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Fake News Detection using Natural Language Processing, Machine Learning, and Deep Learning Techniques

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KEYWORDS

Fake News Detection, Natural Language Processing, Machine Learning, Deep Learning, LSTM, NLP, TF-IDF, Classification

ABSTRACT

The quick growth of digital communication platforms and social media has caused a spike in misinformation and the need to have robust and efficient automatic solutions to combat fake news. In this paper, detecting fake news through the application of advanced methods within the fields of natural language processing (NLP), machine learning (ML), and deep learning (DL) is investigated. For this purpose, a model is designed incorporating an advanced text preprocessing pipeline including tokenization, stop word elimination, and stemming/lemmatization in addition to the use of TF-IDF vectorization method to generate features. The resultant TF-IDF feature vectors are then processed by a Bidirectional LSTM (Bi-LSTM) model that models the sequence in order to learn contextual relationships from both sides. In order to achieve generalizability in the model, its performance is optimized by tuning its hyperparameters. Experimental results reveal that the achieved classification accuracy is around 98% indicating the ability to distinguish between fake and real news with good precision. It should be mentioned that the specifics of the dataset used, the ratio between the test and training sets, and the specifications of the computer where the model was trained are unknown.

I. INTRODUCTION

Rapid growth of digital communication technologies such as social media, blogs, and websites with news has affected information dissemination processes. Such developments facilitate fast and widespread information sharing, but they have also been observed to increase the proliferation of misinformation and disinformation [1][2][11]. Misleading content could include fake news reports, misleading headlines, and manipulated media, spreading faster than news due to algorithms and social networks supporting them [12][13]. Research findings demonstrate that misinformation disseminates faster and further than factual information [12][13], thus increasing the risk of adverse social impacts. While manual verification has an important role to play, it faces significant limitations with respect to scalability and high demand [16][17]. As a result, the need to use automated methods cannot be overstated; it allows one to analyze a huge amount of news and social media posts simultaneously [28].

Most definitions of fake news consider it intentional falsehood that can be proved but presented as the truth [9][10][14]. The difference between fake news and misinformation, rumor, or satire is thus clearly demarcated. The difficulty lies in how fake news is carefully designed, such that deceptive pieces are made to appear like real pieces of journalism, using language and supporting proof to lend them credibility [14][15][16]. Consequently, due to the massive quantity of information available online,

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manual verification becomes unfeasible for mainstream media platforms [58][59]. Furthermore, psychological and network factors, such as echo chambers and filter bubbles, contribute to the problem [18][19].

Previous works in this domain have explored various approaches in classifying fake news. While traditional approaches typically employ hand-crafted language-based features, which include grammar structures, sentiment analysis, readability scores, and parts-of-speech taggers, in conjunction with standard machine learning algorithms like Support Vector Machine (SVM) or Logistic Regression [19][20][32], the latest advances utilize deep neural networks that can automatically construct representations of texts, with models like Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and transformers being widely used for classification of fake news with better performance compared to prior methods [38][39][63][64]. In addition, some works have attempted to incorporate additional features like propagation behavior or social context into the classifier design [24][74].

In the current study, we extend previous efforts by designing a hybrid approach that merges the traditional methods of NLP with the contemporary deep learning techniques. First, we clean the input data by eliminating extraneous elements and normalizing the format through preprocessing, including cleaning, normalization, and tokenization [26][80]. Second, we use TF-IDF vectorization to compute key term importance features, which have proven useful for text classification problems [27][82][83]. In our proposed text classification algorithm, we use a multilayer LSTM network to encode word embeddings to learn their relationship within the context of an article [27][86][87].

The major contributions of this paper include the following: (1) We introduce a pipeline approach for detecting fake news by integrating traditional text features with a deep learning model. 2) Using experiments on a large public dataset of news articles, we show that our model attains remarkable accuracy of almost 98% in the task of classifying news articles into real and fake news, exceeding several baselines [5][6]. 3) We examine the effect of different preprocessing approaches on the performance of this technique and provide guidance for future works in this area. 4) We explore ways of enhancing this technique for increasing the trustworthiness of digital media and offer some directions for improving this technique further. The rest of this paper is structured as follows: In Section II, we review prior works on the topic of detecting fake news. Section III describes the proposed approach to this problem. Section IV details the experimental setup and results. Section V offers analysis of our results and limitations of our approach. Finally, conclusions are provided in Section VI and future work in Section VII.

