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Fake News Detection Model with Hybrid Features—News Text, Image, and Social Context

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Abstract

With the evolving realm of news propagation and the surge in social media usage, detecting and combatting fake news has become an increasingly important issue. Currently, fake news detection employs three main feature categories: news text, social context, and news images. However, most studies emphasize just one, while only a limited number incorporate image features. This study presents an innovative hybrid fake news detection model amalgamating text mining technology to extract news text features, user information on Twitter to extract social context features, and VGG19 model to extract news image features to increase the model's accuracy. We harness four diverse machine learning algorithms (Logistic Regression, Random Forest, Support Vector Machine, and Extreme Gradient Boosting) to construct models and evaluate their performance via Precision, Recall, F1-Score, and Accuracy metrics. Results indicate the fusion of news text, social context, and image features outperforms their individual application, yielding a noteworthy 92.5% overall accuracy. Significantly, social context attributes, encompassing users, publishers, and distribution networks, contribute crucial insights into detecting early-stage fake news dissemination. Consequently, our study bolsters fact-checking entities by furnishing them with news-content insights for verification and equips social media platforms with a potent fake news detection model—comprising news content, imagery, and user-centric social context data—to discern erroneous information.

Keywords Fake news detection · Text mining · Social context · Machine learning

1 Introduction

With the rapid development of the Internet, many news media and communication models have been developed, which have gradually changed the way people receive information and their habits (Bentley et al., 2019). With the rise of many social media, such as Twitter, Facebook, LINE, etc., the news dissemination model has gradually changed from one-way to two-way or even multi-directional communication (Carpenter, 2010; Fiedler, 2010). This makes people not just the recipients of news information, but also the publisher and forwarders. People can choose their favorite news reports to read and no longer be regarded as passive readers. People live around a lot of fake news every day, but people don't necessarily have the ability to interpret every news report. Additionally, news information is often professional,

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and if people don't have expertise in the field, they cannot easily see the wrong information from it. Moravec et al. (2018) used user behavior and Electroencephalography from 83 different social media platforms to explore whether users have the ability to distinguish between real news and fake news. The study found that only 44% of users can correctly distinguish them. Schetinger et al. (2017) explored whether people have the ability to identify images tampered with. The study found that only 58% of people could identify it. Even 59% of people only read news headlines, but not the news content, or only read tweets but do not necessarily click on the link to read the detailed news.

Not the news content, or only read tweets but do not necessarily click on the link to read the detailed news content and then share the news (Gabielkov et al., 2016). Additionally, the appearance of fake news may lead to a lot of wrong or improper information in the fields of politics, medicine, and the economy (Wasserman & Madrid-Morales, 2019a). Let people be influenced by it and make wrong decisions, even delay treatment time or be deceived. Therefore, if we can effectively find fake news early and prevent it from spreading widely on social networks, the negative effects mentioned above will be reduced.

To end the fake news on social media, fact-checking organizations have been set up worldwide to check whether the news contains false information. According to the survey by Stencel and Luther (2020), there are currently 237 fact-checking agencies in 78 countries around the world. However, the service provided by the fact-checking agency needs evidence. It must collect original or indirect information and manually compare the news content. This process is quite time-consuming and far less than the speed of dissemination of fake news. Therefore, we need a method that can detect fake news more efficiently and automatically to help detect fake news. In the past, most research only used text information to build models that detect fake news (Ahmed et al., 2017; de Oliveira et al., 2020; Ozbay & Alatas, 2020; Potthast et al., 2018; Zhou et al., 2020). Lin et al. (2022) also proposed that an ensemble learning method based on BERT and text sentiment analysis be applied to the identification of harmful news. However, Shu et al. (2018) pointed out that fake news can distort the facts with different writing styles while imitating real news. Therefore, it is difficult to detect fake news only by the news content itself, and other auxiliary information must be considered (Shu et al., 2017). Shu et al. (2019c) discussed the correlation between social media user information and fake news and analyzed the effectiveness of user information in detecting fake news. Shu et al. (2019a) additionally used the network diffusion model to trace the original source of fake news and the dissemination network as auxiliary information, which could reduce the spread range of fake news on social media. Therefore, we should take social situation information into consideration. Knobloch et al. (2003) compared articles with and without matching images and found that articles with images can attract readers' attention, interest, or curiosity more. Newman et al. (2012) pointed out that matching images next to an article can increase the persuasiveness of the article and the credibility of the reader. For this reason, today's fake news often uses provocative pictures to attract and mislead people. Therefore, image information should be considered when detecting fake news. However, most studies only focus on the text information or social situation information of news, and few scholars discuss the image information. Jin et al. (2016) pointed out that the image content of real and fake news has different distribution patterns. Therefore, news image features can be extracted from both the visual content and statistics. (Singh & Sharma, 2022) also discussed and verified the feasibility of using image information to detect fake news.

Based on the above research background and motivation, this study aims to improve the accuracy of the detection model by combining news text information, image information, and social context information. Assist the fact-checking organization in judging whether there is fake information in the news to speed up the whole checking process. It also helps social media to prevent the massive spread of fake news on social networks as soon as possible and reduce the contact rate of other users who are exposed to fake news. The research purposes are as follows:

- Sorting out the past literature to determine the factors that may affect the detection of fake news and using data mining technology to extract the main influencing factors and features.
- Combine hybrid features of news text, social context, and image information to build a fake news detection model and improve the model's accuracy.

The organization of this study is as follows: The second section briefly introduces the related works of this study, focusing on previous research about fake news detection methods. The third section presents the dataset, data preprocessing techniques, and methodology, including the feature extraction methods and the machine learning algorithms applied in this study. The fourth section discusses the proposed methods' experimental setup, evaluation metrics, and experimental results. Finally, the fifth section presents the conclusions and suggests potential future directions.

2 Related Works

2.1 Fake News

Fake news is not a new phenomenon that has developed in recent years, but with the rise of the Internet and the popularity of social media, this problem has become more serious.

Since the 2016 U.S. presidential election and several subsequent large-scale elections in Europe, such as the Brexit referendum in the United Kingdom, the French presidential election, and the German Bundestag election, the phenomenon of fake news has attracted more attention and heightened vigilance (Zhou & Zafarani, 2020). However, there is still no consistent definition or perception of fake news so far. In past research on fake news, there are different opinions on the definition of fake news, and many scholars have different opinions, as shown in Table 1. Although most scholars have different interpretations of fake news, the concepts are similar. It usually covers the following characteristics: (1) intentionally influences the audience, that is, deliberately deceives and misleads the audience into believing a lie or suspecting the truth. (2) It is verified to be false, that is, the title and content of the news are verified to contain wrong information or images, or to tamper with information and images, and to use old photos as new photos to fabricate wrong stories out of context. (3) Presenting in the form of news that is publishing wrong information in the form of news content.

Fake news spreads widely on the Internet, and its influence extends to all areas of people's lives (Wasserman & Madrid-Morales, 2019b; Zhang & Ghorbani, 2020), especially in major fields such as politics, medicine, and economics, which are filled with a large amount of incorrect or inappropriate information that has not been carefully verified, which may make people unknowingly affected by misinformation, making wrong judgments and decisions, or delaying the best time for treatment, It may even lead to being deceived. The harm of fake news has caused many negative effects in various fields, and it not only affects personal judgment but even affects the operation of the country in serious cases. In the political field, fake news not only interferes with democratic politics but also affects the election situation of various countries and has become a tool to manipulate public opinion and reputation; In the medical field, wrong medical information or news will cause misunderstandings among the general public and cause many unnecessary waves of panic, and even worse, delay the golden opportunity for medical treatment; In the economic field, if fake news is widely distributed in the market, it will cause information asymmetry, disrupt the supply and demand of the market, affect the operation of the market mechanism, and then cause market price fluctuations, which will hurt producers and consumers. The above-related literature on the harm caused by fake news is shown in Table 2.

2.2 Related Studies on Fake News Detection

After the rise of the Internet, all countries are faced with the problem of fake news caused by social media. In the face of such a large number of real and fake news, the common method is to use experts to manually identify the source and source of the information. However, this method is not only slow but also unable to cope with such a large amount of news data (Rubin et al., 2015). Therefore, many researchers have begun to explore how to use data mining and analysis techniques to extract information from large amounts of news. Therefore, many researchers have begun to explore how to use data mining and analysis techniques to extract important information from a large amount of news data. This study lists various news features used in the past literature, such as news text features, social context features, and news image features. Related research topics are listed in Table 3.

2.2.1 News Text Features

Potthast et al. (2018) used the BuzzFeed dataset to analyze political news. This dataset has a total of 1627 news, of which 299 are fake news, and of these fake news, there are 97% published by biased media. Scholars extract various writing style features, such as words, stop words, parts of speech, etc., from news content to detect fake news and media bias. The results indicate that fake news cannot be accurately detected (F1 = 46%), but biased news (F1 = 78%) and satirical news (F1 = 81%) can be accurately detected. Zhou et al. (2020) proposed a theory-driven model for detecting fake news, combining research theories from

Table 1 Fake news definition

Scholar	Fake news definition
Allcott and Gentzkow (2017)	A news article is intended to be provably false and likely to mislead the reader
Gelfert (2018)	Labeling something as "fake news" should be limited to cases where false or deceptive statements are deliberately presented as news to manipulate the audience's thinking through structured dissemination channels
Wardle and Derakhshan (2017)	Means a message that is intentionally fabricated with the purpose of deceiving and misleading the reader into believing a lie or doubting a verifiable fact
Baptista and Gradim (2022)	This means "fake news" refers to online disinformation containing misleading or false statements, intentionally designed to deceive or manipulate a specific audience. It adopts a new format with an opportunistic structure to garner attention, clicks, shares, advertising revenue, or ideological influence
Lazer et al. (2018)	Refers to fabricated messages that mimic the content or intent of news media

