Using Fuzzy Clustering with Deep Learning Models for Detection of COVID-19 Disinformation

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Since the beginning of 2020, the COVID-19 pandemic has killed millions of people around the world, leading to a worldwide panic that has fueled the rapid and widespread dissemination of COVID-19-related disinformation on social media. The phenomenon, described by the World Health Organization (WHO) as an "indodemic" presents a serious challenge to governments and public health authorities, but the spread of misinformation has made human detection less efficient than the rate of spread. While there have been many studies developing automated detection techniques for COVID-19 fake news, the results often refer to high accuracy but rarely to model detection time. This research uses fuzzy theory to extract features and uses multiple deep learning model frameworks to detect Chinese and English COVID-19 misinformation. With the reduction of text features, the detection time of the model is significantly reduced, and the model accuracy does not drop excessively. This study designs two different feature extraction methods based on fuzzy classification and compares the results with different deep learning models. BiLSTM was found to provide the best detection results for COVID-19 misinformation by directly using deep learning models, with 99% accuracy in English and 86% accuracy in Chinese. Applying fuzzy clustering to English COVID-19 fake news data features maintains 99% accuracy while reducing detection time by 10%. For Chinese misinformation, detection time is reduced by 15% at the cost of an 8% drop in accuracy.

CCS Concepts: **•Computing methodologies → Vagueness and fuzzy logic; • Computing methodologies → Natural language processing**

Additional Keywords and Phrases: Misinformation detection, COVID-19, Deep learning model, Fuzzy clustering

1 INTRODUCTION

Recently, online social media (OSM) networks have become an important medium of communication, such as Twitter or Weibo. As social media platforms become more popular, users are starting to use online social media to get information rather than from traditional media. This accelerates the dissemination of information, but it also deepens social divisions [1] Due to the unregulated nature of social software, anyone can share and receive any information, which makes fake news extremely influential. People with ulterior motives often spread fake news or misinformation to gain economic or political benefits.

In 2020, the coronavirus disease (COVID-19) spread rapidly and caused large-scale infections. As of April 30, 2022, there were 511.46 million confirmed cases worldwide and 6.24 million deaths [2]. With the growth of the epidemic, many fake news about the COVID-19 has grown rapidly and spread on online social media, causing panic in the society and hatred in the hearts with the people. The World Health Organization calls this phenomenon as "infodemic" [3]. This infodemic misinformation has deepened people's misunderstanding of the COVID-19 epidemic and their distrust of epidemic prevention policies,

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and triggered a series of individual reactions in the society, seriously hindering the society's prevention and control of the epidemic.

Unlike previous information dissemination only through word of mouth, the identification of fake news in online social networks by experts is often labor-intensive and inefficient [4]. But at the same time, to cope with the growth of fake news detection technology, the writing of fake news has become more and more refined, not only the topics are aimed at the fields of concern, but also the same words are not used repeatedly in the writing. People's perception of fake news is very subjective, so there will be important issue, such as how to detect fake news, how to clearly explain where the error is and what evidence can be provided to confront fake news. Fact-checking organizations have been established by many governments and civil society organizations to eliminate fake news [5], such as PolitiFact and Agence France-Presse (AFP) Fact Check are well-known fact-checked organizations. These organizations employ professional fact-checkers to assess the validity of submitted information. When they find that the information contains error or misinformation, they will describe the wrong part in detail.

The volume of fake news centered on COVID-19 has become a common form of information on social media. Such reporting may further magnify the hostility and hatred that already exists in the society and cause more social problems [6]. The current detection work relies heavily on relevant experts first, which can effectively limit the appearance of conflicting opinions and avoid multiple annotations for a single item, thereby reducing the difficulty of training machine learning models or deep learning models, Some research shows the using machine learning model and deep learning model to detect fake news about COVID-19 [7][8][9]. However, training deep learning models is time-intensive given the large number of related text features. Given the dynamic and quickly changing nature of misinformation, it is crucial to develop faster detection methods that use fewer features.

The paper proposes to combine fuzzy logic and deep learning models to detect COVID-19 misinformation, use fuzzy clustering to reduce the number of redundant features in the model, and use three classic deep learning models for learning and detecting fake news. With a large amount of real and fake news texts, it can ensure that the model can distinguish real and fake news through key features, thus forming a detection model that not only has high accuracy but also maintains high computational efficiency. It is expected that the generation of such models can effectively reduce the social impact of the current fake news epidemic.

The structure of this study is as follows. Section 2 discusses related literature. Section 3 describes the specific research framework, including the preprocessing methods of the research, the introduction of the models used in the research, and the model evaluation metrics. Section 4 discusses data description and experimental design. Section 5 discusses the findings and discussion, and Section 6 describes the conclusions.

2 LITERATURE REVIEW

2.1 Fake News on the Web

In general, fake news has no consensus definition, but there is a narrow definition can be seems as rumors, false stories and unsubstantiated misinformation spread for political or economic benefits [10], it can be mainly classified as "disinformation" or "misinformation", disinformation usually refers to incitement rumors that are deliberately created for private gain [10], while misinformation refers to rumors that have not been confirmed by experts [11].

The most common categories of fake news on the web, as mentioned in past research [12], although the research has mentioned most of the fake news categories, but there are other mechanisms that influence fake news in online social media, there are two main factors in the audience's part of receiving fake news: (1) Naive realism: audiences are more inclined to believe that their view of events is correct , while others who hold the opposite opinion are seen as biased, unclear and ignorant [13], (2) Confirmation bias: The audience is relatively receptive to information about their existing point of view [14]. This is due to these cognitive biases inherent in human nature, and fake news that shares the same opinion as the audience is often perceived as real. Moreover, once the audience receives too much fake news of the same opinion, it will produce wrong perceptions, and it will be difficult to receive information from other opinions in the future. According to research, if you try to correct misinformation through real information, not only does not help reduce the user's cognitive misunderstanding, but sometimes even makes the audience more convinced of fake news, especially under the influence of the echo chamber effect [15].

Social media provides audiences with a new form of information creation and reception. The information search and reception process are changing from an indirect type (such as by journalists) to a more direct type [16]. As information appears in summary form on social media homepages, user selectively click on certain types of news, amplifying the spread of fake news. Therefore, it is easy for users on social media to gather users who hold the same opinion to form groups, and then users will spread certain types of information in their respective groups, and form fixed and strong opinions. Thus creating an echo chamber effect. The echo chamber effect facilitates the process of users spreading and believing fake news due to the following factors [17]: (1) social credibility, which means that users are more likely to share information if other users also believe the source is credible, especially when there is insufficient evidence to prove the authenticity of the source. (2) frequency heuristics, which means that users may naturally believe information they hear often, even if it is fake news. Studies have shown that each increase in user exposure to an idea is sufficient for a user to rate an idea positively [18][19], and in echo chambers, users continue to share and disseminate the same messages. Finally, the echo chamber effect creates so-called homogeneous communities. Studies have shown that homogeneous communities become the main carrier of information dissemination and at the same time further strengthen polarization [20].

2.2 COVID-19 Fake News

With the emergence of the COVID-19 pandemic, the rapid generation and dissemination of fake news about COVID-19, there has been a massive increase in COVID-19-related fake news detected by fact-checking organizations [21]. The fact-check report found that much of the fake news was not entirely fictional, but pieced together from a variety of factual sources, but which went through various rhetorical and editing techniques that resulted in an overall misinformation, such as adding fabricated title and images into real information. Thereby significantly improving the credibility of the information [21].

Fake news about COVID-19 is mainly spread on social media platforms. The platforms has already filtered fake news through the review mechanism, but the speed of review cannot keep up with the speed of production and dissemination [22], so that there are still many misinformation on these social platforms, and the sharing and convenience of social platforms accelerates the spread of these fake news [23]. Past research collated categories of COVID-19 fake news that emerged on social platforms [12].

