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Detecting Fake News about COVID-19 Infodemic Using Deep Learning and Content Analysis

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ABSTRACT

With the widespread use of social media, online social platforms like Twitter have become a place of rapid dissemination of information—both accurate and inaccurate. After the COVID-19 outbreak, the overabundance of fake information and rumours on online social platforms about the COVID-19 pandemic has spread over society as quickly as the virus itself. As a result, fake news poses a significant threat to effective virus response by negatively affecting people's willingness to follow the proper public health guidelines and protocols, which makes it important to identify fake information from online platforms for the public interest. In this research, we introduce an approach to detect fake news using deep learning techniques, which outperform traditional machine learning techniques with a 93.1% accuracy. We then investigate the content differences between real and fake news by applying topic modeling and linguistic analysis. Our results show that topics on Politics and Government services are most common in fake news. In addition, we found that fake news has lower analytic and authenticity scores than real news. With the findings, we discuss important academic and practical implications of the study.

Keywords: COVID-19, Infodemic, Fake News Detection, Machine Learning, Topic Modeling, Linguistic Analysis

Ⅰ. Introduction

The COVID-19 pandemic has brought forth an unprecedented challenge to the world. As the novel coronavirus was not yet well understood, the rapid spread of misinformation about the virus itself and its transmission and prevention methods has hampered effective responses to the outbreak. Social media have played a significant role in rapidly disseminating COVID-19 misinformation (Apuke and

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Omar, 2021).

Built on new digital technologies and the Internet, online social media has become the central platform for people's social interactions and information discovery and transmission (Shu et al., 2017). People can find out and share news easily with friends over the world through just a few clicks on online social media such as Facebook, Twitter, and Instagram. While social media offers people easy access to much information, it makes fake news wide-spreading and becomes pervasive at the social level among individuals (Sharma et al., 2019).

With the prevalence of social media, millions of users quickly spread the news through sharing, liking, and retweeting news; thus, verifying the news's validity and the original author's competence has become difficult (Zhou and Zafarani, 2020). Since the beginning, however, online social media have not provided appropriate fact-checking measures or regulations responsible for the veracity of the information, which might stimulate the uncontrolled spread of fake news that manipulates public opinions (Bondielli and Marcelloni, 2019). As a result, online social media has become a major source of the rapid and worldwide spread of fake news (McGonagle, 2017; Rampersad and Althiyabi,, 2020). Especially the fake news issue became more critical when the world faced the COVID-19 pandemic. The widespread dissemination of misleading information about COVID-19 through online social media has seriously hampered the timely response to the virus. World Health Organization (WHO) Director-General Tedros Adhanom Ghebreyesus at the Munich Security Conference 2020 said: "We are not just fighting an epidemic; we are fighting an infodemic." An "infodemic" means an epidemic of misleading information that poses a severe public health problem (Zarocostas, 2020).

The significance of the issue has urged researchers to develop an approach to detect fake news about COVID-19, including binary classification tasks to distinguish real news from fake news by utilizing machine learning (Patwa et al., 2021), robust model (Bang et al., 2021), and deep learning techniques (Goldani et al., 2021; Zhang et al., 2019). However, such approaches have limitations. For instance, even deep learning models, the most powerful models with high prediction accuracy, make it hard to understand how they make decisions because of the black box problem (Tzeng and Ma, 2005). In deep learning, only the input and output data are known, but without a view of the processes between them, so it is hard to understand the results and the context of the results in a straightforward manner. Therefore, even with the high accuracy of the classification model, the content difference between fake news and real news remains unexplored.

This study aims to provide a highly accurate fake news detection model by applying Convolutional Neural Networks (CNN) and exploring the content differences between real and fake reviews. Our study provides content analysis using topic modeling and linguistic news content analysis. Topic modeling is done by the LDA (Latent Dirichlet Allocation). Moreover, linguistic analysis is done with the LIWC (Linguistic Inquiry and Word Count) tool to analyze psychological categories (analytic, clout, authentic, and tone), social, health, and risk variables.

This study makes academic contributions by not only developing a deep learning model to detect COVID-19 Infodemic fake news but also by providing content insights into the differences between real and fake news. Moreover, the practical contribution of this research is that it helps understand the features of fake news related to the COVID-19 Infodemic that improves the way to distinguish real news from fake news.