Table 2 Literature review on the negative impact of fake news

Field	Scholar	Research result
Political field	Bradshaw and Howard (2019)	Seventy countries around the world used social media to create and spread fake news during elections
	Zimmermann and Kohring (2020)	The less people trust traditional news media and politics, the more they tend to believe fake news on the Internet
	Balmas (2014)	Viewing fake news can increase feelings of inefficacy, alienation, and cynicism towards political candidates
Medical field	Waszak et al. (2018)	40% of news on social media related to common diseases and causes of death is wrong
	Jolley and Douglas (2014)	Parents who have been exposed to false information about vaccinations are reluctant to vaccinate their children
	Mavragani and Ochoa (2018)	The number of false information was highly negatively correlated with the vaccination rate ($r=-0.7627$)
Economic field	Kogan et al. (2018)	Fake news has increased abnormal trading volumes in stocks, causing temporary price impacts on smaller companies
	Gu et al. (2017)	Before listing, companies use fake news to package the company's business performance to attract investors to invest. After listing, they make reverse speculation, causing the company to go bankrupt and delist, causing investors to suffer great economic losses
	Braun and Eklund (2019)	Fake news creators gained substantial profits through digital advertising platforms, weakening legitimate news organizations and disrupting the programmatic advertising industry

Table 3 Related research on fake news detection models

Scholar	database source	feature		
		news text	news images	social context
Jin et al. (2016)	Weibo	✓	✓	
Ahmed et al. (2017)	Reuters.com, kaggle.com	✓		
Potthast et al. (2018)	BuzzFeed	✓		
Jang et al. (2018)	Twitter	✓		✓
Wang et al. (2018)	Weibo and Twitter	✓	✓	
Shu et al. (2019c)	FakeNewsNet	✓		✓
Shu et al. (2019b)	FakeNewsNet	✓		✓
de Oliveira et al. (2020)	Twitter	✓		
Singh et al. (2021)	Kaggle	✓	✓	
Ozbay and Alatas (2020)	BuzzFeed, Random, ISOT	✓		
Zhou et al. (2020)	PolitiFact and BuzzFeed	✓		
Zhao et al. (2020)	Weibo and Twitter	✓		✓
Nasir et al. (2021)	ISOT, FA-KES	✓		
Kaliyar et al. (2021)	Kaggle	✓		
Choudhary and Arora (2021)	Horne2017_FakeNewsData	✓		
Guo et al. (2022)	Weibo, Politifact	✓		
Luvembe et al. (2023)	RumorEval19、Pheme、Fakeddit	✓		
Zhang et al. (2023)	Rumor, CHEF	✓		
Singh et al. (2023)	Twitter MediaEval、Weibo	✓	✓	
this research	FakeNewsNet	✓	✓	✓

linguistics and psychology, using lexicon-level, syntax-level, semantic-level, and discourse-level level news text features to detect fake news; The lexicon-level represents the writing style of the news, such as the frequency of the word usage; The syntax-level refers to the compositional structure of sentences, such as using Part-Of-Speech (POS) to count the frequency of nouns and verbs, also using Probabilistic Context-Free Grammar (PCFG) to count the grammar rules of sentences; The semantic-level represents the thoughts that the news content wants to convey, such as positive words and negative words; The discourse-level indicates whether the news content is coherent, such as the correlation between sentences. Scholars pointed out that compared with other news text features, these features can increase the interpretability of the model, even in the case of little news information, the model can effectively detect fake news (F1 = 80% ~ 88%), indicating that the use of these textual features can detect fake news at an early stage of dissemination. Based on the above literature, past research points out that the writing styles of real news and fake news are roughly the same, but fake news contains more subjective consciousness and emotion so that researchers can combine linguistics, psychology, and other research theories to conduct fake news detection research. Ozbay and Alatas (2021) proposed an optimization-based model using Salp Swarm Optimization (SSO) and Grey Wolf Optimizer (GWO) to enhance fake news detection. Their approach improved performance on multiple datasets by optimizing feature selection, achieving higher accuracy and F1 scores (Ozbay & Alatas, 2021). Similarly, Kumar et al. (2024) introduced OptNet-Fake, which combines the Grasshopper Optimization Algorithm (MGO) with Convolutional Neural Networks (CNN). This method uses TF-IDF for feature extraction, followed by MGO for selecting key features, and CNN for detecting fake news, showing superior results across several datasets (Kumar et al., 2024). Many studies use deep learning models such as CNN or combine with language representation models such as BERT to construct fake news classification models using news text features, and achieved accuracy rates of over 60% in different language texts (Choudhary & Arora, 2021; Guo et al., 2022; Kaliyar et al., 2021; Luvembe et al., 2023; Nasir et al., 2021; Zhang et al., 2023).

2.2.2 Social Context Features

The emergence of social media has changed the way readers get news, making social platforms a channel for people with ulterior motives to set new issues, and through the likes, retweets, or manipulation of algorithms by readers, fake news can spread faster and more widely. Therefore, scholars use not only news text features but also social contextual information, such as social media users, news dissemination networks, etc. Shu et al. (2019c) collected social media user characteristics from different aspects, such as user metadata, number of posts, etc., as well as implicit characteristics, such as age, personality, location, political bias, etc., a total of 1000 characteristics. This paper investigates the use of news text features only, social media user features only, and a combination of news text features and social media user features to establish the accuracy of fake news detection. The classification method adopts random forest, and the research results show that the model combining news text features and social media user features has higher accuracy. Shu et al. (2019b) investigate the impact of the correlation between news article stance and social media users on the fake news detection task by considering the bias of news publishers. The paper uses news text features, social media user features, user engagement features, and news publisher features to build a fake news detection model. The results show that integrating the above-mentioned features can effectively improve the performance of the fake news detection model and detect fake news at the early stage of dissemination. From the above-mentioned literature, it is found that there is much important information hidden in social contextual characteristics, such as social media users, news publishers, and news distribution networks, which enable researchers to obtain more information as auxiliary information for detecting social media fake news.

2.2.3 News Image Features

Wang et al. (2018) pointed out that previous scholars used a manual approach to extract news image features, which cannot represent news image features comprehensively because of the complexity and diversity of image information, so scholars used transfer learning to extract news image features with a pre-trained VGG19 model. By adding a fully connected layer to the VGG19 model to control the dimensionality of the extracted feature matrices and using Text-CNN to extract news text features, the two feature matrices are finally concatenated together to form the final multi-modal feature matrix. Comparing the model using a single feature with the model using both features, the results show that the detection model combining news text features and news image features improves the prediction accuracy by 10.3% and the F1 score by 16.5%. Singh et al. (2021) explored past fake news detection studies using only text and image variables and classified these variables into four categories based on Framing Theory, LC4MP, and elaboration likelihood model (ELM): content, organization, emotion, and manipulation. Content refers to the topics covered in the news text and the labeling of the news images; Organization refers to the composition of the content, such as the number of words used in the text, the number of words in each sentence, and visual features such as the size, height, and width of the images; Emotion refers to features of the news content that evoke emotions in the reader, such as positive or negative comments, and violent or gory images; And manipulation refers to the modification of content to disseminate specific information, such as the number of personal pronouns, the number of indefinite pronouns, and the blurring and clarity of images in the text. Based on the above literature, it is found that the visual and statistical features of news images are both important for detecting fake news, and the news image features can use Transfer Learning to speed up and optimize the learning efficiency of the model to significantly reduce the time of model training. Singh et al. (2023) collected two datasets, namely Twitter MediaEval and Weibo. The Twitter MediaEval dataset consisted of approximately 17,000 tweets with their related images. Their approach combined both text and image as well as utilized a stack ensemble model with two deep learning architectures, ELECTRA and BERT. The method was tested on the Twitter and Weibo datasets and outperformed recent research achievements, achieving an accuracy of 86.83%.

3 Method

In this study, the FakeNewsNet dataset constructed by Shu et al. (2020) is used to capture news text and image data, and the social context data is captured according to the Twitter ID provided by the dataset, such as the number of tweets published by social media users and the number of followers. After the data collection, the Stanford parser and the Linguistic Inquiry and Word Count (LIWC) are respectively used to preprocess the news text data, and transfer learning is used to extract the news image feature from the VGG19. The social context features are the statistics of social media users.

Subsequently, the data mining algorithm provided by the scikit-learn suite in Python 3 was used to construct and evaluate the fake news classification model, and the model was established by Logistic Regression (LR), Random Forest (RF), Support Vector Machine (SVM) and Extreme Gradient Boosting (XGBoost) for the experiment. By comparing the models based on different feature combinations and different data mining algorithms, the best fake news detection model is selected for research. Figure 1 is the framework of this study.

Figure 1 illustrates the overall research framework, combining news text, images, and social context features to construct a hybrid fake news detection model. The dataset for this study is derived from FakeNewsNet, which provides news text, images, and associated social context data from Twitter. During preprocessing, news text data is processed using the Stanford Parser and LIWC for syntactic and linguistic feature extraction, while VGG19 is employed to extract image features. Social context data, such as user metadata and social media interactions, is also incorporated to provide additional insights into the dissemination and influence of news. Once the features are extracted, they are integrated and used to construct a fake news detection model through the application of various machine learning algorithms. The best-performing model is selected to enhance the detection accuracy by comparing different feature combinations and algorithms. The following will discuss the dataset, data preprocessing, and data mining technology.

3.1 Dataset

In order to investigate the effects of news souses and news categories, this study adopts the FakeNewsNet dataset, which contains the true and false news captured from two fact-checking websites. They are collecting news in the political field from the PolitiFact website and news in the entertainment field from the GossipCop website. The true and false news in the FakeNewsNet dataset includes titles, contents, images, hyperlinks, etc. The experiments are conducted in both subsets, PolitiFact and GossipCop.

In addition to news text and images, the FakeNewsNet provides relevant information about the dissemination of true and false news on social websites. However, because Twitter's privacy policy cannot disclose complete social context information, it can only provide the Twitter ID from the news. This study can also collect complete social context data from the Twitter ID through the Twitter API, including the number of social media users and followers.

A total of 308 fake news, 301 real news, 414,634 Twitter IDs, and 10,098 images were obtained from the PolitiFact subset, and a total of 4,464 fake news, 13,851 real news, and 1,144,528 Twitter IDs and 608,927 images were obtained from the GossipCop subset as experimental data for this study. Both subsets utilized undersampling to achieve class balance in the experiments.