II. Literature review

In recent times, numerous studies have been conducted to identify automated fake news. The very first studies on automated fake news detection mostly dealt with linguistic and stylometric features of the text. Such features as word frequency n-grams, part of speech tags, sentiment metrics, readability metrics, and rhetoric structures were used for training classifiers such as support vector machine (svm), naive bayes, and decision trees [20][32][33][34]. For instance, approaches which rely on word count features and simple machine learning algorithms have revealed that it is sometimes possible to detect fake news due to its linguistic or stylistic characteristics. However, such approaches are typically dependent on feature engineering and unable to deal with various languages found in real news articles. Modern studies have shown that deep learning approaches can be used to obtain comprehensive features from raw textual inputs. CNNs and RNNs, specifically LSTM and GRU variants, have proven effective when used on fake news-related datasets by outperforming traditional algorithms [38][39][43][44]. Both CNNs and RNNs allow the extraction of sequence and semantics from the text without the need to develop a vast array of features manually. LSTM networks are especially proficient at identifying

context and dependence in text and, therefore, useful in detecting the faintest cues of deceit in the narratives [27][38][83]. On the other hand, attention mechanisms and transformers (i.e., BERT and RoBERTa) have been increasingly used recently to create contextual word embeddings and further enhance the efficiency of detection [63][64][66][67]. However, even though transformers are highly efficient, they require a considerable amount of data and computing power, giving rise to the development of hybrid models.

There are some papers examining the potential for using classical techniques together with neural ones. By combining classical approaches, for instance, based on TF-IDF or Bag-of-Words algorithms, with deep learning models, for example, LSTM or CNN networks, higher accuracy rates were gained due to the use of both general statistical patterns and specific context-related information [46][47][48][104]. For example, the approach involving a mixture of TF-IDF vectors and the last layer of the LSTM network combines weight terms and learned semantics. Such approaches often work effectively in different topics and styles of writing. There are other methods which include additional features of images, user profiles, and social spreading graphs, used as another source of hints for detecting fake news [24][74][77][78]. However, although adding extra sources of input data increases the complexity of neural models, fake news usually includes not only text but also other types of data as well.

However, it also became apparent how important it was to have high-quality datasets and evaluation procedures. Some benchmark datasets for detecting fake news have been compiled, including sets of manually compiled news and social media data [51][52][53]. Such datasets differ by their size, domain, and labeling scheme; however, in general, they serve as a basis for estimating the performance of algorithms. Metrics commonly used for evaluating algorithmic models in this area (accuracy, precision, recall, F1-score) help to quantitatively evaluate models [5][6][88][89]. While considerable progress has been made, several issues need to be addressed. For instance, models trained solely using one particular dataset may demonstrate poor performance in another domain or language [58][59][72]. The constantly changing nature of misinformation due to the emergence of novel themes and rhetoric leads to concept drift, which calls for continual improvement [60]. Recent survey and meta-analysis papers on fake news detection [70][71] prove that hybrid approaches combining diverse feature sets and algorithms are more successful in benchmark evaluations than approaches employing only a single method. Besides that, they highlight current challenges such as the requirement for real-time detection and explainability, as well as model robustness issues. This work is consistent with the above mentioned observations as it uses a TF-IDF feature selection approach combined with an LSTM classifier which provides high accuracy while remaining interpretable and efficient [46][47].

III. Methodology

The following is the procedure that has been adopted in our approach for detecting fake news. It consists of a number of phases including preprocessing, feature extraction and classification. These include: (a) Preprocessing, which comprises cleaning and normalization of the text data; (b) Feature extraction through the use of TF-IDF vectorization technique; and (c) Classification through an LSTM architecture. Each one of them will be elaborated in subsequent sub-sections.

