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FULL PAPER

Detecting Fake and True News by Applying Text Analysis and Deep Recurrent Neural Network

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Abstract:

Detecting fake news is a significant topic; it is valuable for warning people and protecting them from the consequences of such news. In this paper, a Deep Recurrent Neural Network (DRNN) is applied for detecting or recognizing fake and true news. Text data is first exploited and pre-processed. The pre-processing includes tokenizing, converting to lowercase, and erasing punctuation. Then, data is translated into sequences of values, which are utilized in the DRNN. The DRNN involves multiple layers: the sequence input layer, the word-embedding layer, the Long Short-Term Memory (LSTM) layer, the fully connected layer, the softmax layer, and the classification layer. A useful database from Kaggle named Fake News Detection (FND) is used; it has a huge amount of data. The obtained result achieved 99.77% accuracy, which is obviously very high.

Keywords: *Deep Recurrent Neural Network, Fake News, True News, Text Analysis*

المستخلص

يعد الكشف عن الأخبار المزيفة موضوعًا مهمًا، فهو مفيد جدا لتحذير الناس وحمايتهم من عواقب هكذا أخبار. في هذا البحث، تم تطبيق الشبكة العصبية العميقة المتكررة (DRNN) للكشف أو التمييز بين الأخبار المزيفة والحقيقية. يتم أولاً الاستفادة من بيانات النصوص ومعالجتها معالجة مسبقة. تتضمن المعالجة المسبقة الترميز، والتحويل إلى أحرف صغيرة، ومحو علامات الترقيم. ثم يتم ترجمة البيانات إلى تسلسلات من القيم، والتي يتم استخدامها في الـ DRNN. تتضمن هذه الشبكة طبقات متعددة وهي: طبقة إدخال التسلسل، وطبقة تضمين الكلمات، وطبقة الذاكرة طويلة المدى (LSTM)، والطبقة المتصلة بالكامل، وطبقة سوفت ماكس، وطبقة التصنيف. استخدِمت قاعدة بيانات مفيدة من Kaggle تسمى بيانات كشف الأخبار المزيفة (FND)، وهي تحتوي على عدد كبير جدا من العينات. وقد وصلت النتيجة التي تم الحصول عليها إلى 99.72%، من الواضح أنها هذه النسبة هي لدقة عالية جدًا.

كلمات مفتاحية: *الشبكة العصبية المتكررة العميقة، الأخبار المزيفة، الأخبار الحقيقية، تحليل النص*

1. INTRODUCTION

Detecting fake and true news is such an important issue. It is a part of pattern recognition. These patterns are represented by news. Many studies have focused on this subject, such as (Berrondo-Otermin & Sarasa-Cabezuelo, 2023; Dey et al., 2018; Mishra et al., 2022; Pranave et al., 2021; Zhang et al., 2023). This reflects the importance of this topic. Announcing fake news may cause big problems. Some of them may even lead to big consequences.

As mentioned, detecting fake and true news is part of pattern recognition, but their patterns can be texts, images, videos, etc. Recognizing or detecting fake and original patterns has also been considered in many works (Al-Hussein et al., 2022c, 2022a; Al-Nima et al., 2023; Al-Nima & Al-Hbeti, 2024; Ibrahim et al., 2021). Moreover, applying artificial intelligence to fake patterns, specifically deep learning, is a recently obtained concentration (Agarwal, Farid, El-Gaaly, et al., 2020; Agarwal, Farid, Fried, et al., 2020; Chadha et al., 2021; Suganthi et al., 2022; Yang et al., 2019).

Various studies in the literature consider patterns of recognition of fakes and originals. In 2018, fake news recognition was concentrated by using linguistic analysis (Dey et al., 2018). In 2019, deep fakes were exposed by utilizing inconsistent head poses (Yang et al., 2019). In 2020, deep-fake videos were recognized based on behavior and appearance (Agarwal, Farid, El-Gaaly, et al., 2020). In 2021, fake and original fingerprint images were classified by a deep network (Ibrahim et al., 2021). In 2022, Deoxyribonucleic Acid (DNA) samples were recognized between clients and imposters (Al-Hussein et al., 2022b). In 2023, artificial intelligence applications were surveyed to detect fake news (Berrondo-Otermin & Sarasa-Cabezuelo, 2023). In 2024, fingerprints were clustered for fake and original by proposing unsupervised deep learning (Al-Nima & Al-Hbeti, 2024).