3.2 Data Preprocessing

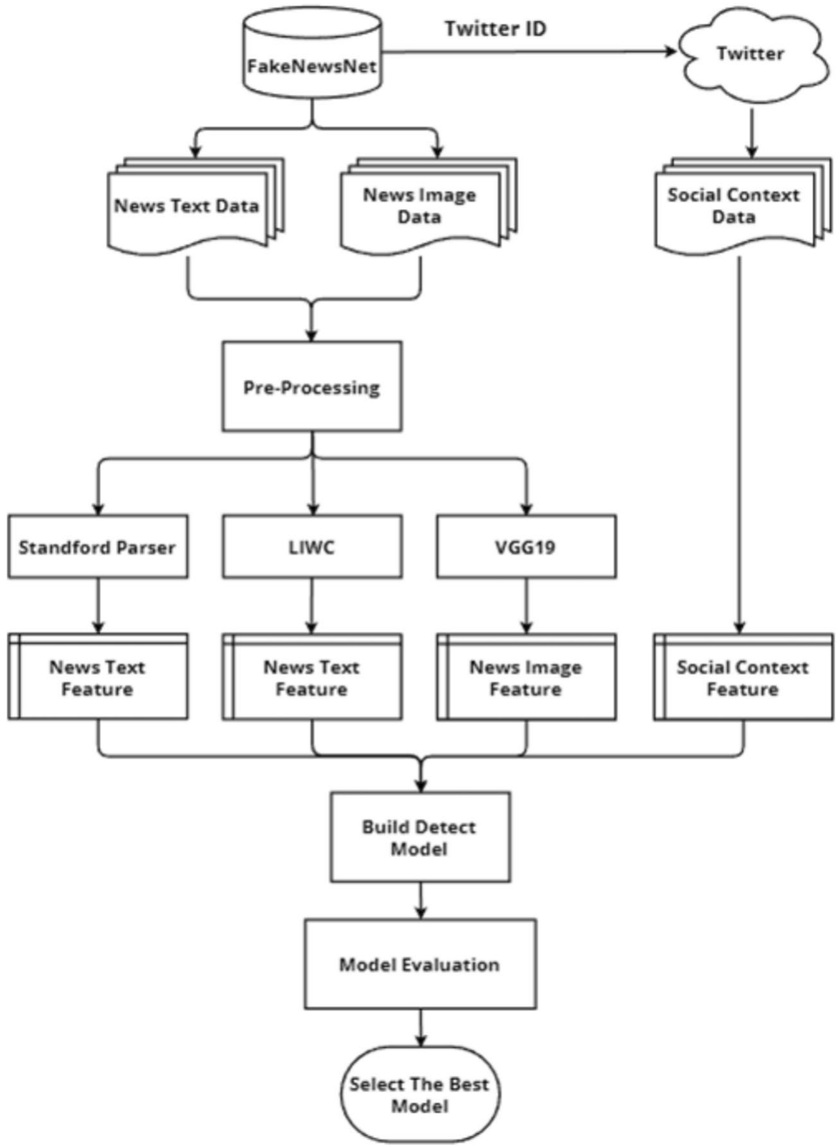
Since the news text data is natural language and is also unstructured data like the image, they cannot directly input it into the machine learning model for analysis. They must first convert the news text and image into structural data. In this study, Stanford Parser and LIWC are used to transform the news text data, and VGG19 model is used to extract the features of news images.

3.2.1 Stanford Parser

Natural Language Processing (NLP) technology is essential for understanding English articles. This process begins with analyzing individual words, then moves to phrases, sentences, and includes grammar and semantic analysis to capture the article's meaning. However, natural language grammar is often ambiguous, and the intended meaning can only be inferred from the sentence's context. Since machines cannot inherently grasp meaning, syntactic parsing is used to assist. Syntactic parsing breaks down sentences into phrases and words, represented in a tree diagram to illustrate the sentence structure, its components, and the relationships between words.

This study uses the Stanford parser syntax analysis tool developed by the Stanford Natural Language Processing Group to analyze the news text data. The output results include the number and proportion of various structures (token, nonterm, unknown) and parts of speech (e.g., noun, verb, objective, etc.).

Fig. 1 Research flow chart



3.2.2 Linguistic Inquiry and Word Count (LIWC)

LIWC calculates the frequency of use in an article of a certain specific word or psychological meaning word categories from a psychological point of view and has two parts: processing component and dictionaries. The processing component mainly calculates the proportion of different parts of speech in the article, compares words with parts of speech in dictionaries one by one, and determines the category to which they belong. For example, the word "I" belongs to the first-person pronoun. When compared with the first-person pronoun in the dictionaries, increase the number of times, and repeat this process until the comparison is completed and the proportion is output. Dictionaries build multiple word categories and words into dictionary files and provide processing components for word comparison (Pennebaker et al., 2015).

This study used LIWC2015 to analyze news text data, and the output included the total word count, seven summary language categorical variables, 21 language characteristic categorical variables, 41 psychological characteristics categorical variables, six individual categorical variables, five informal language marker variables, 12 punctuation mark categorical variables, for a total of 93 variables. For example, enter a news article, and the analysis results after comparison calculation by LIWC are shown in Fig. 2.

3.2.3 VGG19

Wang et al. (2018) pointed out that the VGG19 of the pre-trained model (Simonyan & Zisserman, 2015) can effectively extract useful image features from complex and diverse images, and the knowledge and experience learned in the source field can be applied to the target field using transfer learning. This makes it unnecessary for the target area to learn from scratch, creating models in a time-saving way (Rawat & Wang, 2017). Therefore, this study uses a VGG19 to extract news image features.

VGG19 is an image classification model trained using the ImageNet dataset, which contains 14 million images for 1000 categories (Deng et al., 2009). Its architecture has 19 layers, including 16 layers of the Conceptual Layer and three layers of the Fully Connected Layer, as shown in Fig. 3. First, the image size of 224×224 is transmitted into the input layer. Then the convolutional layer uses a 3×3 size kernel to slide on the image to extract the local features in the image. The Max pooling layer is used to select the maximum value in the local value of the box selection, which is used to reduce the problem of parameter quantity and overfitting. Finally, the output features are input to the fully connected layer, and the classification results are obtained by adjusting the weights and deviations. This study extracts 1000 category probabilities of the output from the fully connected layer of the VGG19 model as news image feature variables.

3.3 Data Mining Technology

This study uses supervised learning, including Logistic Regression (LR), Random Forest (RF), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost), to detect whether news spreading on the Internet is fake news.

3.3.1 Logistic Regression (LR)

LR is the discrete choice model (DCM), which is a type of multivariate analysis. It can develop a mathematical model for predicting the output by analyzing the collected data to confirm the correlation between variables and their strength and to find a function that best represents all observations (Wright, 1995). Logistic Regression differs from Linear Regression's approach in that the dependent variables in Linear Regression are usually continuous and are often used to predict a continuous value, while the dependent variables discussed by Logistic Regression are mainly categorical and mainly applied to classification. Many previous fake news detection studies have also used this algorithm to build detection models (Ahmed et al., 2017; Jin et al., 2016; Ozbay & Alatas, 2020; Singh et al., 2021).

LR uses the output of linear regression to classify the data by bringing data points into the regression line equation: $(x) = \beta 0 + \beta 1$. The output result is greater than or equal to 0 and less than 0 in two categories, as shown in Fig. 4. The independent variables of LR can be continuous, categorical, or a mixture of the two, and the dependent variable in this study is categorical (whether it is fake news) and the independent variable is a discontinuous continuous variable, so it is suitable for LR.

3.3.2 Random Forest (RF)

RF is a type of supervised learning, an Ensemble Learning based on Bootstrap aggregating (Bagging). RF uses the

WC	Analytic	Clout	Authentic	Tone	WPS	Sixltr	Dic	function	pronoun	ppron	i	we	you	shehe	they	ipron	article	prep	auxverb	adverb	conj	negate
118	97.93	50.00	45.61	92.90	39.33	27.12	69.49	36.44	2.54	0.00	0.00	0.00	0.00	0.00	0.00	2.54	8.47	16.10	1.69	3.39	9.32	0.00

verb	adj	compare	interrog	number	quant	affect	posemo	negemo	anx	anger	sad	social	family	friend	female	male	cogproc	insight	cause	discrep	tentat	certain	differ
4.24	6.78	4.24	0.00	1.69	0.85	4.24	4.24	0.00	0.00	0.00	0.00	0.85	0.85	0.00	0.00	0.00	10.17	4.24	2.54	0.00	0.00	3.39	0.85

percept	see	hear	feel	bio	body	health	sexual	ingest	drives	affiliation	achieve	power	reward	risk	focuspast	focuspresent	focusfuture	relativ	motion	space	time	work	leisure
0.00	0.00	0.00	0.00	5.93	0.00	5.93	1.69	0.00	3.39	0.85	0.85	1.69	1.69	0.00	0.00	5.93	0.00	15.25	0.85	10.17	4.24	4.24	0.85

home	money	relig	death	informal	swear	netspeak	assent	nonflu	filler	Allpunc	Period	Comma	Colon	SemiC	QMark	Exclam	Dash	Quote	Apostro	Parenth	OtherP
0.85	0.00	0.00	0.00	0.85	0.00	0.00	0.00	0.85	0.00	16.10	5.93	5.93	0.85	0.00	0.00	0.00	0.00	0.00	0.85	0.00	2.54

Fig. 2 Diagram of the results using LIWC

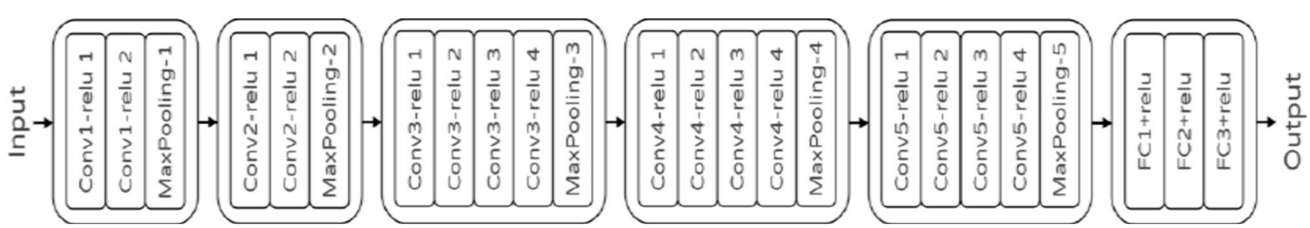


Fig. 3 The architecture of VGG19

bootstrap sampling method to randomly select sub-training samples from the training dataset and uses new training data from several sub-training samples to build the Classification and Regression Trees (CART). According to the establishment of several unrelated CART trees to carry out the majority voting method prediction, the largest number of votes is in the prediction category. (Breiman, 2001). As Fig. 5 shows. RF has good noise immunity, and their randomness makes it difficult for classification models to fall into overfitting, so many studies have also used this algorithm to build fake news detection models (Jin et al., 2016; Singh et al., 2021; Zhou et al., 2020).