Table 1: Types of COVID-19 related fake news [12]

Category	Description
Home remedies	What's the secret recipe for a quick cure for a COVID-19 infection
Transmission prevention	What's the secret recipe for accurate prevention of COVID-19 infection
Uncontrolled transmission	Which regions or celebrities have been hit by COVID-19
Virus origins	How is the COVID-19 outbreak?
Virus characteristics	Symptoms you may experience after contracting COVID-19
Medicines and vaccines	Effectiveness of medicines and vaccines related to COVID-19
Discriminatory views	Hostility towards specific ethnic groups due to the pandemic
Anti-pandemic policy and material assistance	Misinformation about epidemic prevention policies and supplies
Conspiracy theories	Conspiracy to make unsubstantiated inferences based on scientific data

2.3 Fuzzy Clustering

Clustering methods for high-dimensional data has always been an important topic in the fields of data mining, machine learning, and computer vision [24][25]. When collecting data, it is often faced with the task of clustering the data during data preprocessing. Since it is difficult to obtain label information for high-dimensional data, clustering algorithms are proposed to solve the problem. Fuzzy C-means (FCM) clustering method is an important branch of clustering algorithms. By assigning each sample to a cluster with a high degree of relationship with itself, FCM clustering aims to soft group the samples and has more advantages than hard clustering [26][27].

In general, FCM clustering algorithms can be divided into two categories according to the dimension of features. First is to directly perform fuzzy clustering on the original multidimensional data. Second, is called projected FCM clustering, it will learns fuzzy memberships in low-dimensional spaces. For the first FCM algorithm, all features provide the same weight basis for cluster membership. In recent years, many research have been devoted to utilizing fuzzy theory and methods to improve the performance of FCM clustering [28], the research had proposed new FCM algorithm in which FCM and possibly K-Means are combined with looser constraints on clustering samples [29], the research redefine the text encoding step through the learning process of fuzzy membership between samples and cluster groups, and a fuzzy affinity lasso objective function is introduced to maintain the local affinity relationship between membership vectors [30]. Based on an entropy-type penalty term, some research proposed an enhanced FCM clustering method in which not only the clustering results are insensitive to initialization, and also the number of clusters is learned rather than predefined [31]. Unlike traditional FCM methods that can only handle Gaussian distributed data, the research proposed a K-Multiple-Means algorithm to divide each cluster into multiple sub-clusters to accommodate the complex distribution of the data [32].

To improve the effect of noise and outliers on clustering. The research proposed to reduce the sensitivity of FCM to noise by using two different weights, cluster-independent weight and cluster-dependent weight [33]. The research has developed a joint model of FCM and non-negative spectral clustering based on an adaptive loss function to enhance the processing of outliers by the clustering model [34].

The FCM research can achieve good performance, but most of the research perform fuzzy clustering in the original vector space, treat all features in equally weight basis, and ignore the differences in features. As a result, irrelevant features of high-dimensional data may degrade performance. The traditional method to deal with the problem is to first reduce the dimensionality of the data, and then perform fuzzy clustering in the low-dimensional space. However, this separates dimensionality reduction and fuzzy clustering into two separate processes. The features learned by this method may not be optimal for fuzzy tasks [35]. The research figures out that the fuzzy index plays an important role in determining the fuzzy membership, and proposed a projective FCM algorithm based on discriminative embedding, this method improves clustering results by fuzzy membership and automatically updated projection matrices [36]. To maximize the separation resolution of data in low-dimensional space. Since previous FCM methods ignore the local feature structure of the data, the research to enhance the ability of FCM by keeping the local feature structure of the data in a low-dimensional vector space [37].

Regardless of the projected FCM clustering algorithm, the effect of the outlier on the cluster model learning is ignored. Furthermore, dimensionality reduction leads to loss of information, which reduces clustering performance. The research proposes a novel projected FCM clustering method to solve and get better performance [38].

2.4 Detecting Fake News

Recently, fake news has spread rapidly on social media, and the task of prediction has become more challenge. Most previous research using machine learning and deep learning model to seek the differentiate between fake and true information data., shown as Fig. 1.

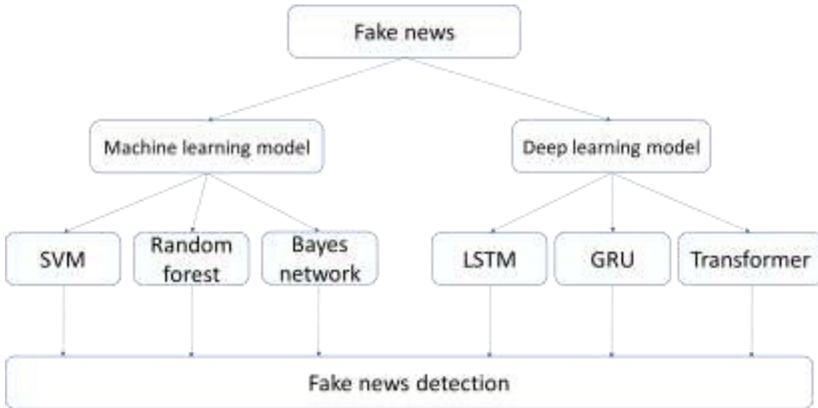

Figure 1 The commonly method of fake news detection [12]

The machine learning methods are often used in detect fake news, most of them are the supervised. Support vector machine (SVM) is the most common method in the machine learning, there are some research used SVM to detect fake news and compare with other machine learning methods, resulting shows well performed on F1-score [39]. The research uses various machine learning approach to detect fake news, and the SVM with TF-IDF feature extraction method get the best performance [40]. The research has proposed a model that utilizes semantic analysis combined with SVM and Naive Bayes techniques in machine learning to detect fake news and achieve good results [41]. The research proposes a new algorithm called DETECTIVE to detect fake news, which operates using Bayesian theory. To verify the efficacy of the study, a post-test method was also used [42]. The research detecting political misinformation on social media with tern frequency-inverse document frequency (TF- IDF) as feature extraction method and uses random forests as detection model, resulting in accuracy rates achieved 85% [43]. The research using random forest to classify the misinformation relative to the field of medical on the Snopes fact-checking website, the accuracy achieves 96 % [44]

Deep learning is also often used for fake news detection, and many classic models are widely used. The research using deep learning model to detect four fake news datasets and the research uses back-translation method to deal with the problem of data imbalance [45]. The research building models using LSTM neural networks. Besides neural networks, Glove word embeddings are also used for text vector representation. And the N-grams concept uses to enhance the performance of the model. The comparative analysis with multiple other fake news detection research. Resulting in achieves 99.88% accuracy [46]. The research team proposed a web framework called Grover to detect fake news by collecting and detecting fake news from the 5,000 most visited news sites in Google News. The model framework finally discriminates human-written news from AI-written news with very high accuracy in the results [47].

Transformer based deep learning have been applied into fake news detection, such as bidirectional encoder representation technology (BERT), XLNET, etc. The research utilizes the XLNet model to build a comprehensive detection framework with over 80% accuracy on two classic fake news datasets [48]. The research proposes a framework that utilizes pretrained BERT and three parallel 1d-CNN models with different kernel size convolutional layers using different filters to enhance model learning. Compared with other advanced deep learning model, it achieves high accuracy on the fake news classification task [49]. The research using BERT model on sarcasm detection focuses on context-based feature techniques for sarcasm recognition using deep learning, Transformer, and traditional machine learning models on different datasets, the result has been indicating that BERT performs well in learning contextual features from data [50]. The research had proposed a new fake news detection framework. It constructs by Transformer model and integrates additional features related to fake news to make predictions. At the same time, to reduce the detection time, the research also proposes an effective labeling method to solve the problem of data unlabeled [51].

The appearance of fake news is not always in English language, and recently more research have been focused on detecting fake news not in English language. The research shows even if the news are not in English language, the fake news detection model also provide good results [52]. The research has compared different text detection models in Indian language, and finally found that the LSTM method can achieve an accuracy of 92.36% [53].

Although in recently, no relevant literature on the use of fuzzy theory to enhance efficacy in fake news detection research, there are many research used in semantic analysis, the research have carried out sentiment analysis on product reviews. To reduce the interference of various language features on sentiment analysis, the study uses fuzzy functions to enhance the feature extraction of the model. The results show that sentiment analysis using fuzzy logic performs very well [54]. The research use sentiment analysis in the field of e-commerce. To improve the problems faced by the past product recommendation systems, the research uses fuzzy rules combined with the results provided by recommender systems, and additionally based on the user's search history to provide more accurate decisions [55]. The research using sentiment analysis on product reviews. The soft grouping methods such as fuzzy logic used in research, relevant comments and wordings are collected into the model as the basis for future research on brand management and sales [56].