In this paper, the aim is to distinguish between fake and true news. Multiple processes are applied, including pre-processing texts, preparing data, and implementing a Deep Recurrent Neural Network (DRNN).

The paper's sections are arranged as follows: Section 1 provides the introduction; Section 2 explains the theoretical part; Section 3 illustrates the practical part; and Section 4 announces the conclusion.

2. THEORETICAL PART

As mentioned, the aim here is to detect fake and true news. The data in the news involves texts or strings, so they require pre-processing, preparation, and detecting classifiers. Figure 1 shows the detailed steps for analyzing the data. Honestly, all the applied processes are recorded with the help of Matlab (Matlab, 2020).

As can be seen from this figure, the process begins with news texts. In this case, valuable database named Fake News Detection (FND) (PATEL, 2021) was utilized. This database contains a large number of fake and true news texts; specifically, it includes 23488 fake news texts and 21417 true news texts (PATEL, 2021).

The employed texts require pre-processing. The applied pre-processing steps are tokenizing, converting to lowercase, and erasing punctuation. Tokenizing a text means considering the separated strings inside the text as tokens. Converting to lowercase obviously means changing all uppercase letters to lowercase letters. Erasing punctuation clearly means removing any existing punctuation.

To prepare the pre-processed text outputs for the detection classifier, they are translated into sequences of values. This process utilizes initialized token indices, where the same index is used for repeated tokens. Thus, sequences of values are represented by these indices. Subsequently, the Deep Recurrent Neural Network (DRNN) is employed, comprising multiple layers: the sequence input layer, word-embedding layer, Long Short-Term Memory (LSTM) layer, fully connected layer, softmax layer, and classification layer.

The sequence input layer accepts the translated sequences of values. The word-embedding layer maps indices to vectors (Matlab, 2020). The LSTM layer stores important information for a long time. This information can be deleted if more implementation is implemented. It actually learns which information to discard and which information to keep (A. Al-Obaidi et al., 2022; A. S. I. Al-Obaidi et al., 2022). A fully connected layer fully connects the output nodes of the previous layer to all determined nodes in this

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layer. The Softmax layer provides the probability of relating a DRNN input to each output class. The classification layer outputs the recognition or detection decision.

The DRNN works in three phases: training, validation, and testing. In the training phase, it uses a set of data to learn how to distinguish between fake and true news. In the validation phase, it utilizes another set of data to check the validity of the train. In the testing phase, it exploits the remaining set of data to intelligently determine the fake and true news.