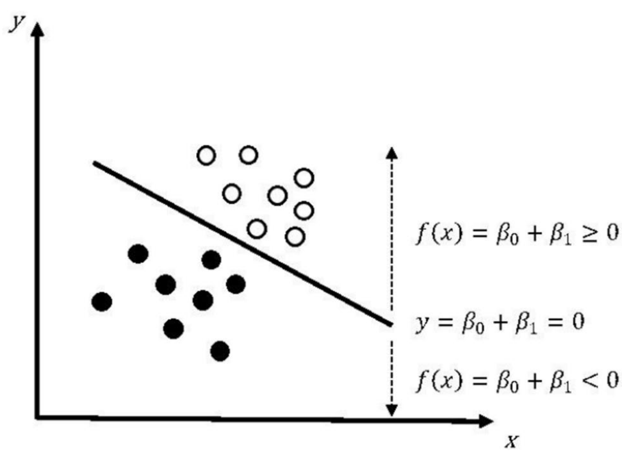


Fig. 4 Schematic diagram of LR

3.3.3 Support Vector Machine (SVM)

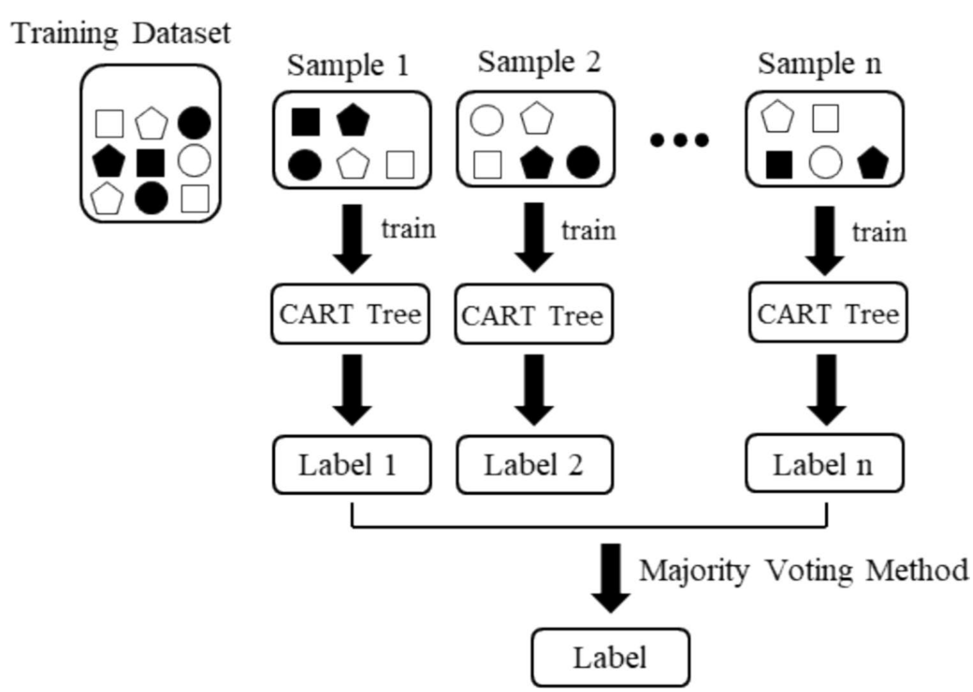
SVM, proposed by Cortes and Vapnik (1995), is a kind of supervised learning in machine learning suitable for dealing with high-dimensional, nonlinear classification and regression-type data problems. It is often used in text classification, image classification, and predictive classification. It works by mapping input and output variables to a higher-dimensional space in the feature vector space formed by the training data, using the Structural Risk Minimization (SRM) principle, to find a hyperplane that maximizes the distance between the two types of data. As Fig. 6 shows.

The performance of the model depends on the distance of the hyperplane from different classes, and too small a distance can lead to overfitting. The greater the distance, the more categories of the training data can be classified, and the Generalization error of the classifier is reduced to accurately determine which data belongs to which category. Ahmed et al. (2017); de Oliveira et al.(2020) used news text features to detect fake news and used SVM to classify, which proved that the SVM algorithm has the characteristics of efficiency and flexibility.

3.3.4 Extreme Gradient Boosting (XGBoost)

XGBoost is an improvement and extension of the Gradient Boosted Decision Tree (GBDT) and is an Ensemble Learning method. It combines Gradient Boosting (GB) and Decision Tree (DT) with Classification and Regression Trees (CART) as the base classifier. Not only that, but XGBoost also supports linear classifiers, which can be

Fig. 5 Schematic diagram of RF



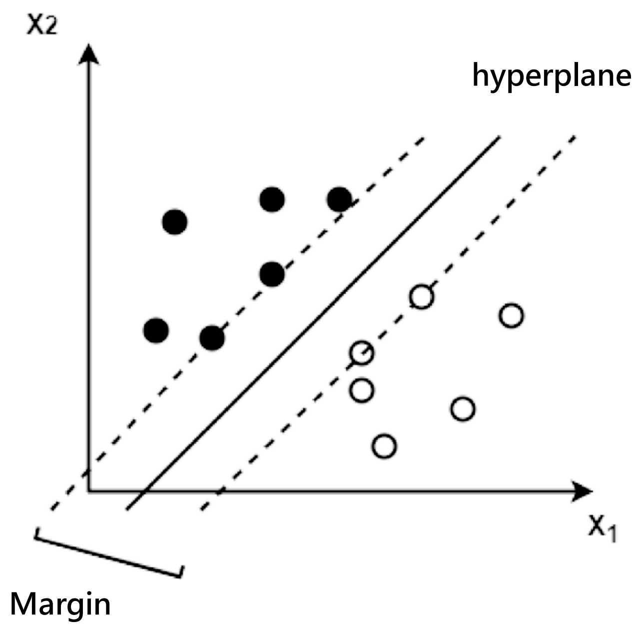


Fig. 6 Schematic diagram of SVM

applied to solve classification and regression problems of supervised learning. Unlike traditional GBDT, XGBoost uses the Greedy Algorithm to optimize the maximum gain of the objective function during each layer of the tree (choosing new trees, finding the best trees, and pruning) (Chen & Guestrin, 2016).

Since we need to consider the optimization of multiple CART parameters and the problem that they cannot be trained simultaneously, we can add a new function to the original training model by incremental training to help correct the deficiencies of the previous function and improve the target function, as shown in Fig. 7. For example, Helmstetter and Paulheim (2018) detected and classified fake news spread on Twitter, and the results showed that GBDT was the best for classification, and the results of Zhou et al. (2020) also showed that GBDT had the best classification performance.

4 Experiments

4.1 Experimental Design

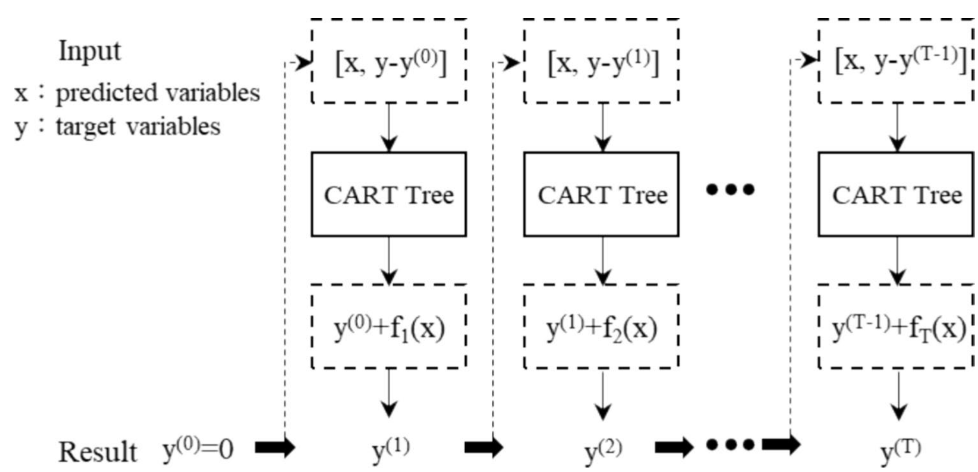
The first three experiments use news text features, social context features, and news image features to generate feature matrices as the data source for the model input and use four classification algorithms: Logistic Regression, Random Forest, Support Vector Machine, and Extreme Gradient Boosting to build a fake news detection model and discuss different features and classification models. The fourth experiment selects the best combination of features in the first three experiments and uses different image feature dimensions to explore the effect of different image feature dimensions on the model.

Experiment 1 uses a single feature to build a fake news detection model, as shown in Fig. 8, and the features used are as follows:

Stanford Parser: Extracting news text features using Stanford Parser.
LIWC: Using LIWC to extract news text features.
VGG19: Using VGG19 pre-training model to extract news image features.
User: Extracting social context features from social media users' personal information.

Experiment 2 will combine the two features used in Experiment 1 to generate five different feature matrices for constructing the fake news detection model, as shown in Fig. 9, namely Stanford Parser + VGG19, Stanford Parser + User, LIWC + VGG19, LIWC + User, and VGG19 + User.