In addition to the physical pain caused by the COVID-19 epidemic, fake news related to the COVID-19 epidemic will blame and increase hostility to certain groups through the Internet. The "infodemic" increases social division and anxiety, which has aroused the concern of experts and government units in various countries. Therefore, many researches have been proposed on how to deal with and detect fake news. The research proposed a hybrid deep learning model framework to detect fake news related to COVID-19 and compared with existing models. For comparison, the results are better than the existing single model [57]. The research has proposed a new model and compare the performance with the other Transformer based model on COVID-19 fake news detection. resulting in highest accuracy [58]. The research has proposed a method to analyze information related to the COVID-19 in online social media which using different Transformer based models to detect misinformation, resulting in 98.55% on F1-score [59]. The research had construct new deep learning model with the transformer-based model, to test the model performance, the research used the model to detect tweets related to COVID-19, and the results showed that the model achieved high accuracy and f1-score [60]. but the above research have largely focused on English-language news data. Another research group has collected the COVID-19 new data in

Hindi and Bengali language from Indian social media, and then using a BERT model to detect the news data and achieve high F1-score of 89% [61]. The research group has applied various machine learning and deep learning models to multilingual datasets and obtained very good results in terms of accuracy and F1 score [62]. For the research on COVID-19 detection in Chinese language, the research collected fake news data related to COVID-19 from Chinese social media platforms, and then collated the dataset after discussions with professionals. After the sentence is translated into English, the deep learning model is used for detection, and resulting in achieves a good accuracy [63]. The research collected Chinese-language fake news related to COVID-19 from Chinese social media and public datasets on the Internet, and to confirm the integrity of the data, the research compared news headlines and articles related to COVID-19 appearing in English websites, in the detection part, the accuracy of the proposed model has improved a lot compared with previous research [64].

In summary, the detection of COVID-19 fake news includes methods such as machine learning and deep learning, and the purpose of most studies is to seek breakthroughs in various detection indicators. However, few studies use fuzzy theory in feature extraction to reduce the number of parameters required by the model and reduce the model computing time.

3 RESEARCH METHODS

3.1 News Content Preprocessing

In the research, deep learning models detect real and fake news, but items in the news dataset are not marked as "true" or "fake" category at the outset, it is marked in detailed items. The research according to previous research [12] to convert the detailed items to true/fake categories, In these categories, except the most common label as true and fake, there are many additional categories that are highly correlated with one of the true or fake label, such as explanatory, misleading, etc. but some of the data will be similar to both categories at the same time, then these data will be excluded from the research, such as partly true/fake, half true/fake, mixture, etc.

3.2 Word Embeddings

In the field of natural language processing (NLP), since the model cannot directly use the original text data to discriminate, it is necessary to convert the original text data into Word-embeddings to enable the deep learning model to process text data. Word embeddings can be considered as converting words in article sentences into numbers coding to represents the current word in the deep learning model. There are many conversion methods, such as word frequency, thesaurus, and Word2Vec. The research refers to the past research on the conversion method, converts the words of the data according to the order of their frequency of occurrence, and sets a threshold to select the most common words. For example, there is a sentence shown as Fig. 2. First, the frequency of word occurrences is sorted, and each word is converted into each word embedding according to the sorting. then when converting the text vectors, if the threshold is set to 5000, only the top 5000 common words can be converted, and other words are converted to 0, which means that the deep learning model only uses key features to do the detection.

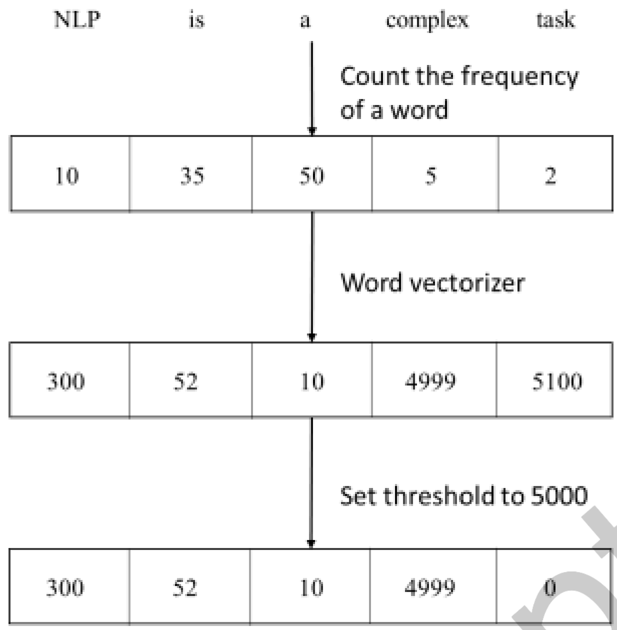

Figure 2 Word frequency sequence word embeddings

A uniform-length sentence vector matrix is the required input format for most text-related detection models However, since the sentence lengths of different types of data are different, a fixed length of the sentence vector matrix corresponding to the input model is usually set, so that the data can be completely input into the model for calculation. When the sentence length is less than the model settings, 0 will be added to the vector matrix for the insufficient part to ensure that each input in the same data is a matrix of sentence vectors of the same length.

3.3 Fuzzy Clustering

Clustering is an important topic in machine learning, and applies rules to aggregate large amounts of data. Common clustering algorithms such as k-means, SOM, etc., only assign each data to a single group, a method called hard clustering. Given a large and extremely diverse data set, this approach will have a very good classification effect. However, in many tasks, data collection can be time-intensive and the resulting raw data will contain lots of noise, thus greatly reducing classification performance. Soft clustering was proposed to address issues such as data collection, data patterns or noise processing, the most famous implementation of which is the Fuzzy C-Means (FCM) algorithm. Unlike hard clustering, this approach indicates the degree to which the cluster result can represent the data, and express the probability of the data belonging to each cluster, rather than directly classifying the data into a certain cluster. Thus, soft clustering has a higher tolerance for noise in the data [65]. Hard and soft clustering are compared in Fig. 3.

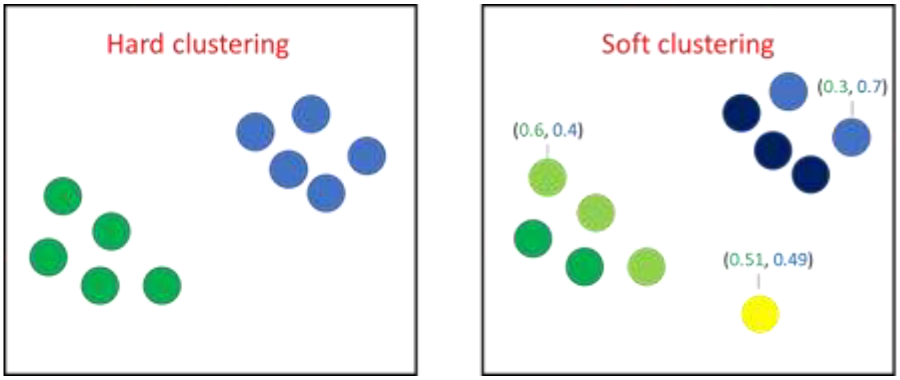

Figure 3 Comparison diagram of hard grouping and soft grouping

The FCM algorithm is similar to the k-means clustering algorithm, but FCM allows data to belong to multiple clusters to varying degrees, while k-means classifies data into a single cluster. Fig. 4 illustrates the FCM clustering method.

The objective function of FCM is shown in Eq.1. The objective of FCM is to minimize the objective function and calculate the degree of correlation between the data and each cluster [65].

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^{m} \, ||x_i - c_j||^2 \tag{1}$$

In the process of repeatedly calculating the optimization objective function, fuzzy clustering will continuously update the degree of data aggregation (u_{ij}) and the cluster center point (c_j), as shown in Eq.2 and 3 [65].

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\left(\frac{2}{m-1}\right)}} \tag{2}$$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} * x_i}{\sum_{i=1}^{N} u_{ij}^{m}} \tag{3}$$

3.4 Research Model

The proposed detection model according to the past research, using deep learning models to detect fake news in Chinese and English related to COVID-19. First, the data set is preprocessed, including normalizing the content and labels, removing stop words and URLs that appear in the data, and then convert words into Word-embeddings. When conversion to a vector, text feature extraction uses the word frequency threshold and fuzzy clustering to identify key features. Then use models like Long Short Time Memory, Gate Recurrent Unit, and Bidirectional Long Short Time Memory for detection. Finally, the model performance is evaluated through the model's evaluation metrics. The overall architecture is shown in Fig. 4, and the pseudocode of the proposed model is shown in Table 2.