The structure of this paper is as follows. First, Section 2, Literature Review, introduces the main terms of fake news and the COVID-19 Infodemic and describes the fake news detection and content analysis methods. Then, Section 3, Research Frameworks and Experiments, presents our research framework, data description, and explanation of the prediction model and content analysis. Next, Section 4 provides the results of the fake news detection model and content analysis. Finally, Section 5 discusses our findings, contributions, and limitations.

Ⅱ. Literature Review

2.1. Fake News and the COVID-19 Infodemic

There are multiple alternative definitions of fake news. For instance, Zhang and Ghorbani (2020) described fake news as: "fake news refers to all kinds of false stories or news that are mainly published and distributed on the Internet, in order to purposely mislead, befool or lure readers for financial, political or other gains." McGonagle (2017) proposed a definition of fake news as news created with the deceitful intent of spreading misinformation or lies and manipulating mass opinions. On the other hand, Wang et al. (2019) described fake news as fraud, including conspiracy theories, myths, rumors, and fraudulent or deceptive information that is unintentionally or intentionally spread through social media. According to the study by Shu et al. (2017), fake news usually spreads through online social media or platforms, and its styles and topics can be very intrusive. In sum, fake news can be referred to as misinformation in online social media created to mislead readers (Girgis et al., 2018), which spreads faster and more widely compared to that in traditional media (Balmas, 2014)

As such different researchers have defined fake news differently, but they agree that manipulators use it to confuse and persuade online users. This malicious intention of fake news has become a significant issue for the government, academia, and industry. Especially in healthcare, fake news can risk people's safety, making them take some false precautionary measures that can lead to health damage (Pulido et al., 2020). Moreover, fake health news or Infodemic is critical during a pandemic's chaos, therefore related to the issue of COVID-19.

According to Abu Arqoub et al. (2022), there are two motivations for creating fake news: getting readers' attraction and providing good advertising strategies. For example, during elections, fake news can help to promote specific candidates by creating fabricated news against the opponent. Ha et al. (2021) stated that the motivation for producing fake news is related to the source's intention and bias. It is difficult to change people's perceptions of information, even if the previous impression is inaccurate and biased. Thus, fake news should be detected before it becomes widespread and has such negative effects on people in media and SNS (Silva et al., 2021).

The massive panic caused by the emergence of a novel coronavirus has prompted people to search for information about the virus on the Internet, sometimes relying on completely unverified sources. According to Huynh (2020), scared and confused people tend to search for and believe information online to be truthful and valuable where it really is not, which makes fake news spread among mass users and this, in turn, leads to the emergence of "infodemic." According to the description of "infodemic" by the World Health Organization (WHO), "an infodemic is too much information, including false or misleading information in digital and physical environments during a disease outbreak (https://www.who.int/health-topics/infodemic)." The "infodemic" concerning COVID-19 has become more pronounced on social media platforms such as Twitter, Facebook, etc. (Russonello, 2020). For example, since people usually seek preventive tips and cures for coping with the virus, fake news has proliferated online suggesting that people could get cured by drinking bleach or salty water (Lampos et al., 2021).

Research conducted by Hou et al. (2020) discovered that the more people spend time on online social platforms to find information about COVID-19, the more anxious people become about the situation. Furthermore, the lack of information about COVID-19 encourages people to share misleading information about the virus and cannot verify whether the information is true or false (Pennycook et al., 2020). Therefore, it is worth studying how to identify false information, which helps people distinguish fraud information before they share information with others.

2.2. Fake News Detection Using Deep Learning

Since fake news detection has become an emerging issue in online social media, many social media platforms seek more efficient solutions for identifying fake news. For example, Facebook allows users to flag and report posts or news that are potentially fraudulent and inappropriate (Zhang and Ghorbani, 2020). Mainstream media organizations commonly perform fact-checking tasks. Since news in online social media and platforms can be a mix of true and false information, classifying news can be difficult. Recently, online fact-checking resources such as Classify.news and Factcheck.org have become available as tools to check the veracity of online news. However, such online fact-checking resources have some limitations and disadvantages. The main disadvantage of maintaining online fact-checking resources is that they are expensive, time-consuming, and require a vast human resource (Dale, 2017). Furthermore, some online fact-checking resources can monitor only statistical information.

