The problem of identifying false news and separating it from accurate information has been addressed using a variety of strategies and techniques.

The review includes studies that use deep learning models, natural language processing methods, and machine learning algorithms to identify fake news. In order to spot suspicious patterns and language cues in news items, rule-based systems have been extensively deployed. To categorize news articles, feature-based techniques employ manually created features such lexical, syntactic, and semantic aspects. Accuracy has also been examined using ensemble methods, such as combining several classifiers or applying stacking strategies.

The literature review also examines the application of RNNs, LSTMs, and other sequential models to the identification of fake news. These models are efficient in analyzing the sequential character of news items because they are excellent at capturing temporal dependencies and contextual information in textual data. The poll sheds light on the benefits and drawbacks of various approaches while also offering information on their efficacy, scalability, and suitability for use in practical situations.

The study also discusses the difficulties in detecting fake news, such as its dynamic nature, the adversarial tactics used by those who spread false information, the dearth of labeled datasets, and the interpretability of complex models. For the purpose of creating effective and dependable fake news detection systems, understanding these difficulties is essential.

This paper seeks to extend previous work, identify loopholes, and suggest a novel strategy employing RNN-LSTM for fake news identification by completing a thorough literature review. The survey serves as a basis for the remaining sections, directing their creation and assessment of the suggested system.

III. Objective

The main objective of this study is to propose an RNN-LSTM based fake news detection system that leverages sequential modeling techniques to accurately identify and classify fake news. The specific objectives include:

1. Develop an RNN-LSTM architecture: The study aims to design a robust architecture that utilizes Recurrent Neural Networks (RNNs) with Long Short-Term Memory (LSTM) units. This architecture enables the model to capture the sequential nature of textual data, effectively identifying patterns and temporal dependencies that distinguish fake news from genuine information.
2. Enhance accuracy and reliability: The objective in to develop a system that achieves high accuracy in fake news detection. By training the model on labeled datasets and leveraging word embeddings, the system should be capable of making precise predictions and effectively distinguishing between real and fake news articles.
3. Address challenges of fake news detection: The study aims to tackle the challenges associated with fake news detection, including the dynamic nature of fake news, the adaptability of fake news creators, and the scarcity of labeled datasets. By considering these challenges, the objective is to develop a system that can mitigate these issues and perform well in real-world scenarios.
4. Evaluate system performance: The proposed system's performance will be rigorously evaluated using appropriate evaluation metrics and benchmarked against existing approaches. The objective is to demonstrate the effectiveness and superiority of the RNN-LSTM based fake news detection system in terms of accuracy, precision, recall, and F1-score.
5. Contribute to the fight against fake news: Ultimately, the objective of this study is to contribute to the efforts in combating fake news and promoting the dissemination of accurate and reliable information. By developing an efficient and accurate fake news detection system, the study aims to support individuals, fact-checkers, and social media platforms in identifying and mitigating the spread of fake news.

Overall, the objectives of this study encompass the development of an RNN-LSTM based fake news detection system that addresses the challenges in fake news detection, achieves high accuracy, and contributes to the fight against misinformation.

IV. Outcomes

- Development of a robust RNN-LSTM based fake news detection system with high accuracy in distinguishing between real and fake news.

- Evaluation and benchmarking of the proposed system's performance against existing approaches, showcasing its effectiveness and superiority in fake news detection.

- Mitigation of challenges associated with fake news detection, such as the dynamic nature of fake news and the adaptability of fake news creators, resulting in a more robust and reliable system.

- Contribution to the fight against fake news by providing individuals, fact-checkers, and social media platforms with an efficient tool to identify and mitigate the spread of fake news.

- Advancement of the field of fake news detection through the utilization of sequential modeling techniques and the exploration of the strengths and limitations of RNN-LSTM models in tackling the issue of misinformation

. V. Challenges

The field of fake news detection presents several challenges that researchers and practitioners face in developing effective and reliable systems. Some of the key challenges include:

1. Dynamic nature of fake news: Fake news is constantly evolving, with new techniques and strategies being employed by creators to deceive detection systems. Adapting to the ever-changing landscape of fake news poses a challenge in designing detection systems that can effectively keep up with the evolving tactics used by malicious actors.
2. Adversarial strategies: Fake news creators often employ adversarial strategies to evade detection. They may use obfuscation techniques, alter the content subtly, or incorporate legitimate information to make their articles appear more credible. Developing robust models that can withstand such adversarial attacks is a significant challenge.
3. Scarcity of labeled datasets: An essential component in training machine learning models is the availability of labeled datasets for supervised learning. However, creating large-scale, high-quality labeled datasets for fake news detection can be challenging and

time-consuming. The scarcity of such datasets limits the training and evaluation of detection systems.