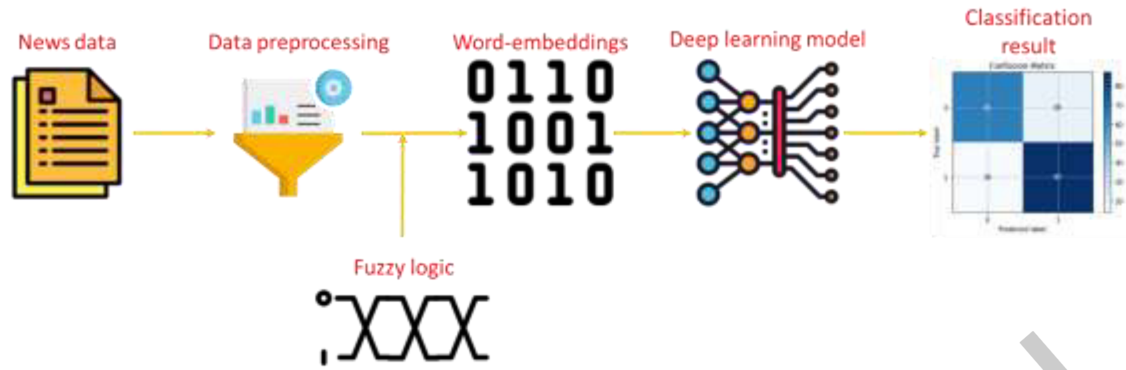

Figure 4 Research architecture

Table 2: pseudo-code of the proposed model

Fake news detection based on deep learning model
Input: COVID-19 fake news data in English and Chinese language
Text data normalization
If text has stop words or URL:
Remove stop words and URL
Convert the news text data to word-embeddings
If the experiments setting is baseline model:
Set threshold as 5000
Else if the experiments setting is fuzzy residual features:
Use the fuzzy method to get the key feature of the news data, and the maximum number is 5000, and if it is less than 5000, subsequent supplements will not be performed
Else if the experiments setting is fuzzy padding features:
Use the fuzzy method to get the key feature of the news data, and the maximum number is 5000, and if it is less than 5000, subsequent supplements will be performed
Using the above settings to filter features, and convert unqualified features to 0
Put the training data into the deep learning model to train the model
Put the testing data into the deep learning model to predict the result
Using the evaluation metrics to evaluate the model performance
Output: The model prediction result and each model's evaluation metrics

3.4.1 Long Short Term Memory

Long Short-Term Memory (LSTM) is a sequential deep learning model that is widely used in the field of natural language processing. Evolved from a Recurrent Neural Network (RNN), the model uses the current word or sentence as an input feature to predict the next output. This method can effectively enhance the output of the model according to the context relationship, but as the amount of data increases and the length of the sentence increases, the relationship between the past feature and the current word will become smaller and smaller after each training. Finally, become zero, this phenomenon is called "gradient disappear". But this phenomenon ignores a person's ability to remember specific events. In order to improve the memory problem of RNN, LSTM increases long-term dependencies by adding memory functions to the model [66].

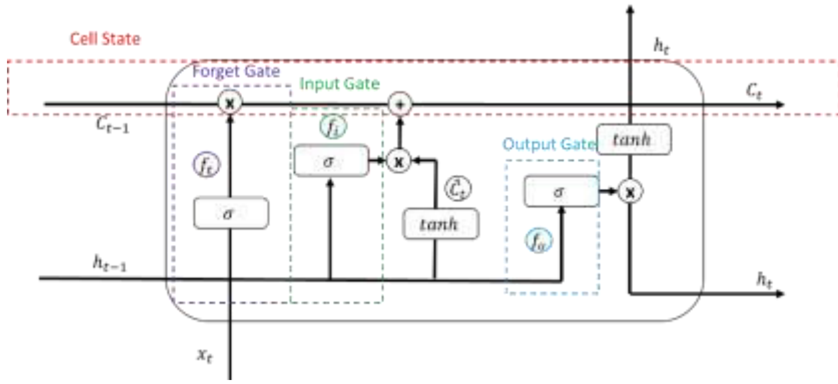

Figure 5 LSTM diagram [66]

Fig. 5 shows the LSTM cell. forget gates, input gates and output gates are added to the model to allow the model to determine the use of access and memory. In addition to these three gates, the LSTM state also includes a state update as the basis for updating the memory unit.

- ✓ Input gate: The function of the input gate is to decide whether the current input is to be added to the long-term memory of the model.
- ✓ Output gate: The function of the output gate is to decide whether the current input is to be used as the output of the feature training model.
- ✓ Forget gate: The function of the forgetting gate is to evaluate the correlation between the current input and the long-term memory of the model to decide whether to add the current input to the long-term memory or discard it.

When the data enters the LSTM unit, it passes through the forget gate and the input gate to determine the correlation between the current input and the long-term memory, and to adjust the content of the long-term memory. The calculation method is shown in Eq. 4 and 5.

$$f_t = \sigma\left(W_f . [h_{t-1}, x_t] + b_f\right) \tag{4}$$

$$f_i = \sigma(W_i . [h_{t-1}, x_t] + b_i) \tag{5}$$

When the data passes through the forget gate and the input gate, the model uses the cell state to determine whether the long-term memory should be updated. The operation method is shown in Eq. 6.

$$C_t = f_t . C_{t-1} + i_t . tanh(W_c . [h_{t-1}, x_t] + b_c) \tag{6}$$

After the data is calculated in the LSTM unit, the model output is made according to the output gate weights and model parameters. The calculation method is shown in Eq. 7 and 8.

$$f_o = \sigma(W_o . [h_{t-1}, x_t] + b_o) \tag{7}$$

$$h_t = o_t * tanh(C_t) \tag{8}$$

After the current input becomes the current output after passing through the LSTM, it can be incorporated into the long-term memory state in the LSTM unit, or become part of the input to the next LSTM unit [66].

3.4.2 Bidirectional LSTM

Bidirectional LSTM Simultaneous forward-predicted LSTM model and backward-predicted LSTM model. The purpose of the two-way is that because the association between the contextual semantic words of the sentence can not only predict the future through the past features, but also predict the past features from the future state, so first predict through the forward LSTM, and then carry out backward prediction. After the operation is completed, the results of the two LSTMs are integrated to provide better detection performance [67]. Fig. 6 shows the model architecture diagram of BiLSTM.

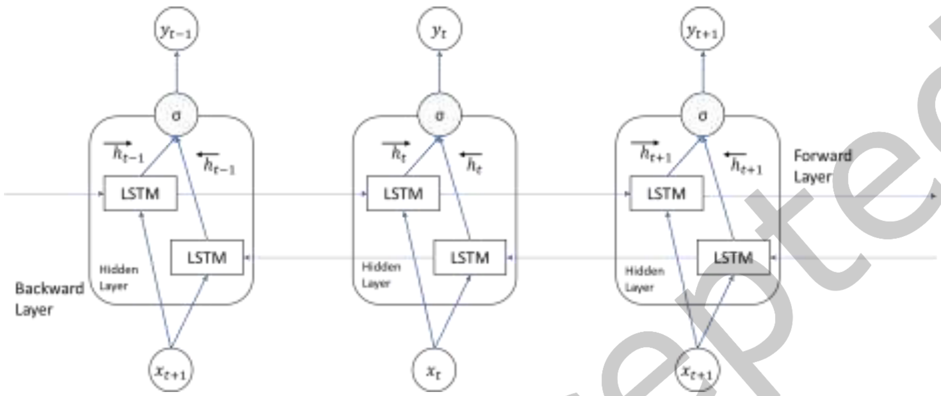

Figure 6 Bidirectional LSTM architecture [67]

3.4.3 Gated recurrent unit

Although the use of the LSTM model effectively improves the generation of the gradient vanishing problem, with the increase of a large amount of data, the operation speed of the LSTM will still be significantly affected. Therefore, some studies have proposed another gated recurrent unit (GRU) model also based on the RNN-based concept [68], which integrates the forgetting gate and the input gate in the LSTM model to form an update gate. And update the model calculation method to reduce the number of parameters and calculation time. Fig. 7 shows the GRU unit.