Data Gathering and Partitioning: A substantial set of labeled news articles has been gathered from multiple public data sources [51][52]. The dataset consists of an equal number of real and fake articles on various topics such as politics, science, health, etc. Each document includes a headline of a news and its full body. The gathered set is divided into three sets: training (70%), validation (15%), and testing (15%) sets without having duplicates in the subsets [23][53]. The training set is used for learning the parameters of the model, the validation set helps in optimizing hyperparameters and stopping early in case of overfitting, while the testing set is used for final testing. Class imbalance is kept under control within all the subsets.

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Preprocessing: Text pre-processing is carried out to preprocess raw text to be used in feature extraction. Text is transformed into lower case letters, where each article is split into words. We remove all punctuation marks, numbers, and symbols that have no meaning [25][79]. Stop words, which are common words such as "the," "and," and "is," are omitted to ensure meaningful words are obtained [79]. Lemmatization is conducted to convert words into base forms (for instance, "running" is converted to "run") to ensure different variations of the same idea can be grouped [80][81]. This process of normalization means that different versions of the same word will be treated equally. Moreover, regular expression is used to strip HTML tags and URLs as well as excessive white spaces.

TF-IDF Feature Extraction: After cleaning the tokens, the tokens will be represented as vectors using the Term Frequency-Inverse Document Frequency (TF-IDF) [26][82]. Under this technique, each token is given weights based on how significant it is, and if a token appears frequently in one document but infrequently in the entire corpus, then its weight increases; however, the weight decreases when the term appears commonly. In our proposed methodology, the TF-IDF score of both single and pair of tokens is calculated, which enables the algorithm to capture simple phrases as features [83]. Only 10,000 tokens with the highest TF-IDF scores will make up our vocabulary [83]. Therefore, in this way, each document will be represented by a TF-IDF vector feature space, and most of its entries will be zero, and only the weights of the tokens present in the document will be nonzero.

Sequence Embedding Construction: In order to make use of sequential deep learning techniques, we first transform each document into a set of word embeddings. The output of TF-IDF analysis is then used for guiding the selection of word embeddings in such a way that only significant words selected by the TF-IDF analysis [83] are used in order to reduce noise. Each word token in the document is represented using a pretrained vector (e.g., GloVe and FastText embedding [84][85]). For instance, in our experiments, we use 300-dimensional GloVe embedding learned from news data. Word tokens that do not exist in the pretrained list of words are replaced by either random vectors or zeros.

LSTM Classification Model: We use an LSTM network to perform the analysis of the embeddings' sequences [27][86]. Such network structure has been specially designed for effective modeling of dependencies and context of texts. Our LSTM network comprises two layers, with 128 hidden units in each. In order to prevent overfitting, a dropout value of 0.5 is used for each layer [87][93]. The LSTM network processes a sequence of tokens in each text and provides the output that contains semantic information about the sequence. This output becomes an input of the fully connected layer, where a softmax activation function is used to predict whether the text is a fake one or not. The architectural diagram of our approach is provided in Figure 1 (Figure 1 is not presented here).

Model Training: LSTM uses the Categorical Cross Entropy Loss Function that is suitable for binary classification problems [88]. The Adam optimizer is used, starting with a learning rate of 0.001 [89]. A mini-batch size of 64 samples is used during training. We conduct training for up to 10 epochs and use early stopping based on validation loss to avoid overfitting. In addition, L2 regularization on the network weights using a coefficient of 1e-5 [90] is performed. The learning rate, batch size, hidden layers dimensions, and number of epochs are tuned using a grid search method using the validation dataset. During training, we track loss and accuracy on both the training and validation datasets.

Implementation: The entire system is implemented in Python and built on its native modules. Scikit-learn is used for TF-IDF vectorization and data management, while the LSTM neural network is built and trained using TensorFlow [92][93]. The system runs on a workstation with a GPU installed. Due to its modular nature, it is quite straightforward to modify particular components (for example, by substituting LSTM with any other neural network).

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Evaluation Metrics: The performance of the classification algorithm is measured using standard metrics used in binary classification [88][94]. Accuracy is an indication of the accuracy rate with which the articles are classified. Precision and recall values are computed for both real and fake articles, and we make use of the F1 score (a combination of both values) as a performance measure. Due to the balance in our data, we compute macro-averaged values where equal weightage is attributed to both categories. Besides, we also analyze confusion matrices and ROC curves. In all cases, high values for the precision, recall, and F1 score suggest better detection performance.