4. Trade-off between complexity and interpretability: Deep learning models, including RNN-LSTM, are often highly complex and exhibit a black-box nature. While these models can achieve high accuracy, their interpretability and transparency may be limited. Striking a balance between model complexity and interpretability is a challenge when developing fake news detection systems.

VI. Architecture

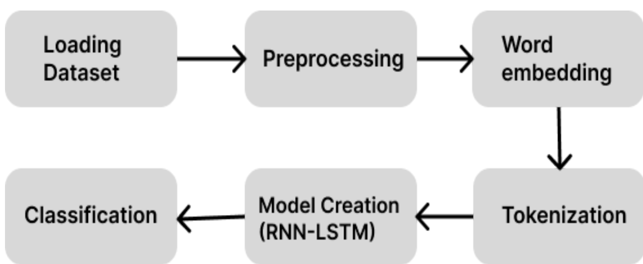


fig. 6.1 Architecture flow of the proposed system

LSTM model:

A recurrent neural network (RNN)'s layers are constructed from long short-term memory (LSTM) units. A cell, an input gate, an output gate, and a forget gate make up an LSTM unit. The cell is in charge of "remembering" values over a very long time interval so that the relationship between the word at the beginning of the text and the word's output later in the phrase can be affected. It looks like a big flaw since traditional neural networks cannot remember or keep track of what is said before they are executed, which prevents the desired influence of the words that come in the sentence before from having any impact on the final words.

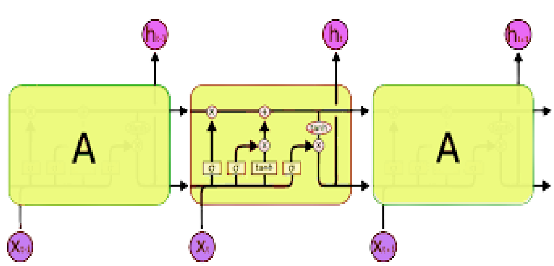


Fig. 6.1: LSTM Architecture

Implementation :

I. PREPROCESSING :

The data set needs to be preprocessed in order to be converted into the relevant format. First, we purged the dataset of all NAN values. A 5000-word vocabulary limit has been decided. The dataset is then cleaned up using the NLTK (Natural Language Processing) Tool Kit. Stop words are words like "and," "the," and "I" that don't transmit a lot of information and are converted to lowercase while also being stripped of punctuation from the NLTK toolbox. If a word in a document is not a stop word, the postage tag for that word is used. Then, the paper is annexed with this list of words.

2. WORD INDEX OF TOKENIZE DATASET :

Word tokenization adds text to a list that is then referred to as a document list. The list of all the words used in the narrative is the stage's output.

WORD EMBEDDING:

One Hot Representation: The method cannot accept input in text format, thus we must convert it into a numeric form, for which we are employing one hot representation. Each word in the dataset will have its index from the defined vocabulary size provided in the one-hot representation, and these indices are substituted in sentences. We must provide the word embedding the fixed length when providing it input. Each sentence is changed into a fixed length padding sequence. While padding the title, we took the maximum length of 20 words into account. Pre- or post-sentence padding can be added, and these sentences are then used as input for the word embedding algorithm. Applying feature extraction to the supplied input vector is what word embedding does. 40 vector features in all are taken into account.

3. MODEL:

The model is given the word embedding's output. The machine learning model used in this application is a sequential model with a first layer that embeds values for vocabulary size, number of features, and sentence length. The next step is LSTM, which has 100 neurons per layer, followed by a dense layer with sigmoid activation function as we only need one output in the end. In order to prevent overfitting, we have employed binary cross entropy to calculate loss, Adam optimizer for adaptive estimation, and ultimately adding a drop out layer in between. The model was then trained and tested.