Previous studies investigated news content features such as linguistical features, topic features, and syntactic features. For example, Hamid et al. (2020) analyzed raw news content in a bag-of-words model, representing a set of words for each news. However, this model ignores the semantics of words, which may miss important information. To overcome such limitations, research uses other natural language processing techniques (NLP), such as word2vec (Mikolov et al., 2013).

In general, studies on manipulation detection techniques can generally be classified into two research techniques: supervised machine learning and unsupervised machine learning. Machine learning algorithms widely use sample data based on a mathematical model for prediction and classification. However, in non-machine learning cases, research does not have training data to provide a statistical model and thus cannot calculate the model's accuracy (Shmueli et al., 2011). In the literature about fake news detection, supervised learning is the most common method for fake news detection. Supervised learning in the case of fake news detection classifies news into two categories: fake and non-fake. For instance, Patwa et al. (2021) tested the fake news detection model on four different techniques: Logistic Regression, Decision Tree, Gradient Boost, and

Support Vector Machine. Bang et al. (2021) proposed a machine learning-based model - CONSTRAINT 2021- for detecting fake news.

Recently, new approaches based on neural networks were developed for text classification tasks. For instance, convolutional neural networks (CNN) were initially invented for computer vision (Gandarias et al., 2019), face recognition (Amato et al., 2019), and image classification. However, researchers recently started using CNN for natural language processing as a technique in classification (Kim et al., 2019). Convolutional neural networks (CNN) are a class of deep learning neural networks used for effective learning and improving prediction performance (Goldani et al., 2021). CNN was applied by Ajao et al. (2018) to predict fake tweets and performed an accuracy of 80%. Nasir et al. (2021) proposed a hybrid CNN-RNN-based approach for fake news detection and showed results of 60% accuracy. However, extant studies did not cover the explanation of the content difference between fake and real news.

2.3. Content Analysis for Fake News

Despite already developing multiple theories and methods to detect fake news, researchers are motivated to develop more sophisticated and effective methods. The content-based analysis is one of the most common approaches for detecting fake reviews. According to the study by Zhang and Ghorbani (2020), "a piece of fake news contains physical contents (e.g., body text, image or video) as well as non-physical contents (e.g., purpose, sentiment, and news topics)." Since online media news is usually in a textual format, news content features are the most critical for fake news detection (Bondielli and Marcelloni, 2019). The content-based approach in fake news detection is based on exploring the content differences between fake and real news (Sharma et al., 2019). These differences could be measured both quantitatively and qualitatively (Song et al., 2021).

Content analysis is a common technique for analyzing a large volume of data. According to Holsti (1969), content analysis is "any technique for making inferences by objectively and systematically identifying specified characteristics of messages." The content-based analysis could help understand the context of social attention, group, or individuals (Stemler, 2000). As we mentioned previously, content analysis plays an essential role in analyzing textual data. One of the most common contextual analysis techniques is topic modeling and linguistic analysis.

Topic modeling is an unsupervised learning technique that learns variables according to the frequency of simultaneous occurrences between words. Latent Dirichlet Allocation (LDA) is a widely used topic modeling method for analyzing text data. Using LDA, topics of reviews can be extracted and classified by related topics (Blei et al., 2003). Several studies have analyzed online news on social media platforms using text mining techniques. Among them, Carracedo et al. (2021) used the clustering technique to capture changes in the circumstance during the period of COVID-19. Mutanga and Abayomi (2022) applied LDA to analyze tweets and highlight the most popular topic related to the COVID-19 pandemic. This study uses topic labels related to COVID-19 based on the study by Goyal and Howlett (2021), which highlighted 16 topics of over 13,000 COVID-19 policies announced by 190 countries from December 31, 2019, to July 6, 2020.

Another technique for content analysis is linguistic analysis. We provided linguistic analysis by applying Linguistic Inquiry and Word Count (LIWC). LIWC is one of the most common tools for a dictionary-based linguistic analysis, which counts in percentage the proportion of words related to features such as psychological states, different emotions, social concerns, and thinking styles. Some studies applied LIWC for COVID-19-related fake news detection; for example, Chen et al. (2020) applied LIWC to classify COVID-19-related tweets into controversial and non-controversial terms. In addition, Huerta et al. (2021) explored COVID-19-related tweets for presenting discussions about health and risk by using LIWC's features, such as analytics, health, anxiety, and risk.