Fig. 7 Schematic diagram of XGBoost



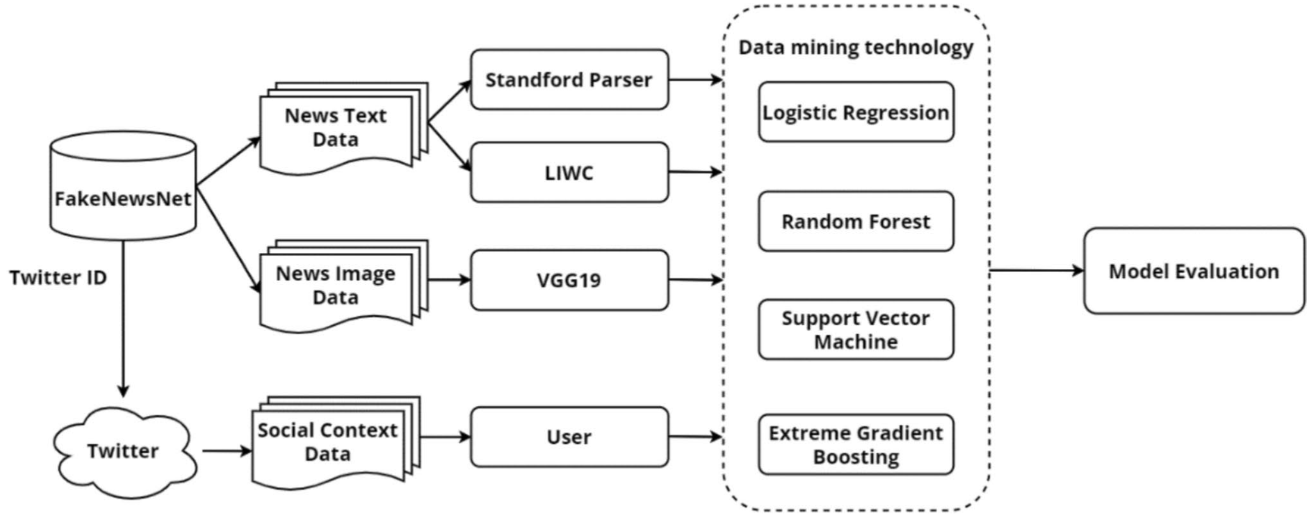


Fig. 8 Flowchart of experiment 1

Experiment 3 combines the three features to generate two feature sets as input sources for the model to construct a fake news detection model, as shown in Fig. 10, namely, Stanford Parser + VGG19 + User and LIWC + VGG19 + User.

Experiment 4 selects the best feature combinations from the first three experiments and uses different image feature dimensions of 1000, 500, and 300 dimensions to investigate whether reducing the image feature dimensions can still maintain the performance of the model while reducing the complexity of the model, as shown in Fig. 11.

4.2 Data Validation and Evaluation Indicators

This study employs tenfold cross-validation to validate the model, as illustrated in Fig. 12. Using tenfold cross-validation, we can mitigate the reliance on specific training and test data by dividing the dataset into 10 subsets. Each subset is sequentially used as a validation set, while the remaining subsets are combined as the training set, ensuring that each data point is used for validation exactly once. This approach reduces the risk of overfitting and minimizes sampling bias, leading to a more robust and generalizable model (Azuaje, 2006).

True positive (TP): The number of fake news correctly classified as fake by the model.
False positive (FP): The number of real news incorrectly classified as fake by the model.
False negative (FN): The number of fake news incorrectly classified as real by the model.
True negative (TN): The number of real news correctly classified as real by the model.

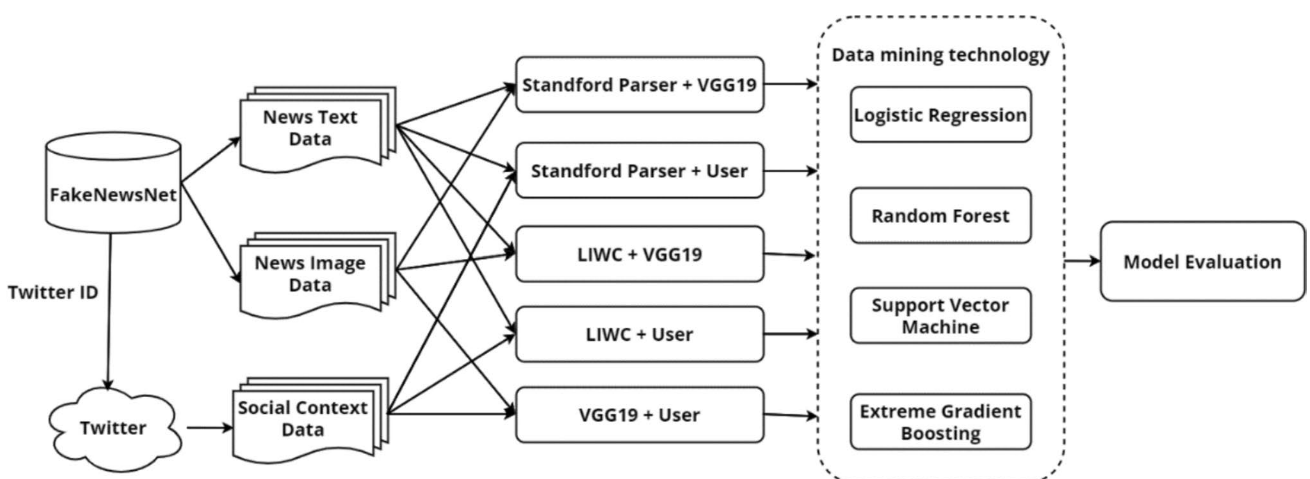


Fig. 9 Flowchart of experiment 2

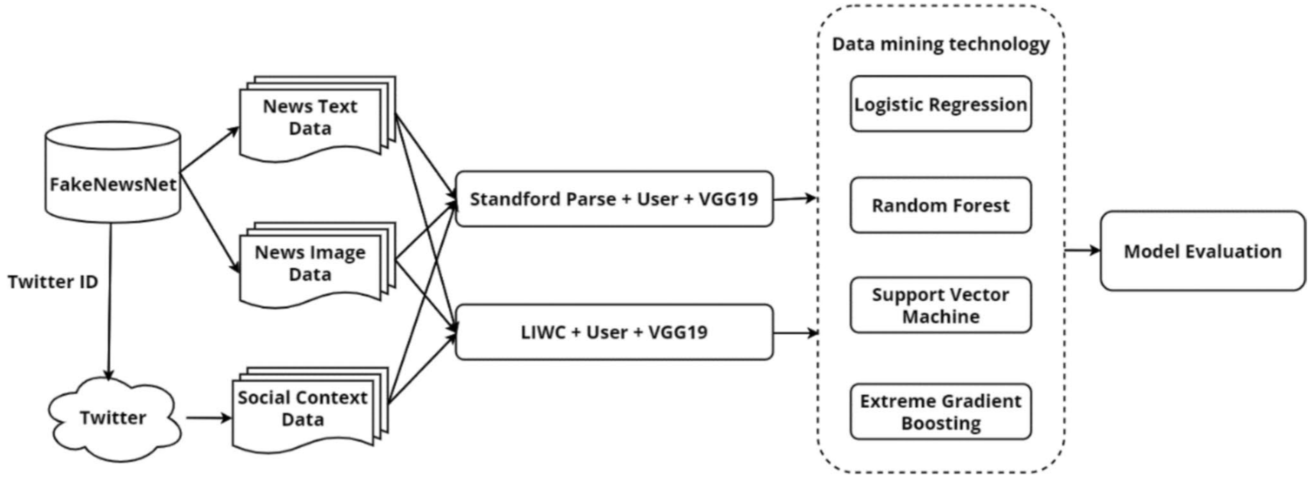


Fig. 10 Flowchart of experiment 3

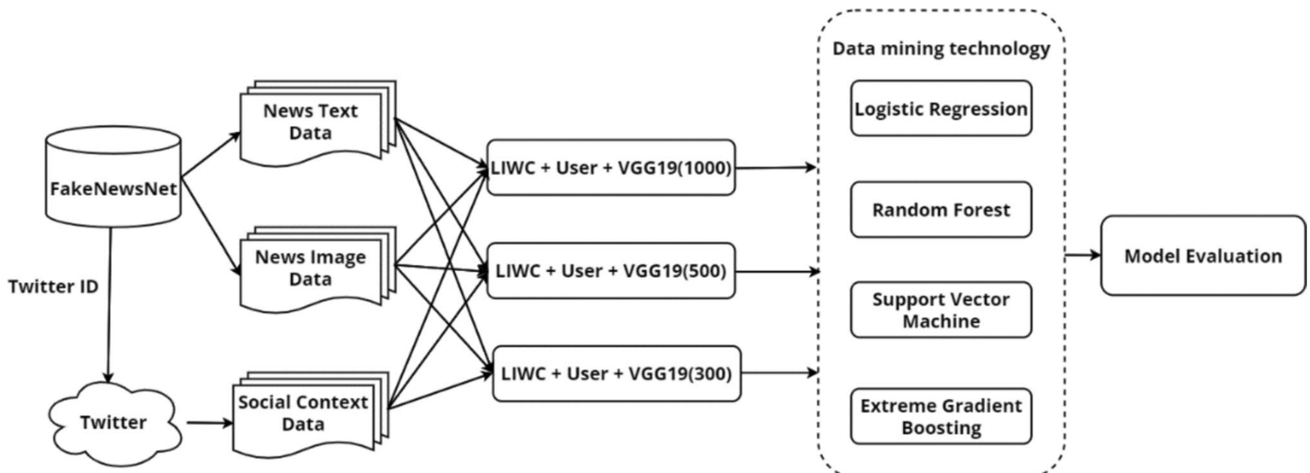
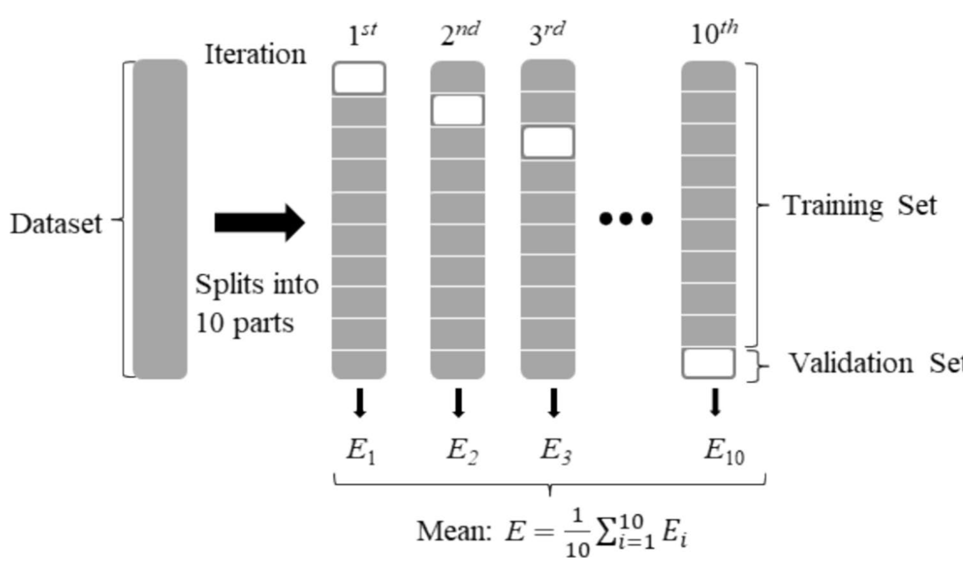