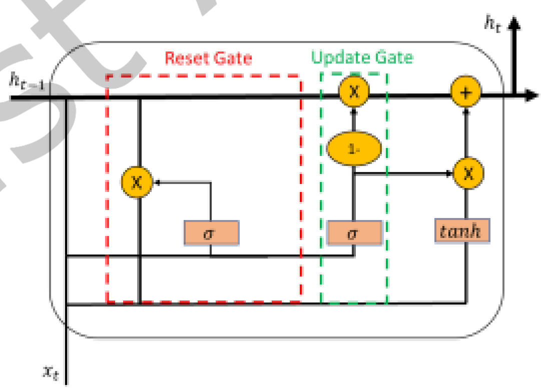

Figure 7 GRU unit diagram [68]

When data enters the GRU, it will go through the update gate, the update gate is used to determine the correlation between the current word and the previous long-term memory, and to decide whether to update the model's long-term memory. The operation method is shown in Eq. 9

$$Z_t = \sigma(W_Z.[h_{t-1}, x_t]) \tag{9}$$

When the data passes through the update gate in the GRU unit, the reset gate is used to determine the correlation between the current sentence and the previous long-term memory, and to generate an update for long-term memory. The calculation method is shown in Eq. 10 and 11.

$$r_t = \sigma(W_r.[h_{t-1}, x_t]) \tag{10}$$

$$\tilde{h}_t = tanh(W.[r_t * h_{t-1}, x_t]) \tag{11}$$

After the update gate and reset gate in the GRU unit, the output proceeds according to the weights and parameters of the previous operation. The operation method is shown in Eq.12.

$$h_t = (1 - Z_t) * h_{t-1} + Z_t * \tilde{h}_t \tag{12}$$

After the current input passes through the GRU and becomes the current output, it can becomes the long-term memory incorporated into the GRU unit, or as part of the input of the next GRU unit.

3.5 Evaluation Metrics

The research evaluates the classification performance of the deep learning model from various evaluation indicators.

Table 3 is the confusion matrix, marking the variables in the definition of each indicator.

Table 3: Confusion matrix

	Actual Positive	**Actual Negative**
Predicted Positive	Truth Positive (TP)	False Positive (FP)
Predicted Negative	False Negative (FN)	Truth Negative (TN)

The research uses the following indicators to test the model performance, as shown in Eq.13, 14, 15,16.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{13}$$

$$Recall = \frac{TP}{TP+FN} \tag{14}$$

$$Precision = \frac{TP}{TP+FP} \tag{15}$$

$$F1\text{-}score = 2 * \frac{precision * recall}{precision + recall} \quad (16)$$

4 EXPERIMENTAL DESIGN

4.1 Data Collection

The English-language fake news related to COVID-19 is taken from the FakeCovid dataset [69], which collects fact-checking reports on COVID-19 from national fact-checking websites in 2020, each sourced by the International Federation of Fact-Checking Organizations (IFCN) certification, fields for datasets. As shown in Table 4, there are 7686 pairs of samples in the dataset. A total of 5,041 records were collected after sorting the data through the data pre-processing method described in Section 3.

Table 4: FakeCovid data fields [69]

Data Field	Description
Fact-checked article	IFCN (Poynter and Snopes) collects weekly fact-checking reports from lists provided by each fact-checking website.
Fact-checked reference material	Fact-checked report reference link provided by IFCN.
Title	News titles collected by IFCN (Poynter and Snopes), including English translations if the original title is not in English, can also be regarded as abstracts.
Release date	Date the fact-checked article was collected and published by IFCN.
Article content	News content, country of origin, and category data originally crawled by web crawlers.
Check category	IFCN fact-checking result.
Social network link	A lot of fake news spreads on social media, so provides the link if the source is from social media.
Fact check website	Fact-checking sources, including which fact-checking agency the report was verified by, and a link to the verification report.
Country/region	The country or region where fake news spreads.
Fake news category	Topics of fake news (e.g., source of infection, disease state, treatment, etc.).
Language	Publishing language of the checked report.

Real English language COVID-19 related news were collected from the GitHub COVID-19-News-Corpus [70], especially the covid-19 English news published by internationally renowned news media from April 19, 2020 to September 3, 2020, with a total sample of 5112 items.

Chinese COVID-19-related fake news comes from Cofacts' true and fake open dataset [71] and CHECKED open dataset [72]. The Cofacts' dataset includes misinformation spread on social media via the LINE chatbot. The misinformation has been mentioned by crowdsourcing and labeled as fake news by experts, and the program integrates public and government resources to combat rumors, misinformation and fake news on the internet. The CHECKED dataset collects misinformation about COVID-19 found on Chinese Weibo, including post content, timing, and responses, as of November 7, 2020. A total of 958 pairs of fake news were used in the research.

The real news in Chinese on COVID-19 is mainly sourced from major news websites in Taiwan, and the method of acquisition is to use web crawlers. Since various websites may report the same content, a total of 1300 document sets were compiled for this research.

Table 5 shows the features and content of the Chinese and English datasets.

Table 5: Features and content of the Chinese and English datasets [12]

	English COVID-19 fake news datasets [69][70]	Chinese COVID-19 fake news datasets [71][72]
Data features	A collection of COVID-19 related news posted on public media and online social media in English-speaking countries of the world. The source of the real news dataset is the COVID-19 news reported by well-known foreign media, and the source of the fake news dataset is the inspection reports of various websites on COVID-19 fake news collected by international fact-checking agencies.	Gather news about COVID-19 posted in Taiwanese media and online social media. The real news data comes from news released by well-known media in Taiwan. The sources of fake news data are the fake news data about COVID-19 in the Cofacts public dataset and the CHECKED public dataset.
Data contents	The dataset includes news headlines, news sources, news articles, verification agencies, verification labels, etc. However, the content of the news article field in the fake news dataset is each fact-check report, not the news article been detected.	The dataset includes news headlines, news sources, news articles, verification agencies, verification labels, etc.

4.2 Data Analysis

Since the source of the content fields of the English Fake News Dataset is fact-checking reports provided by various fact-checking organizations, the content of the data may be presented in a language other than English. International Federation of Fact-Checking Organizations (IFCN) summarizes the articles and translates them into English, the research uses English abstracts as English fake news data. In the English COVID-19 real dataset, the dataset includes news title and content descriptions, the research uses news content descriptions as English real news data.

In terms of Chinese fake news datasets, the Cofacts' true and false open datasets only provides content description of the article and the CHECKED open dataset also provides content descriptions of the article. In terms of Chinese real news datasets, the real news data obtained through the web crawler contains the title and content description. To allow the model to fully learn the text features, the content description is used as the real and fake data input to the model.

To compare the impact of different text feature extraction methods on the model, the research designs three experiments: the first uses the original article text features, the second uses the fuzzy residual feature method, and the third is to use the fuzzy feature padding method.

4.3 Text Feature Extraction

The research divides text feature extraction into 3 modes, the first is the original word frequency mode, which calculates the frequency of each word in the data and sorts them using the threshold to extract key features, such that the subsequent deep learning model can perform misinformation detection.

The remaining two modes use the fuzzy clustering method to classify the part of speech for each word frequency feature to identify more important features that affect the determination of misinformation. The specific method is described in Section 3. Following fuzzy clustering, some features are excluded because, so some data lack effective judgment features for text extraction, and thus the model regards them as invalid data model and are deleted. Table 6 summarizes the total counts.