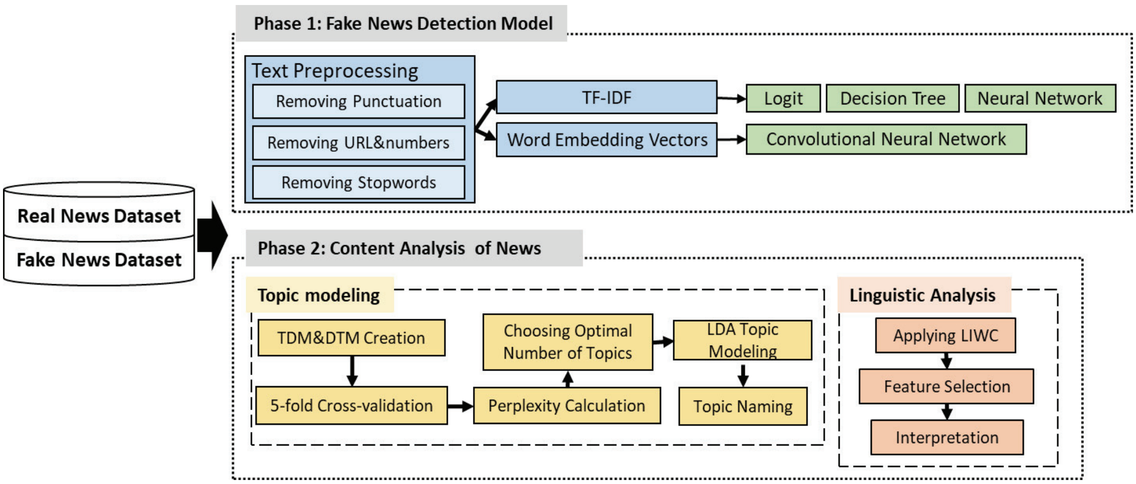
Ⅲ. Research Framework

We propose a research framework for detecting and exploring fake news features about the COVID-19 Infodemic, as presented in <Figure 1>. Our study aims to detect fake news by applying machine learning techniques and analyzing the differences between real and fake news related to the COVID-19 Infodemic. Our framework consists of two phases: the fake news detection model and content analysis. In phase 1, we provided news preprocessing and fake news detection by using Logit, Decision tree, NN and CNN. In phase 2, we analyzed news content through topic modeling and linguistic analysis. A more detailed explanation of each phase is provided as follows.

We collected the fake and real news datasets from Patwa et al. (2020) study. The dataset contains labeled data: 5,600 tweets with real news and 5,100 tweets with fake news. Some examples of real and fake news related to COVID-19 are shown in <Table 1>. The fake tweets were collected from fact-checking websites like Politifact, NewsChecker, Boomlive, and tools like Google fact-check-explorer and IFCN chatbot. On the other hand, real tweets were collected from verified sources, such as the World Health Organization (WHO), Centers for Disease Control and Prevention (CDC), Covid India Seva, and the Indian Council of Medical Research (ICMR).

3.1. Phase 1: Fake News Detection Model

The Fake News Detection Model starts with news



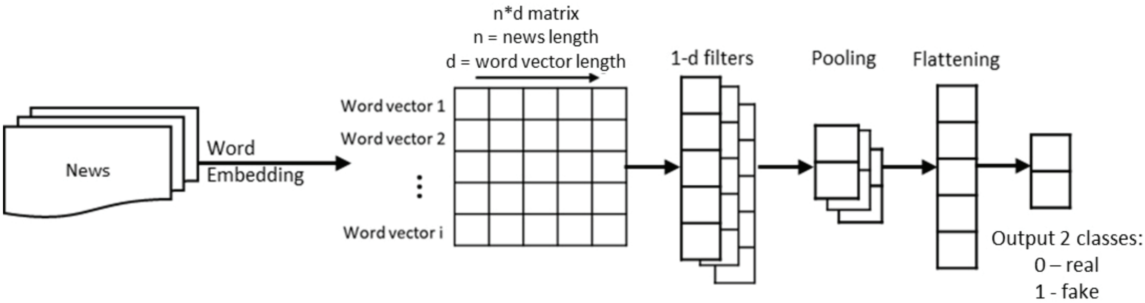
<Figure 1> Framework for Detection and Exploring the Features of Fake News