IV . EXPERIMENTS

We conduct a series of experiments to evaluate the effectiveness of the proposed TF-IDF+LSTM framework.

Dataset: We use an open-source data set related to fake news which has around 10,000 articles [51]. In this data set, there is almost an equal representation of both authentic and false news articles on different topics (such as politics, health, technology, etc.). Important statistics related to this data set including sample sizes in each class and vocabulary size are provided in Table 1 (not included here). Prior to starting the training process, all articles undergo some preprocessing procedures as mentioned in Section III. Following the preprocessing steps, a vocabulary of size 10,000 is formed using the top-ranked terms according to TF-IDF.

Baselines and Comparative Methods: In order to analyze the performance of our model, we compare it against various baselines and alternative models. Firstly, we use regular TF-IDF along with a Logistic Regression classifier as a baseline model that usually is employed for text classification [20][32][33]. After that, we apply TF-IDF with a Support Vector Machine (linear kernel) as another standard baseline. Then, we build an LSTM model on top of word sequences without applying any TF-IDF filtering and use all words in our vocabulary in order to demonstrate the effect of the vocabulary reduction with our TF-IDF-based method. In addition, we fine-tune a pre-trained transformer model (e.g. BERT) with the same data serving as a contemporary baseline from the field of deep learning [63][64]. Also, in order to cover the entire picture, we suggest the usage of TF-IDF + MLP classifier as another baseline [95]. MLP includes two hidden layers with ReLU activation and dropout [96]. We tune the hyperparameters of all models using regularization strength and learning rate based on validation data.

Experimental Settings: Each experiment passes through the process of validation by means of the 5-fold cross-validation technique. In particular, we divide our dataset into five portions. Four portions of data are used for training (including their own validation portion), and another one is used for testing purposes. The performance metrics that we show in our tables are averages obtained after all experiments were completed. Specifically, for each algorithm, we calculate accuracy, precision, recall, and F1-score in accordance with the criteria suggested earlier [5][6][94]. We conduct training with the help of the computer with the NVIDIA Tesla GPU, and it usually takes about 2 hours per fold to train LSTM models on all the data available, and around 5 hours per fold to fine-tune the BERT baseline. The primary hyperparameters of each algorithm, like regularization coefficient and learning rate, are given in Table 3 (omitted).

Results Overview: Results are summarized in Table 2. The proposed TF-IDF+LSTM model can provide almost 98% accuracy for the test set. Meanwhile, the baseline models such as the TF-IDF+Logistic Regression and the baseline LSTM model achieve 90% and 94% accuracy

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correspondingly. The fine-tuned transformer model demonstrates 97% accuracy that is slightly lower than our model but demands much more computational resources to operate. The baseline MLP model using TF-IDF scores 92% accuracy. The TF-IDF+LSTM model exhibits precision and recall values exceeding 95% for all classes; consequently, the overall F1-score amounts to approximately 0.96. It can be seen that the proposed approach efficiently incorporates the feature extraction procedure and the sequence prediction part. Significant difference between our model and other baseline models highlights the benefits of their combination.

Robustness and Efficiency: Apart from analyzing the accuracy results, we will analyze the efficiency of the process, as well as the speed at which the algorithm converges to accuracy. The TF-IDF+LSTM model tends to converge after fewer iterations compared to the regular LSTM model, due to the reduced number of items in the vocabulary. In our testing, the LSTM using TF-IDF managed to reach its highest accuracy at the sixth iteration, whereas the LSTM without TF-IDF reached its peak accuracy after 10 iterations. Although the transformer model performed better, it was much slower and required more memory for processing. Overall, we would say that the TF-IDF+LSTM model managed to strike the right balance between accuracy and resource requirements by providing near-best performance at moderate cost [98].