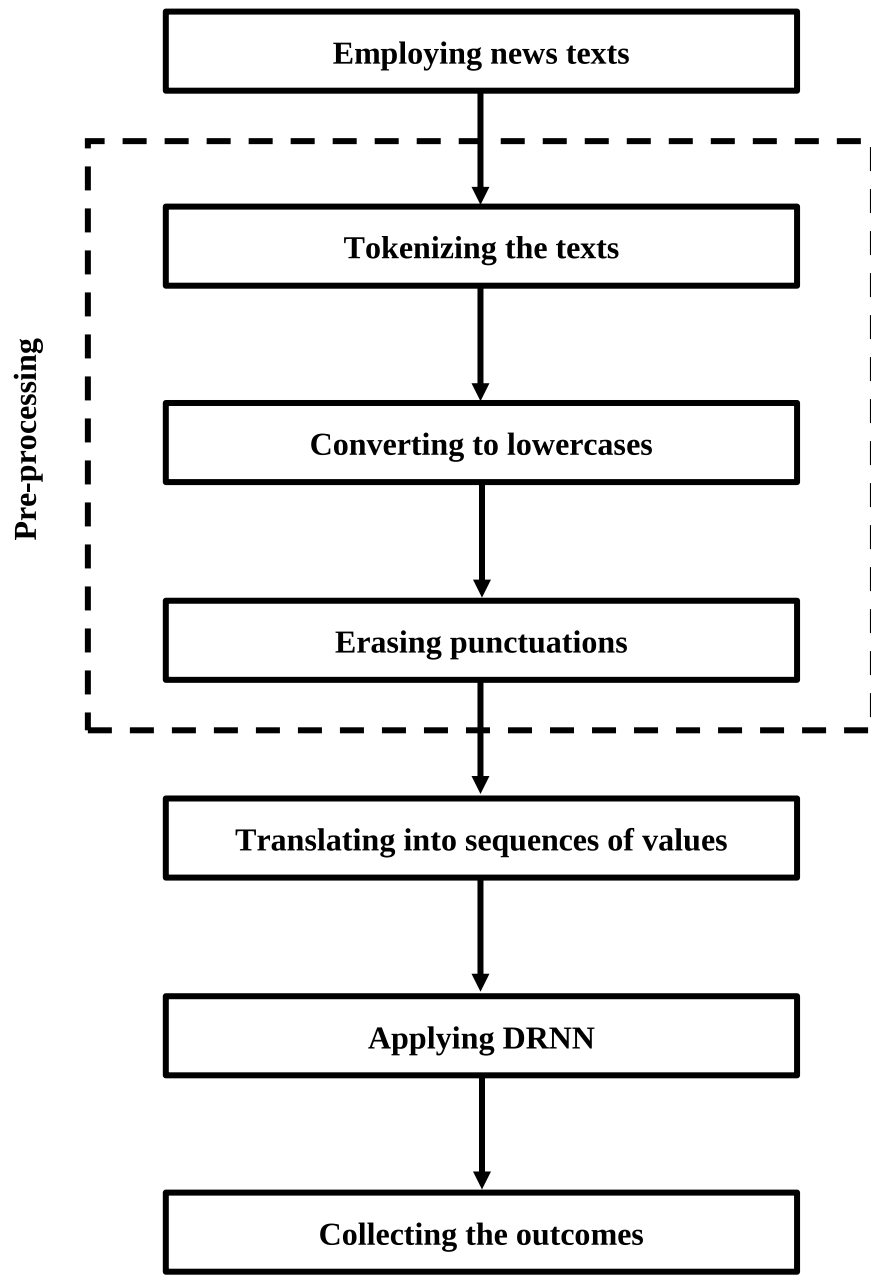

Figure 1: Detailed steps of analyzing data of news texts

3. PRACTICAL PART AND RESULTS

First of all, the FND (PATEL, 2021) is used, which is a useful database from Kaggle. It has a very large amount of fake and true news texts, as mentioned. In this work, the number of overall training data is 17960, the number of overall validation data is 4490, and the number of overall testing data is 22448. The fake and true class distribution of all utilized data is given in Figure 2.

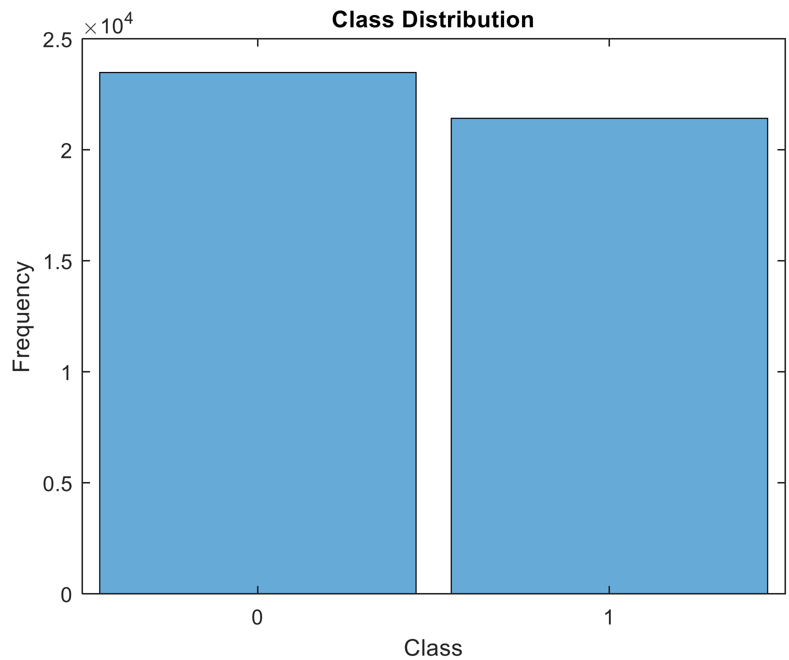

Figure 2: Fake and true classes distribution of all utilized training, validation and testing data

Figures 3 and 4 show Word cloud demonstrations for training and validation texts. These figures show that many news texts are considered, so this can provide advantages for the testing phase in evaluating any new text. Table 1 shows the DRNN architecture descriptions. Table 2 shows the DRNN training options and their values.