<Table 1> Examples of COVID-19 Fake and Real News

News	Label
BREAKING NEWS# The president Cryill Ramaphosa has asked all foreign nations to depart south Africa before June 21 2020 due to increasing cases of COVID 19.	**Fake**
Yesterday our laboratories completed 2899 tests of those 726 were testing of people in managed isolation and quarantine for the routine testing on either days 3 or 12 of their stay. That brings the total number of tests completed to date to 436233.	**Real**
Football player Cristiano Ronaldo turned all his hotels into hospitals to help coronavirus patients and is paying doctors and the staff.	**Fake**
Masks can help prevent the spread of #COVID19 when they are widely used in public. When you wear a mask you can help protect those around you. When others wear one they can help protect people around them incl. you. #WearAMask #DoYourPart #WorldMaskWeek	**Real**

text preprocessing. First, we deleted punctuation, numbers, hashtags, and URLs for preprocessing news. Second, we tokenized and lemmatized each news by returning to its primary forms (example: “spreading” become “spread”). Third, we removed stopwords such as also, really, around, will, even, now, upon, and else. Before detecting fake news, the next step in preprocessing varies depending on whether it is traditional machine learning or deep learning - convolutional neural networks (CNN). In the case of traditional machine learning, we converted each tweet of news into a row in the term frequency-inverse document frequency matrix (TF-IDF). The number of times a term appears in the news is term frequency (TF) (Rajaraman and Ullman, 2011). However, terms that occur too often in the news could lack discriminative power, so calculating the weight of each term in the news is important. For that reason, we applied the inverse document frequency factor (IDF) that decreases the weight of terms that occur too frequently, such as “the,” “and,” “to,” etc., and increases the weight of rare terms (Robertson, 2004). The TF-IDF method has a limitation in feature representation and calculating relationships between terms inside the text so that data loss could occur (Gao and Huang, 2018). Therefore, in our deep learning, we used the word embedding model.

Word Embedding represents particular text in a coordinate system, and each term is represented as a continuous vector space. That means that terms with similar or related meanings are close to each other in a coordinate system, which allows for calculating the relationship between terms in the text (Jang et al., 2019). Compared with other word embedding techniques, word2vec (Mikolov et al., 2013) shows better performance by calculating the cosine similarity of terms’ vectors, thereby counting the meaning of words. In our study, we applied the word2vec word embedding technique. Word2vec includes two learning algorithms: continuous bag-of-word (CBOW) and skip-gram algorithms. According to the study by Jang et al. (2019), for analyzing tweet text data, the word2vec Skip-gram algorithm performs better than the continuous bag-of-word. In other words, the Skip-gram algorithm fits better for short texts. Therefore, this study constructed CNN with the word2vec Skip-gram algorithm to classify tweeter news. <Figure 2> shows the architecture of CNN with the word2vec model. Twitter news was tokenized by words, and tokens were assigned to vectors. We created matrics where n is equal to the length of news and d is equal to the word vector length. After



<Figure 2> The Architecture of CNN with the Word2vec Model

we applied CNN by passing the matrics to the input layer and our CNN model contains convolutional layers, pooling layers, flattening layers, and output with two classes of fake and real news.

In the next step, after tweets news text preprocessing, we split the data into the train set (6420 rows), validation set (2140 rows), and test set (2140 rows). In the case of traditional prediction models, we applied Logit, Decision Tree, and Neural Network. For the deep learning prediction model, we applied CNN with the word2vec. Since the performance of the model could decrease due to learning unnecessary words in the document, vectorization was not performed on words with low word frequency, the minimum frequency words were 5. The dimension size is critical for embedding; for example, in the case of 3-dimensional continuous vectors, the term "virus" may represent as [0.2, 0.9, 0.8] According to Goldberg (2016) and Pennington et al. (2014), the word2vec module 100 dimension size shows good performance. Therefore, in our research, we applied the word2vec with 100 dimensions. Next, CNN was applied with two 1-dimension filters (for images, 2-dimension filters) with a dropout of 0.5 after each layer and provided max pooling and flattening. In the first convolutional layer was used 128 filters, and in the second layer was used 64 filters. Moreover, for each convolutional layer, the activation function was relu, and in the final dense layer, the activation function was softmax.