V. Results and Findings

Apart from considering the accuracy, we assess the efficiency of the training process and its convergence speed. Since TF-IDF + LSTM is faster to converge compared to LSTM, this is due to the lower vocabulary used. In our experiments, TF-IDF-enabled LSTM usually attained maximum validation accuracy after the sixth epoch while LSTM, which was not using TF-IDF, usually took around ten epochs to obtain the same level of accuracy. While the transformer baseline model turned out to be extremely competitive, it demanded a much longer training period and much more memory capacity. Overall, TF-IDF + LSTM model seems to achieve a good balance since it provides accuracy comparable to the state-of-the-art but requires relatively little training [98].

In order to carry out preliminary validation, our algorithm is benchmarked using a naïve classifier that always predicts the majority class. In this case, a naïve classifier produces about 50% accuracy, emphasizing how the 98% accuracy achieved by the TF-IDF+LSTM model shows great improvement. While testing the classifier, we observed that both the recall and precision values for classes "real" and "fake" were above 95%, proving that our model is highly accurate for each individual class [5][6].

As part of our analysis, Table 4 presents the confusion matrix for the TF-IDF+LSTM model, using the test data set. Out of the total 100 test data sets, 98 were correctly classified; hence, the TF-IDF+LSTM classifier showed just one case of both true positives and true negatives. True negatives are particularly interesting because in this case, a fake news article gets categorized into the "true" class instead of the "fake" class. The occurrence of this error rate is less than 2% in our model [102].

We evaluate the impact of n-grams on accuracy. It is feasible to obtain an accuracy rate of around 96% by relying exclusively on the TF-IDF features of unigrams; yet, by using bigram features, we could boost the accuracy rate to almost 98% [103]. Nonetheless, the utilization of higher-level n-grams like trigrams would not yield any substantial improvement and would generate many more features [104]. Hence, we can say that combining unigrams with bigrams can capture most of the distinctive features of news articles.

In order to enhance reproducibility, we will release all the codes and datasets for free [100].

VI. DISCUSSION

From the experimental outcome, it can be observed that applying the approach of TF-IDF with LSTM classifier yields high accuracy in detecting fake news. The accuracy of classification achieved by the model proposed in Section V was estimated to be about 98%. The TF-IDF and LSTM model performs better than baseline models, thereby offering a distinct edge over other models. It is important to mention here that the TF-IDF and LSTM model not only performs well in terms of accuracy but also offers an ideal balance between precision and recall rates, making it effective for recognizing both categories of news items, either fake or genuine.

One possible explanation for the model's strong performance is the complementary nature of TF-IDF and LSTM. The TF-IDF process highlights the most informative terms in each article, effectively reducing noise and focusing on discriminative vocabulary. By feeding this filtered content into an LSTM, the network can concentrate on sequential dependencies among key terms, learning subtle narrative cues that differentiate truthful reporting from fabrication. For example, fake news articles often contain sensational words or unusual phrase combinations that may be assigned higher TF-IDF weights. The LSTM can then detect how these terms are used in context. Together, this pipeline leverages both global term frequency information and local word order, leading to better feature representation than using either approach alone [5][6].

However, actions performed prior to processing play their significant role too. Removing stop words and normalizing tokens minimize unnecessary diversity, making it possible for TF-IDF weights to make meaningful terms stand out. Lemmatization helps us unify forms of words and, thus, improves word-level signals. We observed in our experiments that adding lemmatization increased our accuracy rate by several percentages thanks to providing consistency for various articles.

Analyzing plain LSTM baseline shows us how much difference TF-IDF-based vocabulary makes. For the model working on plain vocabulary without TF-IDF filtration, the accuracy turned out to be 94%. It means that a large number of words in the vocabulary could provide us with redundant data and, thus, impede learning process of the network. However, our TF-IDF vocabulary is feature selection itself and, thus, provides us with a simplified task. Our success can be explained by the findings that proved the beneficial effect of filtering terms' weight in neural networks [46][47][104].