Table 6 : Summary of Data Characteristics and Frequency Counts

Feature Description	English COVID-19 Data	Chinese COVID-19 Data
Total number of data features	67211	21659
Total data features following Fuzzy C-means (features with impact >0.6)	66211	17413
Number of residual features following Fuzzy C-means (Total data features intersected by features extracted with a threshold of 5000, and total data features following Fuzzy C-means)	4049	1137
Total number of data	Train:9842 Test:2461	Train:1580 Test:678
Number of residual data following Fuzzy C-means	Train:8614 Test:2140	Train:1098 Test:484
Number of data features filled following Fuzzy C-means	Train:8805 Test:2188	Train:1405 Test:590

In the research, two thresholds are set under the updated features. The first method is to use the fuzzy residual features, after excluding the features with influence <0.6 from the original total word frequency features, and the key found by the first method word frequency threshold The features are intersected, and the intersection features are retained for subsequent misinformation detection. The operation method is shown in Fig. 8

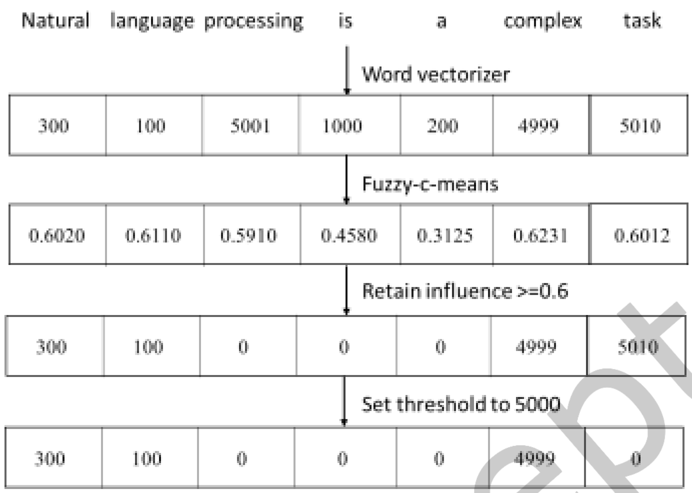

Figure 8 Fuzzy C-means residual function operations

The second mode uses padding features. After excluding the features with an impact <0.6 from the original total word frequency features, we resort the new total feature list and reselect the same features as for the word frequency threshold to identify features, removing features that are ignored due to low word frequency using the operation shown in Fig. 9.

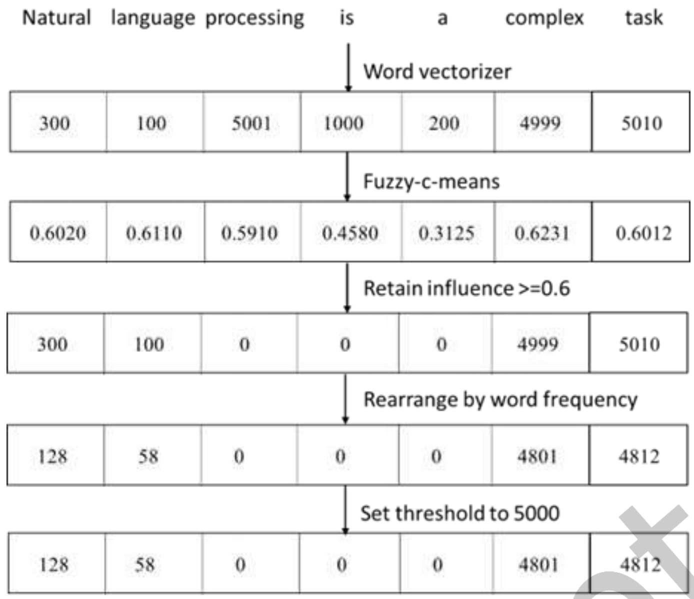

Figure 9 Fuzzy C-means padding features operation

4.4 Parameter Settings

The research uses a deep learning model to detect pre-annotated news data related to COVID-19 in English and Chinese language. Stop words and URLs are removed during data preprocessing, and then text is converted into text vectors using different feature extraction methods. Each experimental vector matrix is set to different lengths with different data set characteristics. 70% of the data is used for model training, and the other 30% is used for model testing. The parameter settings for this study follow previous studies, setting the LSTM units to 64 or 128 to let the model learn with different neurons. To reduce the overfitting of the model to the training data, we used dropout values of 0.2 or 0.5. The batch size is set to 64 to gradually put the data into the model for learning, and the training epoch is set to 10 to increase the accuracy of the model with the number of trainings. The activation function of the model. Since this research is for binary classification, the activation function of the fully connected layer uses Sigmoid [12].

There are 3 experiments in the experimental design, and all parameters setting is decided by trial and error. In the 1st experiment, the goal is to extract key features for detection of COVID-19 fake news by word frequency threshold, and the embedding layer of the model sets the parameter to 5000 and converts the text in the matrix to word embeddings. In the 2nd experiment, the goal is to extract key features for detection of COVID-19 fake news by residual fuzzy features. After fuzzy clustering, the embedding layer of the model sets parameter to 4049 on the English data, as opposed to 1137 for Chinese data. Then converts the text in the matrix to word embeddings. In the 3rd experiment, the goal is to extract key features for detection of COVID-19 fake news by fuzzy padding features, and the embedding layer of the model sets the parameter to 5000 and converts the text in the matrix to word embeddings.. In the three experiments, the matrix length of the input layer is uniformly set to 1000 due to the long length of news sentences.

4.4.1 *Baseline model Parameter Setting*

According to the past research [12], the baseline model is construct as 5-layers structure, it includes an input layer, an embedding layer, a dropout layer, a deep learning model layer, and a fully connected layer. The role of the input layer is to allow the data matrix to be input into the model. The role of the embedding layer is to convert the data matrix into a text vector matrix through the feature extraction method, The role of the dropout layer is to set the dropout value so that part of the data in the vector matrix is not learned by the deep learning model, so that the model does not overfit on the training data. The role of the deep learning model layer is to train the model and use the model for detection. Finally, the role of the fully connected layer is to integrate the results of the model test and output them into two categories. The text vector matrix of each layer of the model, and the text feature threshold settings and deep learning model units settings are as shown in the above experimental parameter settings. The parameters in the Input Layer are set to the same length as the text vector matrix, which is uniformly set to 1000 because although the data lengths of English and Chinese data are different, the average length will not exceed this set value. The parameters in the Embedding Layer are set to convert the input text vector matrix to a text vector by setting a threshold value is uniformly set to 5000, and then enters the deep learning layer after passing through the dropout layer. The training of the deep learning model will start, and then the model outputs in the dimension set by the model units. Finally, the fully connected layer is used to transform the output of the deep learning model to detect real or fake results. Fig. 10 shows the model parameter settings.

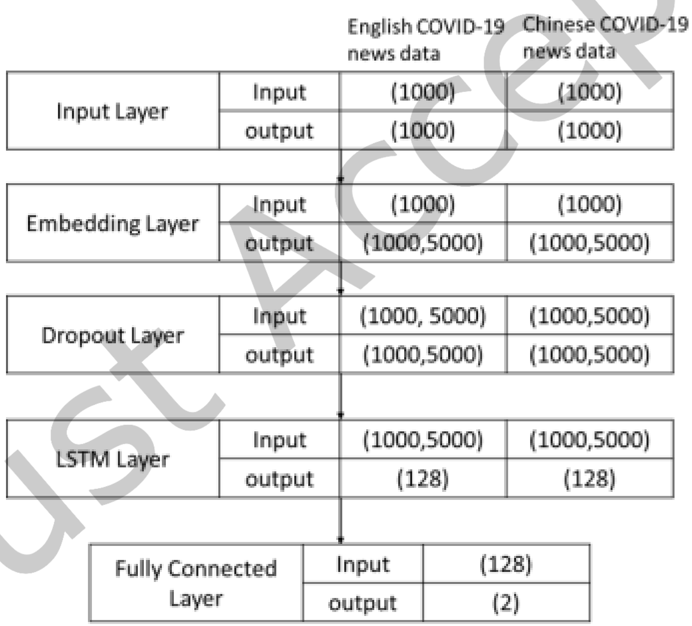

Figure 10 Model parameter settings for baseline model

4.4.2 *Fuzzy Residual Feature Parameter Settings*

The deep model architecture for the second mode is identical to that of the baseline model: it also includes the input layer, the embedding layer, the dropout layer, the deep learning model layer, and fully connected layer. The role of the input layer is to allow the data matrix to be input into the model. The role of the embedding layer is to convert the data matrix into a text vector matrix through the feature extraction method, The role of the dropout layer is to set the dropout value so that part of the data in the vector matrix is not learned by the deep learning model, so that the model does not overfit on the training data. The role of the deep learning model layer is to train the model and use the model for detection. Finally, the role of the fully connected layer is to integrate the results of the model test and output them into two categories. The text vector matrix of each layer of the model, text feature threshold settings and the deep learning model units are set as shown in the above experimental parameter settings. The parameters in the Input Layer are set to the same length of the text embedding matrix, which is uniformly set to 1000, because although the data lengths of English and Chinese data are different, the average length will not exceed this set value The parameters in the Embedding Layer are set to convert the input text vector matrix into a vector with different thresholds, and the number of residual features in the English data is 4049, while that of the Chinese data is 1137. After passing through the dropout layer, it enters the deep learning model layer. By training the deep learning model, the model outputs in the dimension set by the model units, and finally the fully connected layer converts the deep learning model output to detect real or false results. Fig. 11 shows the model parameter settings.