As a result, the CNN model classified tweeter news into two classes - fake news and real news. In our research, we applied traditional and deep learning prediction models to compare them, thereby evidence of the better performance of deep learning models for detecting fake news.

3.2. Phase 2: Content analysis of news

In our study for content analysis, we did topic modeling and linguistic analysis. For topic modeling through LDA, we extracted and classified COVID-19-related tweet news into related topics (Blei et al., 2003). First, to find an optimal number of topics for each dataset (real and fake tweet news datasets), we calculated the perplexity by using a 5-fold cross-validation (Chernyaeva et al., 2021). The results of k perplexity by the number of topics for real and fake tweets news are shown in <Appendix>. Then, we tested the number of topics from 2 to 100 topics. The optimal topic number is the number of topics with the lowest k perplexity value. In the case of real news, the optimal topic number is 30, but for fake news is 20. Second, we applied LDA and extracted keywords per the dataset's optimal topic number for each topic. Finally, based on the study by Goyal and Howlett (2021), we assigned the topics into ten dimensions: Health screening (HS), Testing & treatment (TT), Information Management (IM), Health resources (HR), Curfew & lockdown (CL), Physical distancing (PD), Protective equipment (PE), Government services (GS), Politics (P), Misinformation (M).

In the case of linguistic analysis, we used the LIWC tool, which was introduced previously. Our study applied LIWC 2015 version with 30 different variables. According to studies by Huerta et al. (2021), which explored COVID-19-related tweets for discussing health and risk, and a study by Chen et al. (2020), which classified COVID-19-related tweets into controversial and non-controversial terms, we combined variables that were used in these previous studies. As a result, for analyzing the content difference between real and fake tweet news, we chose seven variables related to COVID-19 Infodemic: analytic, clout, authentic, tone, social, health, and risk. Analytic, clout, authenticity, and tone variables can be grouped as psychological categories. The methods and studies used to highlight these categories are described in detail on the official website of LIWC (www.liwc.app). The dimension *analytic* represents the degree of the text's hierarchical thinking patterns and logic. *Clout* measure an author's social status and her confidence in written text. *Authenticity* represents an author's honesty, genuine feelings, and thoughts, which are usually more spontaneous. *Tone* evaluates a text's emotional tone (positive tone and negative tone). The more positive the emotional tone, the higher the value number of the tone. A tone value number below 50 means a more negative emotional tone. *Social* variables represent an author's level of connection with others, society, family, and friends. *Health* variables measure relation to medical terms such as hospital, cough, health, and symptom. *Risk* represents the level of existence of words related to a risky situation, doubt, and danger, to name a few.

Ⅳ. Analysis and Result

4.1. Results of Prediction Model

The results of fake tweet news prediction are shown in <Table 2>. We used accuracy, precision, recall, and F1-score to evaluate the performance of fake news detection models (Powers, 2020). The definitions and equations of these performance metrics are as follows:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

Accuracy is a metric that shows the ratio of accurate predictions of fake news.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

Precision is a metric that shows the ratio of fake news that was correctly predicted to the total number

<Table 2> Results of Fake News Prediction

Prediction Model	Results of Test Set			
	Accuracy	Precision	Recall	F1-score
Logit	90.8%	90.5%	90.2%	90.3%
Decision Tree	78.9%	94.6%	70.9%	81%
Neural Network	91%	91.7%	91.9%	91.8%
CNN	**93.1%**	**93.9%**	**93.4%**	**93.6%**

of examples predicted as fake news.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

Recall is a metric that shows fake news that was correctly predicted to the actual number of fake news.

$$\text{F1 score} = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{4}$$

F1-score is a metric that shows the weighted average score of precision and recall.

Where True Positive (TP) is the number of the actual fake news that was predicted as fake news, and True Negative (TN) is the number of the actual real news that was predicted as real news. False Negative (FN) is the number of actual fake news that was predicted as real news, and False Positive (FP) is the number of actual real news that was predicted as fake news.