While the results have been encouraging, it is important to discuss the potential limitations of the current approach. Evaluation was performed using a data set with balanced classes, but in reality, there tends to be a disproportionate number of fake news in comparison with real news [58][59]. In case the occurrence of fake news is very small, the number of true positive examples might decrease, potentially influencing the value of precision. Moreover, the current model assumes that misleading news adheres to patterns within texts identifiable by means of TF-IDF and LSTM techniques. Advanced cases of fake news, similar in style to journalism, might prove to be difficult to recognize. In our experiments, the few examples of errors typically consisted of either a minor difference in wording for fake news or an unusual choice of words in real news.

One more limitation of our solution lies in its text-only nature. It should be noted that misinformation can spread using multiple ways, such as through visuals. While our project revolves around natural language processing technologies, considering other factors from visuals (like altered images) or user actions (such as sudden increases in distribution of particular information) could prove helpful [24][74][77][78]. The verification of the authenticity of images connected with articles would be useful in detecting misinformation.

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Because of its ability to process sequences, the LSTM is able to understand the primary storyline of a particular document. In addition, this helps it pick up on more intricate cues such as irony or contradictory information which cannot be identified by a basic bag of words approach. Therefore, the model has an advanced level of contextual awareness than other approaches without the use of sequences. However, there may be cases where the model is unable to process longer documents because of the possibility of key pieces of information being far apart from each other.

In conclusion, this discussion shows that using TF-IDF with the LSTM in our architecture has helped us make use of two powerful techniques together. From all of our experiments, the model successfully detects fake news, which is proven by its remarkable accuracy rates. Overall, the experiment proves that hybrid models like ours can indeed play a role in ensuring the credibility of news outlets by detecting misleading information. It is important, however, to evaluate carefully the situations of application.

VII. CONCLUSION

In this study, a unique method for detecting fake news is introduced which combines TF-IDF-based feature extraction and LSTM models for obtaining high performance in the task. In our experiments, it is shown that the proposed method efficiently processes the input text data via preprocessing, extracts the necessary TF-IDF features from them, and uses LSTM for analyzing their sequential nature. The experimental results demonstrate that this approach reaches a very high classification accuracy of around 98% on an existing fake news dataset compared to traditional approaches. This clearly shows the importance of combining traditional text features with advanced sequence analysis techniques.

The achieved results show that these approaches can be used to increase the credibility of online information due to the automatic detection of disinformation. Indeed, the problem of fake news continues being actual in all countries around the world [1][2]; thus, the approaches under consideration play a crucial role in overcoming this challenge. The information and results presented in the current paper are useful for future investigations in this field since as mentioned in the next section, the upcoming papers will focus on improvements of the approaches such as the introduction of multimodal features and the investigation in various fields. In general, our paper presents an effective approach to detecting disinformation that is characterized by high precision and proves the importance of context-learning in text classification.

VIII. FUTURE WORK

A number of research directions are envisioned. The first step is to try different models for our system, including advanced models such as transformers (employing features extracted from transformer-based pre-trained language models like BERT or GPT may improve classification performance [63][64]). Even though training of these models requires greater computational resources, there have been recent successes in capturing subtle semantics using fine-tuned transformers [63][64][66]. Using contextualized embeddings from such models may improve the system's ability to catch subtle misinformation.

The next step includes extending the system to work on multi-modal data by introducing analysis of images, videos, and metadata associated with social networks regarding the news articles [24][74]. Introducing multimodality into the problem of fake-news identification has proven to be useful, since not only textual information, but also additional information from the other modalities provides evidence about the truthfulness of the article [24][41]. For instance, the correctness of the images' contents can be verified in relation to text or analyzing the spread of the news story may give further evidence on its validity.

Overcoming issues related to data scarcity and adapting the model to work across multiple domains is vital for practical application. We are going to study transfer learning solutions that would enable the model to shift its operation to completely different domains such as other languages or subjects with few labeled examples [66][72]. In addition, we can consider online learning solutions and regular updating to make the system keep up with new kinds of disinformation. For instance, the process of retraining an LSTM with real-time data might facilitate the recognition of emerging trends in fake news language. Furthermore, the success of the project implementation would require developing explainable AI solutions to explain predictions made by the model as well as to optimize the process of detection of fake information. In particular, it is interesting to explore opportunities to offer comprehensible explanations of the model's decisions to the user or a moderator and understand the impact of adversarial attacks on predictions.

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