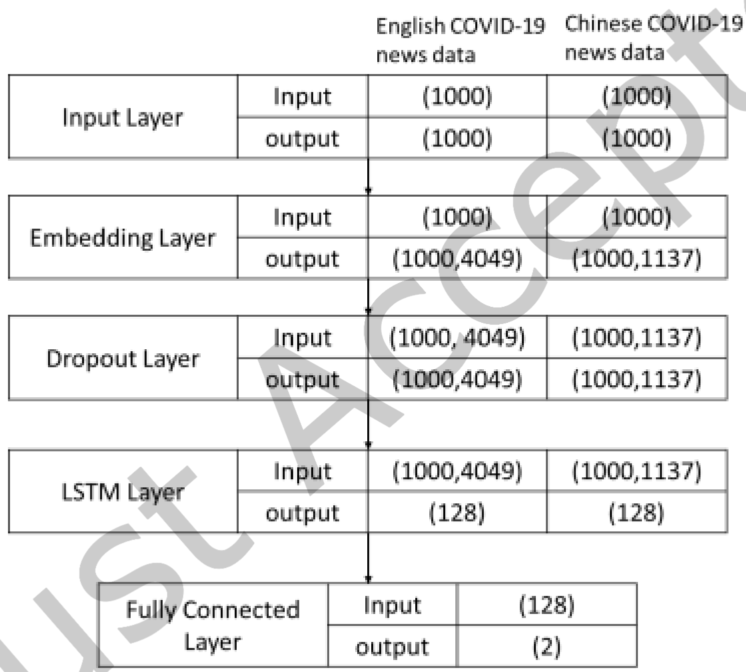

Figure 11 Model parameter settings for residual Fuzzy features

4.4.3 Fuzzy Feature Padding Parameter Settings

In the third mode, the deep model architecture is the same as the first mode: input layer, embedding layer, dropout layer, deep learning model layer, and fully connected layer. The role of the input layer is to allow the data matrix to be input into the model. The role of the embedding layer is to convert the data matrix into a text vector matrix through the feature extraction method, The role of the dropout layer is to set the dropout value so that part of the data in the vector matrix is not learned by the deep learning model, so that the model does not overfit on the training data. The role of the deep learning model layer is to train the model and use the model for detection. Finally, the role of the fully connected layer is to integrate the results of the model test and output them into two categories. The text vector matrix of each model layer, the text feature threshold settings and the deep learning model units are set as shown in the above experimental parameter settings. The parameters in the input layer are set to the same length of the text vector matrix, uniformly 1000, because although the data lengths of English and Chinese data are different, the average length will not exceed this set value. The parameters in the embedding layer are set to convert the input text vector matrix into a vector with the same threshold value, set to 5000, so that the model can extract more important features to input into the deep learning model layer after passing through the dropout layer. This trains the deep learning model, which is then output in the dimension set by the model units. Finally, the fully connected layer converts the output of the deep learning model to detect real or false results. The model parameters are shown in Fig. 12.

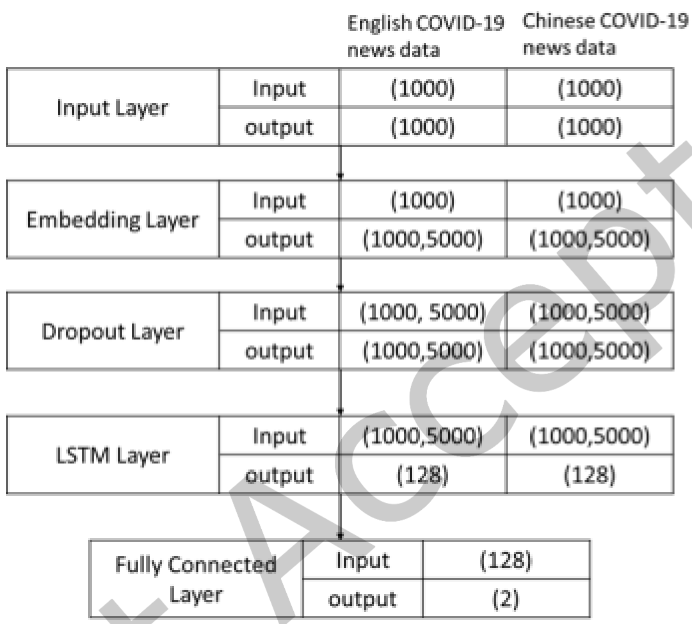

Figure 12 Model parameter settings for Fuzzy padding features

After the model is trained, it will be tested using the test data set, and then the classification accuracy will be generated according to the detection results. Then the model will be modified according to the previous results, and will be trained again. Finally, after the entire model is trained, various evaluation indicators will be used to evaluate the final performance of the model.

5 EXPERIMENTAL RESULTS AND DISCUSSION

The word frequency method and deep learning model were first used to detect English COVID-19 fake news. The best result was obtained using BiLSTM for detection. The results are shown in Table 7.

Table 7: Results of English COVID-19 fake news detection using word-frequency features and deep learning

Model	Data	Units	Dropout	Accuracy	Recall	Precision	F1-score	Time(s)
LSTM	Using word-frequency feature for COVID-19 news data in English	64	0.2	99.07%	99.01%	98.72%	98.86%	1310
			0.5	99.23%	99.60%	98.52%	99.06%	1302
		128	0.2	98.87%	98.43%	98.82%	98.62%	1363
			0.5	98.95%	98.72%	98.72%	98.72%	1335
BiLSTM		64	0.2	99.31%	99.60%	98.52%	99.06%	2299
			0.5	99.47%	99.88%	98.92%	99.40%	2295
		128	0.2	99.35%	99.50%	98.91%	99.20%	2301
			0.5	99.35%	99.50%	98.92%	99.21%	2302
GRU		64	0.2	99.19%	99.21%	98.82%	99.06%	1501
			0.5	99.31%	99.41%	98.92%	99.16%	1520
		128	0.2	99.35%	99.50%	98.92%	99.21%	1532
			0.5	99.19%	99.70%	98.32%	99.01%	1552

Next the Fuzzy clustering method is applied. First, we use the deep learning model to detect the residual text features after excluding those with an attribute value < 0.6. The result is the best BiLSTM detection result. Although the accuracy rate is reduced, the detection time is reduced by 10% compared with the original word frequency method. The results are shown in Table 8.

Table 8: Results of English COVID-19 fake news detection using residual features and deep learning following Fuzzy clustering

Model	Data	Units	Dropout	Accuracy	Recall	Precision	F1-score	Time(s)
LSTM	Using residual features for COVID-19 news data in English	64	0.2	98.08%	98.52%	97.27%	97.89%	1171
			0.5	98.67%	98.52%	98.52%	98.52%	1210
		128	0.2	98.63%	98.72%	98.23%	98.47%	1240
			0.5	98.41%	98.81%	97.66%	98.23%	1218
BiLSTM		64	0.2	98.80%	98.72%	98.62%	98.67%	2009
			0.5	98.72%	98.91%	98.23%	98.57%	2008
		128	0.2	98.94%	98.81%	98.81%	98.81%	1996
			0.5	99.03%	98.02%	99.60%	98.80%	2011
GRU		64	0.2	97.76%	98.22%	97.06%	97,64%	1323
			0.5	98.36%	98.02%	98.51%	98.26%	1300
		128	0.2	97.71%	98.32%	96.78%	97.54%	1355
			0.5	97.94%	98.61%	97.08%	97.84%	1362

Next, use the second experiment in the Fuzzy grouping method. After using the excluded attribute value <0.6 text features, the subsequent features are added until the number of text features is the same as the original word frequency method. The best detection result is obtained using BiLSTM. The accuracy rate is similar to that of the residual features, but the time reduction is less than that of the residual features. The results are shown in Table 9.