We found that the best test accuracy of 93.1% is achieved by Convolutional neural networks (CNN) with the word2vec model. In comparison, neural networks (NN) results show an accuracy of 91%, Logit with 90.8%, and Decision Tree (DT) reported inferior performance with 78.9%. Also, CNN with the word2vec model shows the best recall with 93.4% and F1-score with 93.6%. Therefore, we can assume that word embedding in tweet news preprocessing and Deep learning in classification tasks perform better than TF-IDF in preprocessing and traditional machine learning techniques.

However, deep learning models are a black box that does not provide theoretical logic that explains how the results were made (Tzeng and Ma, 2005). Furthermore, with the results from <Table 2>, it is hard to assume the difference between real and fake tweet news related to COVID-19 Infodemic. Therefore, we explain the difference between real and fake tweet news in the following content analysis results: topic modeling and linguistic analysis.

4.2. Results of Topic Modeling

Based on the results of LDA with 5-fold cross-validation, we named each topic and assigned them to one of ten previously explained dimensions. In the next step, we count the number of each dimension for each dataset (fake and real news). The results of topic modeling are presented in <Table 3>. We found the difference in the distribution of topic dimensions between real and fake tweet news. For fake tweets news, the dimension of Politics (P) prevails with appearances in 8 topics out of 20. Next, Government services (GS) dimension appears in 4 topics of fake tweet news.

For real tweets news, dimensions of Health screening (HS) and Testing & treatment (TT) appear most often in 6 topics each. Information Management (IM) appears in 5 topics out of 30. Moreover, the results show that dimensions are distributed relatively evenly

<Table 3> Results of Topic Modeling

	Topic Number	
Dimension	Real News	Fake News
Health Screening (HS)	**6**	1
Testing & Treatment (TT)	**6**	2
Information Management (IM)	**5**	-
Health Resources (HR)	4	2
Curfew & Lockdown (CL)	3	-
Physical Distancing (PD)	2	-
Protective Equipment (PE)	2	2
Government Services (GS)	1	**4**
Politics (P)	1	**8**
Misinformation (M)	-	1
Total Number of Topics	**30**	**20**

<Table 4> Results of Linguistic Analysis

		Mean of Real News	Mean of Fake News	p-value of t-test
Psychological Category	**Analytic**	88.911	87.888	0.002*
	Clout	63.061	62.653	0.324
	Authentic	27.173	18.826	0.000*
	Tone	36.829	33.212	0.000*
Social		4.989	6.063	0.000*
Health		1.502	2.125	0.000*
Risk		0.589	0.724	0.000*

* *Represent significance levels at 1%.*

among the topics in real news compared to the dimensions in fake tweets news. Furthermore, the Misinformation (M) dimension appeared only in fake tweets news.

4.3. Results of Linguistic Analysis

The second part of content analysis in our research is linguistic analysis. We calculated the average value for each dataset (fake and real news) by each variable of LIWC's results. Also, to determine a significant difference between the means of real and fake news linguistic parameters, we did a t-test. The final results are shown in <Table 4>.

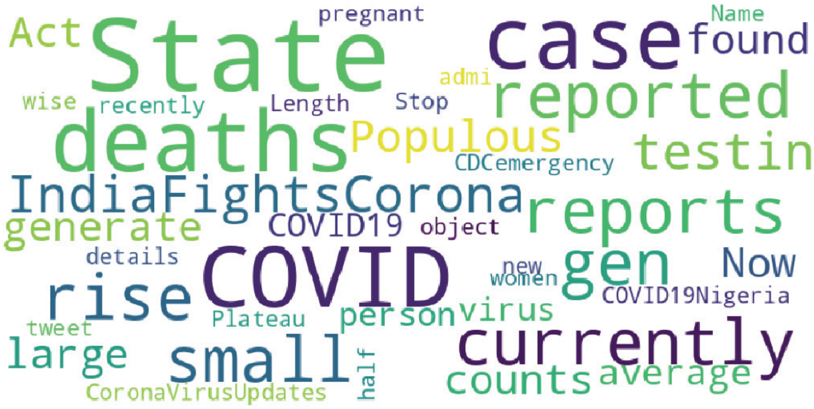
The means of all real and fake news' linguistic parameters are significantly different at the 0.01 significance level except clout variable. Moreover, real news' average values of analytic, authentic, and tone variables are higher than in fake news cases. However, average social, health and risk values are higher in fake news than in real news.