4. CLASSIFICATION :

The result is predicted for both preprocessed testing data sets. If the predicted value is more than 0.5, it is classified as real if 1, and fake if 0. Accuracy is equal to (TP+TN)/Total. The words used were as follows: True Negative (TN), which means that both the test cases and the prediction were in fact negative; True Positive (TP), which means that both the test cases and the prediction were in fact positive; False Negative (FN), in which the test cases were in fact positive despite the prediction being negative; False Positive (FP), which occurs when a forecast is made but the test cases turn out to be negative

```
In [ ]: model.fit(X_train, y_train, validation_split=0.3, epochs=6)

Epoch 1/6
737/737 [==============================] - 36s 38ms/step - loss: 0.1459 - acc: 0.9473 - val_loss: 0.1408 - val_acc:
0.9466
Epoch 2/6
737/737 [==============================] - 27s 36ms/step - loss: 0.0829 - acc: 0.9723 - val_loss: 0.0805 - val_acc:
0.9716
Epoch 3/6
737/737 [==============================] - 28s 38ms/step - loss: 0.0347 - acc: 0.9888 - val_loss: 0.0357 - val_acc:
0.9874
Epoch 4/6
737/737 [==============================] - 27s 37ms/step - loss: 0.0385 - acc: 0.9879 - val_loss: 0.0335 - val_acc:
0.9886
Epoch 5/6
737/737 [==============================] - 29s 39ms/step - loss: 0.0150 - acc: 0.9956 - val_loss: 0.0252 - val_acc:
0.9908
Epoch 6/6
737/737 [==============================] - 28s 38ms/step - loss: 0.0084 - acc: 0.9978 - val_loss: 0.0253 - val_acc:
0.9908
Out[ ]: <keras.callbacks.History at 0x7fa6e04c70d0>

In [ ]: y_pred = (model.predict(X_test) >= 0.5).astype(int)

351/351 [==============================] - 5s 13ms/step

In [ ]: accuracy_score(y_test, y_pred)

Out[ ]: 0.9956347438752784
```

Model

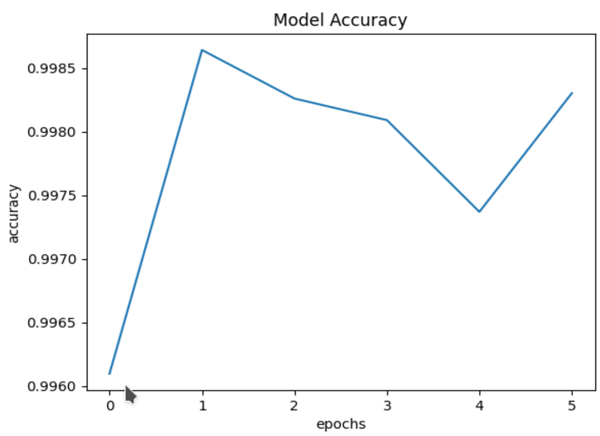
5. ACCURACY :

```
accuracy_score(y_test, y_pred)
```

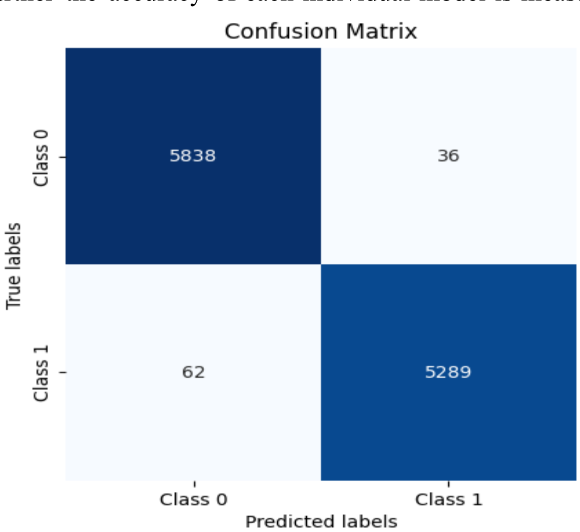
```
0.9956347438752784
```

```
In [ ]: x = ['As India embraces sustainable fashion, there's a need to focus on the traditional upcyclers from the Devip
        x = tokenizer.texts_to_sequences(x)
        x = pad_sequences(x, maxlen=maxlen)

In [ ]: (model.predict(x)>=0.5).astype(int)

        1/1 [==============================] - 0s 28ms/step
Out[ ]: array([[1]])
```

In the above figure we have taken the news from an online news website and used it as an input for our model, and the model has classified that as 1 and the news is actually true news.



6. RESULTS : The classification accuracy for true news articles and false news articles is roughly the same, but classification accuracy for fake news is slightly deviated. By using the confusion matrix and the classification report further the accuracy of each individual model is measured.



	Predicted:NO	Predicted:YES
Actual: NO	5838	36
Actual: YES	62	5289

CONCLUSION : The necessity for fake news detection is essential in the current digital era, as hoax news is pervasive across all digital channels, and our model satisfies that demand by being the indispensable tool. On the web, fake news about delicate subjects creates a toxic environment. Analysis of socially relevant data is done for fake news detection to determine whether it is true or not. According to this study, LSTM is the most successful technique out of all others. The model presented in this research is quite efficient, and the model suggested here performs better with an accuracy of 99.5%, which is very encouraging. By including real-time data, we may further improve outcomes.

VII. Reference Papers :

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