Figure 3: Word cloud demonstrations for training texts

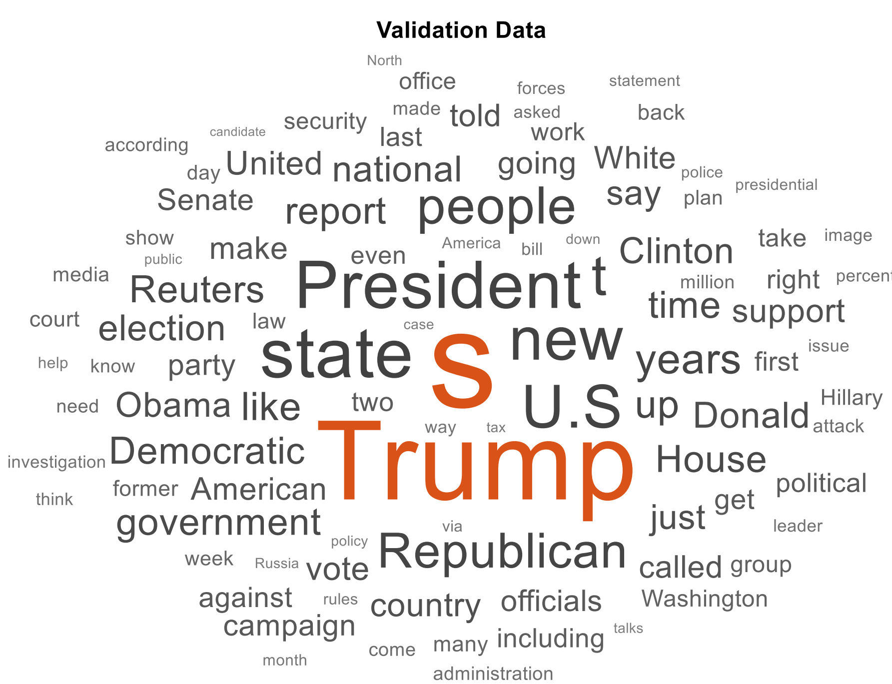

Figure 4: Word cloud demonstrations for validation texts

Table 1: DRNN architecture descriptions

DRNN Layers	Parameters and Values
Sequence input layer	Input size = 1
Word embedding layer	Embedding dimension = 50, Number of words = 100823
LSTM layer	Number of hidden units = 80, Output mode = last
Fully connected layer	Number of classes = 2
Softmax layer	Number of classes = 2
Classification layer	Number of classes = 2

Table 2: DRNN training options and their values

Training Options	Values
Optimizer	Adam
Mini-batch size	16
Gradient threshold	2
Shuffle	Every-epoch
Verbose	False

Figure 5 shows the DRNN training and validation curves. From this figure, it can be seen that a very high validation accuracy of 99.78% is benchmarked. In addition, both curves of accuracy and loss are adjusted toward the optimal values. These are strong evidences for DRNN training success.

Figure 5: DRNN training and validation curves

In the testing phase, the DRNN accuracy attains 99.77%. Furthermore, the evaluation parameters of True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN) obtained were 10671, 11725, 15, and 37, respectively. Hence, the sensitivity, specificity, precision, and f1-score achieve 99.65%, 99.87%, 99.86%, and 99.76%, respectively. Table 3 shows the reported testing results.

Table 3: DRNN testing results

Evaluation Metrics	Testing Results
Accuracy	99.77%
Sensitivity	99.65%
Specificity	99.87%
Precision	99.86%
F1-score	99.76%

The obtained results reveal the high accuracy of detecting fake and true news. Therefore, this clearly indicates our detection study's success.

4. CONCLUSION

This paper concentrated on detecting fake and true news. Text analysis and DRNN were applied. The FND database was exploited; it has a huge amount of data for fake and true news texts. The employed data were first pre-processed. The pre-processing steps involved tokenizing, converting to lowercase, and erasing punctuation. Subsequently, the outcomes were translated into sequences of indices values in order to be used by the DRNN. So, the DRNN was utilized for detection or recognition.

Significant results have been attained. That is, the detection accuracy, sensitivity, specificity, precision, and f1-score have achieved 99.77%, 99.65%, 99.87%, 99.86%, and 99.76%, respectively. Clearly, such evaluations are outstanding and remarkable.

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