Ⅴ. Discussion and Conclusion

The overabundance of misinformation and rumors about the COVID-19 pandemic on online platforms has allowed misleading information to be spread as quickly as the virus itself. Moreover, fake news has significantly prevented an effective response to the virus. In this study, we provided a highly accurate fake news detection model and investigated the content differences between real and fake reviews.

Specifically, we found that the Convolutional neural networks (CNN) with the word2vec model are best-performing for detecting fake tweets news. Overall, our fake news detection model outperforms the traditional machine learning techniques with a 93,1% accuracy. However, we also admit the limitations of the deep learning model results, which cannot explain the difference between fake and real news. Therefore, to overcome such limitations, we applied topic modeling and linguistic analysis to explain the results with respect to the content differences between real and fake news.

Our topic modeling results show that Politics and Government services dimensions are more common in fake news topics. This finding confirms extant studies that argue issues related to politics are often objects of opinion manipulation (e.g., Zhang et al., 2019). The new finding from our study is that dimensions are relatively evenly distributed among the topics in real news compared to the dimensions in fake tweets news. For example, dimensions of Health screening (HS), Testing & treatment (TT), and Information Management (IM) often appear in real news. For further information, we provide word clouds of real and fake teets news in <Figure 3>. In the real news figure (<Figure 3(a)>), we can see that general terms related to COVID-19 are more common such as "case", "currently", "reported", "currently", etc. However, in fake news (<Figure 3(b)>), politics-related terms ("Politically", "Obama", "Administration", "Trump", etc) occur more often.



(a) Word Cloud of Real News

(b) Word Cloud of Fake News

<Figure 3> Word Cloud

Based on the linguistic analysis in our research, we found that real news represents a higher degree of text hierarchical thinking patterns and logic, more genuine feelings, and more positive emotional tones than fake news. However, we did not find a significant difference in social status and confidence in the written text of fake and real news authors. Huerta et al. (2021) state that after the COVID-19 outbreak, users' tweets have increased for risk and health issues. In this study, we focused on news tweets related to COVID-19 and found a significant difference between fake and real news. In fake news cases, the discussion about risk and health is higher expressed than in real news. Also, the level of social connection in fake news is higher than in real news.

Our study makes several theoretical contributions. First, we introduced a robust model with higher accuracy than extant models to detect fake news related to the COVID-19 Infodemic. Second, we explicated the content difference between real and fake news by combining the results of topic modeling and linguistic analysis. We found that fake news is more related to politics and government services topics, with a lower degree of the text hierarchical thinking patterns.

Furthermore, this study makes practical contributions. Our findings may help practitioners and social network users understand the features of fake news related to the COVID-19 Infodemic and improve the content that distinguishes real news from fake news. For example, we found that post-covid fake news tweets are more about risk and health than real news. Thus, online social networks and users may want to be more careful with health-related information and double-check if the information is real or fake.

This study has some limitations, which are good topics for further research avenues. First, we collected the labeled fake news data from Patwa et al. (2020) study, which may have some patterns unique to the dataset concerning fake news. Therefore, further research can use different datasets to validate the generalizability of our findings. Second, we calculated the optimal topic number through 5-fold cross-validation and used LDA for topic modeling, making our findings specific and narrow. Third, in this study, content analysis and ML-based detection were separated; however, as confirmed by several previous studies, future research may attempt to combine the two separate approaches by using the main content analysis results as independent variables of the fake news detection model. Moreover, rather than using content analysis to explain the difference between fake and real news and to examine the characteristics of fake news, future research may attempt to apply XAI. Finally, future research may use other different topic modeling techniques to see how accuracy can change and make a better model.

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<Appendix> The Results of K Perplexity by Number of Topics for Real and Fake News

	K-perplexity	
Topic Number	Real News	Fake News
2	1684.364	3769.221
5	1418.38	3281.904
10	1239.173	3010.392
15	1167.534	2920.221
20	1131.612	**2889.276**
25	1118.292	2898.96
30	**1110.527**	2931.303
35	1113.294	2975.717
40	1118.609	3019.04
45	1133.516	3080.217
50	1148.011	3129.119
60	1180.071	3233.767
70	1216.928	3337.859
80	1251.661	3436.054
90	1285.134	3519.922
100	1308.068	3614.204

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