Table 9: Detection results of English COVID-19 fake news using feature complementation and deep learning following Fuzzy clustering

Model	Data	Units	Dropout	Accuracy	Recall	Precision	F1-score	Time(s)
LSTM	using feature complementation for COVID-19 news data in English	64	0.2	98.41%	98.52%	97.27%	97.89%	1210
			0.5	98.52%	98.52%	99.30%	98.91%	1231
		128	0.2	98.32%	98.32%	98.71%	98.51%	1240
			0.5	98.94%	98.52%	99.11%	98.81%	1260
BiLSTM		64	0.2	98.66%	98.52%	98.52%	98.52%	2028
			0.5	98.84%	98.42%	99.01%	98.71%	2010
		128	0.2	98.79%	98.52%	98.81%	98.66%	2110
			0.5	99.09%	98.42%	99.60%	99.01%	2037
GRU		64	0.2	98.40%	98.42%	98.13%	98.27%	1332
			0.5	98.45%	98.52%	98.13%	98.32%	1331
		128	0.2	98.31%	98.42%	97.93%	98.17%	1281
			0.5	98.72%	98.52%	98.71%	98.61%	1380

Next, the word frequency method and deep learning model are used to detect Chinese COVID-19 fake news. The best result is obtained using BiLSTM for detection. The results are shown in Table 10.

Table 10:Chinese COVID-19 fake news detection results using word frequency and deep learning

Model	Data	Units	Dropout	Accuracy	Recall	Precision	F1-score	Time(s)
LSTM	Using word-frequency feature for COVID-19 news data in Chinese	64	0.2	82.30%	88.25%	81.84%	84.92%	450
			0.5	85.10%	88.25%	85.79%	87.00%	454
		128	0.2	83.92%	88.52%	83.91%	86.15%	450
			0.5	84.96%	87.99%	85.75%	86.86%	444
BiLSTM		64	0.2	84.51%	85.12%	87.17%	86.13%	771
			0.5	86.73%	88.25%	88.25%	88.25%	783
		128	0.2	86.28%	87.47%	88.16%	87.81%	793
			0.5	85.10%	86.95%	86.72%	86.83%	771
GRU		64	0.2	86.58%	88.77%	87.63%	88.20%	504
			0.5	85.55%	89.30%	85.71%	87.47%	532
		128	0.2	83.33%	88.77%	82.93%	85.75%	528
			0.5	82.90%	90.34%	83.78%	86.94%	521

Following Fuzzy clustering, the residual text features and the deep learning model are used for detection. The best detection result is obtained using BiLSTM. Although the accuracy rate drops by 13~15%, the detection time is 30% less than the original word frequency approach. The results are shown in Table 11.

Table 11: Chinese COVID-19 fake news detection results using residual features and deep learning following Fuzzy clustering

Model	Data	Units	Dropout	Accuracy	Recall	Precision	F1-score	Time(s)
LSTM	Using residual features for COVID-19 news data in Chinese	64	0.2	68.39%	68.84%	76.43%	72.44%	329
			0.5	70.45%	74.32%	76.14%	75.22%	320
		128	0.2	69.42%	76.37%	73.84%	75.08%	321
			0.5	68.60%	73.29%	74.31%	73.80%	320
BiLSTM		64	0.2	68.60%	72.95%	74.48%	73.70%	540
			0.5	71.07%	77.40%	75.33%	76.35%	546
		128	0.2	70.45%	76.71%	74.92%	75.80%	541
			0.5	69.83%	74.32%	75.35%	74.83%	549
GRU		64	0.2	69.83%	76.03%	74.50%	75.26%	351
			0.5	70.04%	76.40%	74.58%	75.48%	371
		128	0.2	67.36%	73.29%	72.79%	72.79%	360
			0.5	69.42%	73.29%	75.35%	74.31%	361

Finally, using the Fuzzy clustering method, the text features are supplemented and the deep learning model is used to detect Chinese COVID-19 misinformation. The best detection result is obtained using BiLSTM The accuracy rate is reduced by 8~12%, but the time required is 15% less than that using residual features. Thus, while the accuracy is higher, the time savings is reduced. The results are shown in Table 12.

Table 12: Detection results for Chinese COVID-19 misinformation using feature complementation and deep learning following Fuzzy clustering

Model	Data	Units	Dropout	Accuracy	Recall	Precision	F1-score	Time(s)
LSTM	Using residual features for COVID-19 news data in Chinese	64	0.2	75.76%	82.52%	77.84%	80.11%	407
			0.5	73.73%	85.96%	73.89%	79.47%	409
		128	0.2	72.20%	77.94%	75.77%	76.84%	404
			0.5	75.42%	87.68%	75.00%	80.85%	409
BiLSTM		64	0.2	76.10%	81.66%	85.84%	83.70%	678
			0.5	75.42%	81.95%	77.72%	79.78%	679
		128	0.2	74.24%	88.84%	74.42%	80.99%	687
			0.5	76.27%	80.23%	79.77%	80.00%	694
GRU		64	0.2	71.86%	79.37%	74.66%	75.99%	444
			0.5	74.07%	83.38%	75.39%	79.18%	452
		128	0.2	72.71%	81.38%	74.74%	77.92%	451
			0.5	72.20%	81.95%	73.90%	77.72%	451

The research uses different experimental designs to detect fake news in English and Chinese related to COVID-19 on the Internet, including different feature extraction methods, model selection and parameter settings. The result found that regardless of the differences between data features, using BiLSTM can achieve high accuracy. Since BiLSTM can learn the pre-order and post-order states of sentences at the same time, it can effectively grasp the relationship between sentence features. The results also show that with longer sentences in the data, the accuracy rate is higher than sentences with shorter sentence lengths.

The results show that the method proposed in this study has a very high accuracy in detecting fake news related to COVID-19 in English, mainly because of the completeness of the data description, the amount of data is big and the balance of the data make deep learning model to learn better. Chinese detection underperforms English detection because there are some limits in Chinese COVID-19 news data resources, such as the amount of data is less than that of English data, the representation of some news sentences in terms of true and fake has a high similarity, and the data is unbalanced. Makes deep learning models more difficult to distinguish in terms of text features. Even using fuzzy theory to help deep learning models pick features is affected by the size of the data. To obtain good performance, a large amount of data is required for the model to find key features, and these features must be discriminative, so whether the data set is a balanced data set is also a major point.

In the past, disinformation research mainly focused on effectively improving model accuracy, with little regard for minimizing detection time. The present research uses a newer and improved model with large amounts of data features and time to maximize accuracy. Results show that, given a sufficient data ratio and large numbers of features, for the same model parameter settings, Fuzzy clustering can effectively reduce the time and features required for detection, while maintaining good accuracy.

In the past, fake news would focus on some major fields, and the details of which would be determined according to current events, and fake news detection would make predictions based on these details, such as the outbreak of COVID-19 pandemic, there are many research analyzing the topic. The research apply machine learning and deep learning methods to the COVID-19 datasets, verifies the integrity of the dataset and the effectiveness of the model through testing. However, few studies have attempted to detect fake news materials in non-English languages data and compare the trade-off relationship between detection time and model accuracy, so this research provides the future researchers for using different deep learning model with different feature extraction methods and compare it with different language or data length news data in fake news detection is important.

6 CONCLUSIONS

This research uses multiple deep learning models with different feature extraction methods to detect multilingual profiles related to the COVID-19 pandemic. Regardless of the language or data characteristics of the dataset, the BiLSTM model achieves high accuracy and F1-score, which means that the use of advanced deep learning models to detect relevant fake news can not only accurately in detect the fake news, but also has better performance in different evaluation indicators, so that the purpose of the detection model is not only to improve the prediction accuracy.

The research has shown that using the fuzzy method for data feature extraction will reduce part of the accuracy and detection time at the same time, but in terms of the difference in performance and time, the accuracy in detecting English fake news is almost unchanged, but the time is shortened at least 10%, which can provide a good reference for real-time detection of fake news in the future.

The limitation of this study is that the data set used in this paper only collects data in 2020, and does not collect data on newly emerging fake news categories, which will limit the performance of the model in detection. For the fuzzy mechanism, if the amount of data is small, the addition of fuzzy logic may make the model suffer from large deviations in performance.

Future work will continue to improve the use of fuzzy theory to extract data features, such as using fuzzy theory to find common words that influence the model to detect news as true or fake and organize them, so the subsequent research can use fewer features for more effective classification. Since this research only uses the basic deep learning model for detection, more novel Transformer-based models with more complex structures can be used for more accurate detection in the future. At the same time, on the detection target, it can be extended to multi-label classification without the need to perform label conversion first, and the labels of the original data can be used for detection. With the evolution of the model, the gradual accumulation of data and the analysis and research of more related topics, this big data analysis technology can bring higher judgment accuracy and less judgment time, and finally evolved into real-time detection of fake news detection.

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