Fig. 11 Flowchart of experiment 4

Fig. 12 Schematic diagram of tenfold cross-validation



The primary evaluation metrics in this study include Precision, Recall, F1-Score, and Accuracy, defined as follows:

$$Precision = TP/(TP + FP) \times 100\% \tag{1}$$

$$Recall = TP/(TP + FN) \times 100\% \tag{2}$$

$$F1 - Score = (2 \times Precision \times Recall)/(Precision + Recall) \times 100\% \tag{3}$$

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \times 100\% \tag{4}$$

5 Experiment Results

5.1 Experiment 1

Experiment 1 uses a single feature variable, which is (1) Stanford Parser to extract news text features, (2) LIWC to extract news text features, (3) VGG19 to extract news image features, and (4) User to extract social context features. We also use LR, RF, SVM, and XGBoost to build the detection models, respectively. Table 4 and Fig. 13 show the F1-score values of each feature variable in Experiment 1 with different classification models. In the PolitiFact dataset, we can observe that the F1 value of Stanford Parser is higher than that of LIWC, indicating that news articles in the political domain can extract important news text features more effectively by using Stanford Parser syntactic analysis. Then, comparing the F1-score values of the four preprocessing methods, we found that Stanford Parser > LIWC > User > VGG19, indicating that news articles in the political domain are better detected by using the model based on news text features. In the GossipCop dataset, we can observe that the F1 value of LIWC is higher than that of Stanford Parser, indicating that news articles in the entertainment field can extract important news text features more effectively from a psychological perspective using LIWC. Next, comparing the F1-score values of the four preprocessing methods, we found that User > VGG19 > LIWC > Stanford Parser, indicating that news articles in the entertainment domain are better at detecting fake news using a model based on social contextual features. Table 8 in appendix shows the results of all evaluation metrics in Experiment 1. The results indicate that using Stanford Parser along with RF model has the highest accuracy in both datasets, which follows the same pattern as the F1 score.

Table 4 The F1-score values of each characteristic variable with each classification model in experiment 1

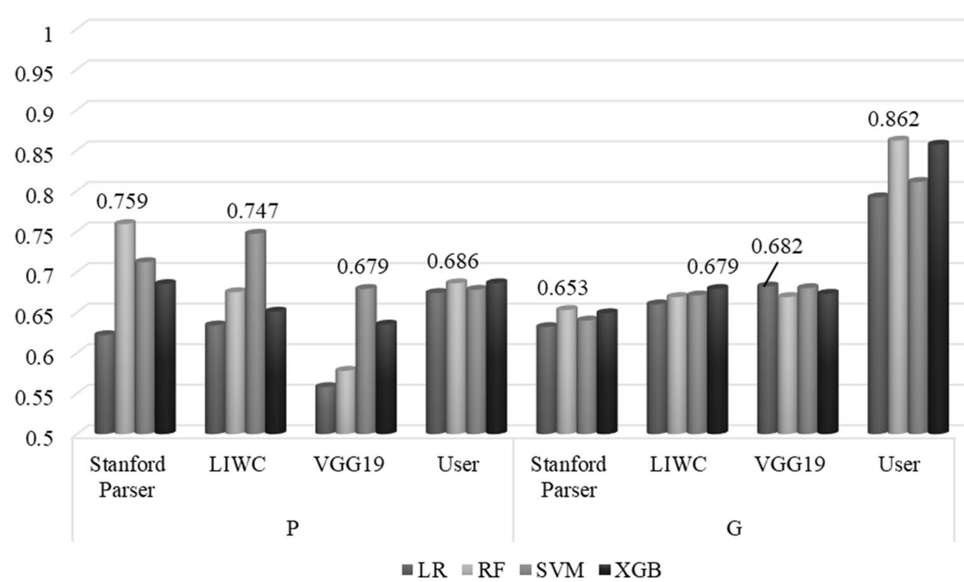
		Stanford Parser	LIWC	VGG19	User
P	LR	0.622	0.634	0.558	0.674
	RF	**0.759**	0.675	0.578	**0.686**
	SVM	0.712	**0.747**	**0.679**	0.678
	XGB	0.685	0.651	0.635	0.686
G	LR	0.632	0.660	**0.682**	0.792
	RF	**0.653**	0.669	0.669	**0.862**
	SVM	0.640	0.671	0.680	0.811
	XGB	0.649	**0.679**	0.673	0.857

P PolitiFact; *G* GossipCop; *XGB* XGBoost

5.2 Experiment 2

Experiment 2 is a combination of two types of features to build the detection model. Using either of the two methods in Experiment 1, five feature matrices were generated

Fig. 13 The F1-score values of experiment 1



as data input sources for the model. They are Stanford Parser + VGG19, Stanford Parser + User, LIWC + VGG19, LIWC + User, and VGG19 + User. Table 5 show the F1-score values of these five feature matrices. Figure 14 compares the F1-score values for Experiment 1 and Experiment 2. In the PolitiFact dataset, the results show that LIWC + VG G19 > LIWC + User > VGG19 + User > SP + VGG19 = SP + User > SP > LIWC > User > VGG19. This means that the LIWC combined with VGG19 model is better at detecting fake news in the political domain. It is also found that the F1-score values obtained from models combining text and image features of news, text, and social context features, or news image features and social context features, are all higher than those obtained from models using a single feature. In the GossipCop dataset, the results show that LIW C + User > SP + User > VGG19 + User > User > SP + VGG 19 > LIWC + VGG19 > VGG19 > LIWC > SP, indicating that the combination of LIWC and User can better detect fake news in the entertainment field. Table 9 in the appendix shows the results of all evaluation metrics in Experiment 2. The results indicate that using VGG19 + User with XGBoost model has the highest accuracy in the PolitiFact dataset and using Stanford Parser + User or LIWC + User with XGBoost model has the highest accuracy in the GossipCop dataset.

5.3 Experiment 3

Experiment 3 uses all feature variables (news text, news image, and social context), where the news text feature uses Stanford Parser and LIWC and then combines them with VGG and User, respectively, to generate two feature matrices as data input sources for the model. These are Stanford Parser + VGG19 + User and LIWC + VGG19 + User, respectively. Table 6 show the F1-score values of combining three

Table 5 The F1-score values of a combination of two types of features

		SP + VGG19	SP + User	LIWC + VGG19	LIWC + User	VGG19 + User
P	LR	0.728	0.677	0.802	0.745	0.698
	RF	**0.775**	**0.775**	0.768	0.784	0.727
	SVM	**0.775**	0.747	0.801	0.769	0.713
	XGB	0.741	0.750	**0.815**	**0.808**	**0.783**
G	LR	0.676	0.766	0.689	0.776	0.710
	RF	0.667	0.863	0.682	0.876	0.822
	SVM	0.676	0.694	0.681	0.723	0.710
	XGB	**0.688**	**0.884**	**0.709**	**0.885**	**0.879**

P PolitiFact; *G* GossipCop; *XGB* XGBoost

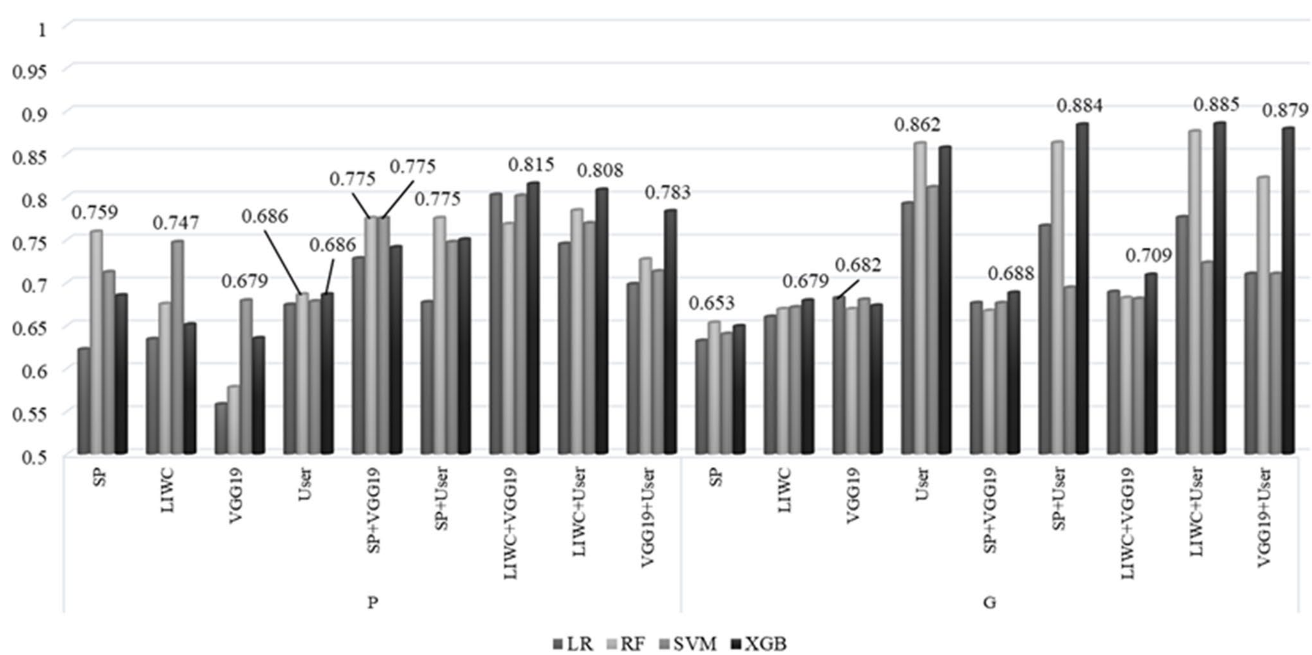


Fig. 14 Compare the F1-score values in Experiment 1 and experiment 2

types of features. Figure 15 compares the F1-score values for Experiment 2 and Experiment 3. In the PolitiFact dataset, LIWC + VGG19 + User > SP + VGG19 + User > LIWC + VGG19 > LIWC + User > VGG19 + User > SP + VGG19 = SP + User, indicating that the F1-score values of the models built with all three features (news text feature, social context feature, and news image feature) are higher than those of the models built with a single feature or two features. This means that the news text feature, the social context feature, and the news image feature all contain important fake news features. In the GossipCop dataset, the results show that LIWC + VGG19 + User > SP + VGG19 + User > LIWC + User > SP + User > VGG19 + User > LIWC + VGG19 > SP + VGG19. This also shows that the best results are obtained by using the news text feature, social context feature, and news image feature simultaneously. Therefore, all three features should be considered when building the detection model. Table 10 in appendix shows the results of all evaluation metrics in Experiment 3. The results indicate that using LIWC + VGG19 + User with LR model has the highest accuracy in the PolitiFact dataset, and using LIWC + VGG19 + User with XGB model has the highest accuracy in the GossipCop dataset.

Table 6 The F1-score values of ombining three types of features

		SP + VGG19 + User	LIWC + VGG19 + User
P	LR	0.820	0.868
	RF	0.837	0.820
	SVM	**0.867**	**0.877**
	XGB	0.860	0.828
G	LR	0.707	0.702
	RF	0.697	0.686
	SVM	0.747	0.827
	XGB	**0.892**	**0.896**

P PolitiFact; *G* GossipCop; *XGB* XGBoost

5.4 Experiment 4

Experiment 4 is to select the best feature combination from the first three experiments, i.e., LIWC + VGG19 + User, and then use 1000, 500, and 300-dimensional image features to investigate whether reducing the dimensionality of image features can still maintain the model performance and reduce the complexity of the model. Table 7 and Fig. 16 show the F1-score values for Experiment 4. In the PolitiFact dataset, the results show that LIWC + User + VGG19 (1000) > LIWC + User + VGG19 (500) > LIWC + User + VGG19 (300), which means the performance is better when using 1000-dimensional image features, and the difference is about 0.04

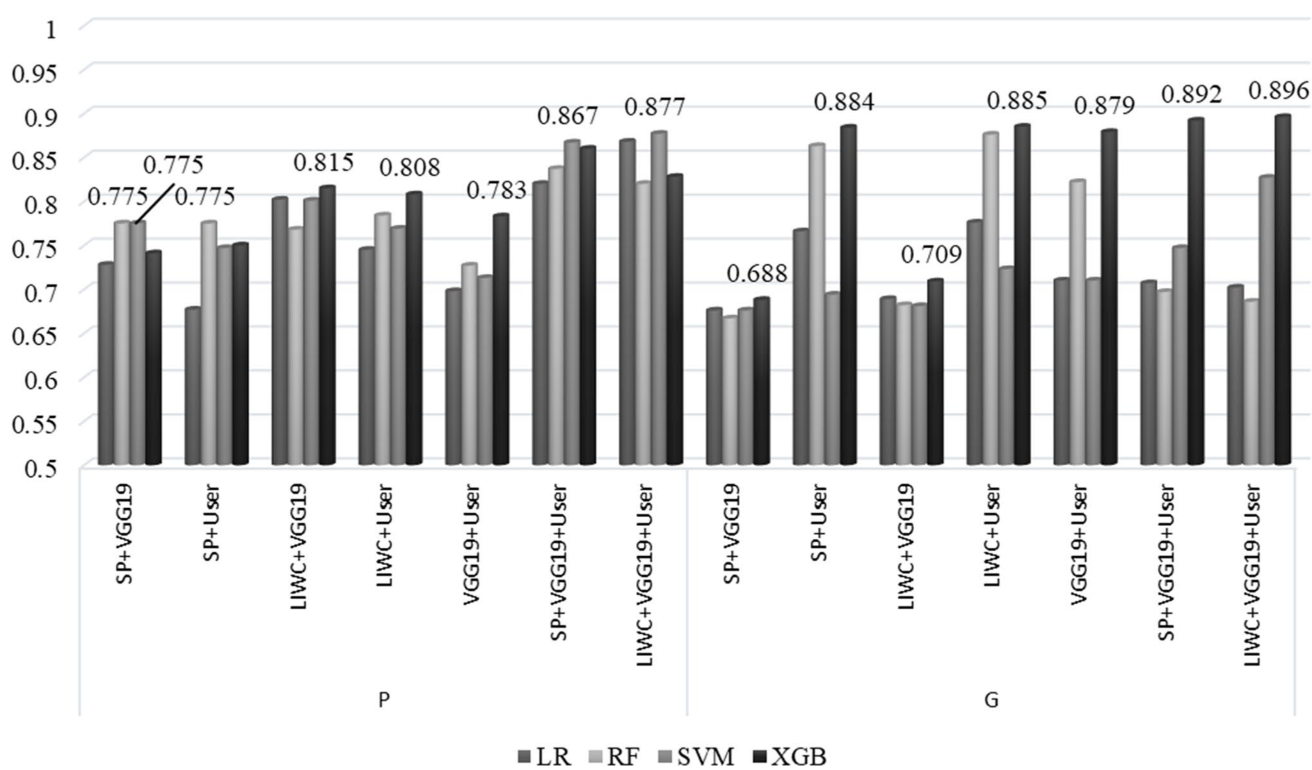


Fig. 15 Compare the F1-score values of experiment 2 and experiment 3

and 0.05 with 500 and 300 dimensions, respectively. Therefore, it is not suitable to reduce the dimensionality of image features when the amount of data is small. In the GossipCop dataset, the results show that LIWC + User + VGG19 (1000) > LIWC + User + VGG19 (300) > LIWC + User + VGG19 (500). This means that the performance is better when using 1000-dimensional image features, which are about 0.03 and 0.01 different from 500 and 300 dimensions, respectively. Therefore, when the amount of data is large, the dimensionality of the image feature can be reduced from 1000 to 300 to reduce the complexity of the model. Table 11 in the appendix presents the results for all evaluation metrics in Experiment 4. The results indicate that using LIWC + User + VGG19(1000) with LR model has the highest accuracy in the PolitiFact dataset, and using LIWC + User + VGG19(1000) with XGB model has the highest accuracy in the GossipCop dataset.

The results of the four experiments were the same as those of previous studies. The models combining news text features with social context features and those combining news text features with news image features outperformed the detection models using only news text features. In addition, it is found that the detection models that consider news text features, social context features, and news image features together are more effective in detecting fake news. Therefore, when constructing a fake news detection model, it is necessary to consider not only news text features but also social context features and news image features, and when the collected data is larger, the dimensionality of image features can be reduced to reduce the complexity of the model.

Table 7 Compare the F1-score values of each model with the image features in different dimensions in experiment 4

		LIWC + User + VGG19(1000)	LIWC + User + VGG19(500)	LIWC + User + VGG19(300)
P	LR	0.868	0.776	0.679
	RF	0.820	0.763	0.725
	SVM	**0.877**	0.781	0.819
	XGB	0.828	**0.836**	**0.823**
G	LR	0.702	0.718	0.733
	RF	0.686	0.738	0.714
	SVM	0.827	0.776	0.779
	XGB	**0.896**	**0.869**	**0.889**

P PolitiFact; *G* GossipCop; *XGB* XGBoost

6 Conclusion

6.1 Research Conclusion

In recent years, the issue of fake news has swept the world, and people's lives are surrounded by much fake news every day. However, people do not always have the ability to interpret every news report, which may make people unknowingly affected by wrong information and make wrong decisions, delay the best time for treatment, or even lead to deception. In previous studies, many scholars have proposed using textual exploration techniques to extract fake news features from news texts, and some scholars have used social contextual information, such as social

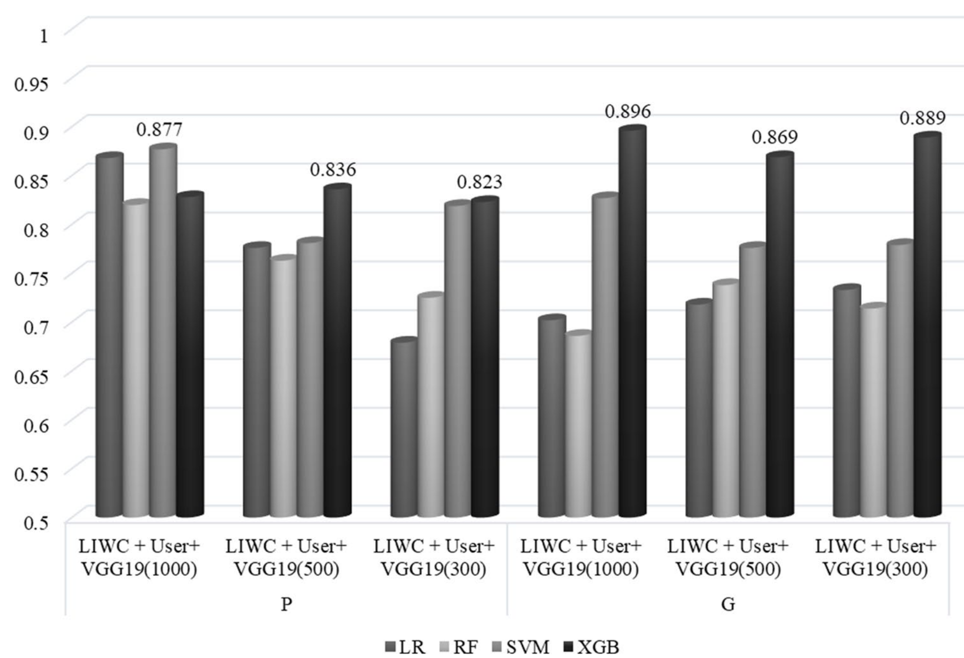


Fig. 16 The F1-score values of experiment 4

media users and news distribution networks, to build fake news detection models, but few studies have considered whether "images in news articles" contain features that affect fake news detection models. Therefore, this study considers news text, social context, and news image features to build a fake news detection model to improve the accuracy of the detection model.

From the experimental results of this study, it can be seen that the models using all three features (news text feature, social context feature, and news image feature) are more effective than those using a single feature or two features in both PolitiFact and GossipCop datasets. This means that the news text feature, social context feature, and news image feature all contain important fake news features that need to be considered when building the detection model. In addition, when identifying fake news based on a single feature, the PolitiFact dataset performs better using news text features, while the GossipCop dataset performs better using social context features. News in different fields does require different features to identify whether it is fake news. Therefore, we cannot use a single model or the same set of features to identify all fake news. When using both features, the PolitiFact dataset uses the LIWC + VGG19 model for best performance, while the GossipCop dataset uses the LIWC + User model. When considering all three features, the PolitiFact dataset and the GossipCop dataset both use LIWC + VGG19 + User for the best performance. In addition, when the number of data collected is large, the dimensionality of the image features can be reduced to simplify the complexity of the model.

The practical contribution of this study is to help fact-checking organizations extract valuable information from news content for reference when conducting fact-checking, to determine whether news contains false information, and to speed up the whole checking process. In addition, we provide a fake news detection model for social media to detect the presence of false information through news content, images, and user-related social context information before users post or retweet messages containing news links to block the widespread dissemination of fake news on social media platforms and reduce the chance of people being exposed to fake news. In terms of academic contributions, this study compiled relevant literature to verify the factors of news text, image, and social context features used in previous studies in the fake news detection model and used data exploration techniques to extract the main influencing factors to construct a fake news detection model. The experimental results show that the model using both news text features, social context features, and news image features is more effective in detecting fake news than the model using only one feature or two features, which provides a reference for future research in this direction and increases the accuracy of detecting fake news.

6.2 Research Limitations

This study uses the FakeNewsNet dataset and the Twitter API key to collect social contextual data and uses news text features, social contextual features, and news image features combined with multiple machine learning to construct a classification model to detect fake news. However, this study may be incomplete due to the following research limitations:

1. The FakeNewsNet dataset only provides the news URLs, and we need to crawl the news content through crawlers, but some of the news URLs are no longer available, which reduces the number of samples obtained, and may not be able to train the best detection model due to the insufficient sample size.
2. Twitter has recently increased the privacy which can not disclose complete social context information of social users, and more and more users do not disclose user information. Therefore, this study can only retrieve the number of follower and the number of following of the Twitter ID using Twitter API and unable to obtain complete data for analysis.

6.3 Future Research Directions and Recommendations

This study combines three feature components (news text features, social context features, and news image features) with various supervised algorithms to develop a fake news detection model. While the current dataset includes news in the political and entertainment domains, news in other fields is diverse and may exhibit different characteristics of fake news. Future research could incorporate fake news datasets from additional domains to examine the factors influencing fake news detection across different fields. Additionally, with access to larger datasets, deep learning could be leveraged to automatically learn feature representations, and semi-supervised or unsupervised algorithms could be applied to enhance the model's generalization ability.

Appendix

Table 8 Experimental results of experiment 1

		Stanford Parser				LIWC				VGG19				User			
		Pre	Re	F1	Acc	Pre	Re	F1	Acc	Pre	Re	F1	Acc	Pre	Re	F1	Acc
P	LR	0.613	0.663	0.622	0.660	0.652	0.673	0.634	0.663	0.602	0.550	0.558	0.645	0.550	0.893	0.674	0.604
	RF	0.706	0.743	**0.759**	**0.768**	0.789	0.667	0.675	0.728	0.666	0.657	0.578	0.678	0.714	0.703	0.686	0.729
	SVM	0.671	0.817	0.712	0.710	0.725	0.833	0.747	0.736	0.655	0.727	0.679	0.695	0.528	0.963	0.678	0.579
	XGB	0.759	0.647	0.685	0.744	0.718	0.670	0.651	0.702	0.683	0.620	0.635	0.678	0.718	0.690	0.686	0.713
G	LR	0.649	0.618	0.632	0.639	0.677	0.646	0.660	0.666	0.681	0.686	0.682	0.678	0.783	0.804	0.792	0.808
	RF	0.677	0.618	0.653	0.669	0.707	0.637	0.669	0.694	0.736	0.630	0.669	0.687	0.877	0.852	**0.862**	**0.883**
	SVM	0.694	0.594	0.640	0.664	0.748	0.609	0.671	0.700	0.718	0.649	0.680	0.694	0.781	0.846	0.811	0.820
	XGB	0.662	0.638	0.649	0.654	0.697	0.663	0.679	0.685	0.718	0.634	0.673	0.690	0.874	0.842	0.857	0.872

P PolitiFact; *G* GossipCop; *XGB* XGBoost; *Pre* precision; *Re* recall; *Acc* accuracy

Table 9 Experimental results of experiment 2

		Stanford parser + vgg19				Stanford parser + user				liwc + vgg19				liwc + user				vgg19 + user			
		pre	re	f1	acc	pre	re	f1	acc	pre	re	f1	acc	pre	re	f1	acc	pre	re	f1	acc
p	lr	0.782	0.710	0.728	0.770	0.635	0.757	0.677	0.693	0.874	0.764	0.802	0.810	0.791	0.724	0.745	0.733	0.776	0.670	0.698	0.753
	rf	0.795	0.677	0.775	0.819	0.734	0.797	0.775	0.768	0.770	0.779	0.768	0.752	0.771	0.871	0.784	0.769	0.862	0.697	0.727	0.785
	svm	0.753	0.817	0.775	0.786	0.707	0.837	0.747	0.743	0.794	0.826	0.801	0.785	0.739	0.829	0.769	0.735	0.714	0.727	0.713	0.737
	xgb	0.852	0.707	0.741	0.785	0.846	0.720	0.750	0.802	0.825	0.826	**0.815**	0.803	0.809	0.826	0.808	0.784	0.861	0.753	0.783	**0.820**
g	lr	0.681	0.673	0.676	0.676	0.787	0.747	0.766	0.770	0.704	0.678	0.689	0.693	0.793	0.761	0.776	0.779	0.716	0.708	0.710	0.710
	rf	0.745	0.615	0.667	0.701	0.876	0.860	0.863	0.867	0.751	0.637	0.682	0.707	0.882	0.867	0.876	0.873	0.859	0.777	0.822	0.821
	svm	0.733	0.630	0.676	0.698	0.756	0.643	0.694	0.716	0.742	0.631	0.681	0.703	0.793	0.665	0.723	0.744	0.767	0.664	0.710	0.728
	xgb	0.730	0.652	0.688	0.704	0.894	0.876	0.884	**0.885**	0.733	0.687	0.709	0.717	0.892	0.879	**0.885**	**0.885**	0.890	0.870	0.879	0.880

P PolitiFact; *G* GossipCop; *XGB* XGBoost; *Pre* precision; *Re* recall; *Acc* accuracy

Table 10 Experimental results of experiment 3

		Stanford Parser + VGG19 + User				LIWC + VGG19 + User			
		Pre	Re	F1	Acc	Pre	Re	F1	Acc
P	LR	0.8249	0.829	0.820	0.800	0.855	0.893	0.868	**0.850**
	RF	0.791	0.902	0.837	0.793	0.779	0.879	0.820	0.792
	SVM	0.821	0.888	**0.867**	**0.826**	0.834	0.907	**0.877**	0.801
	XGB	0.843	0.886	0.860	0.833	0.809	0.860	0.828	0.802
G	LR	0.718	0.699	0.707	0.709	0.700	0.705	0.702	0.692
	RF	0.761	0.646	0.697	0.719	0.791	0.607	0.686	0.715
	SVM	0.811	0.694	0.747	0.781	0.868	0.814	0.827	0.828
	XGB	0.902	0.883	**0.892**	**0.892**	0.902	0.892	**0.896**	**0.894**

P PolitiFact; *G* GossipCop; *XGB* XGBoost; *Pre* precision; *Re* recall; *Acc* accuracy

Table 11 Experimental results of experiment 4

		LIWC + User + VGG19(1000)				LIWC + User + VGG19(500)				LIWC + User + VGG19(300)			
		Pre	Re	F1	Acc	Pre	Re	F1	Acc	Pre	Re	F1	Acc
P	LR	0.855	0.893	0.868	**0.850**	0.766	0.819	0.776	0.776	0.772	0.633	0.679	0.719
	RF	0.779	0.879	0.820	0.792	0.655	0.933	0.763	0.694	0.734	0.733	0.725	0.728
	SVM	0.834	0.907	**0.877**	0.801	0.777	0.852	0.781	0.776	0.786	0.833	0.819	0.802
	XGB	0.809	0.860	0.828	0.802	0.794	0.900	0.836	0.818	0.881	0.783	0.823	0.835
G	LR	0.700	0.705	0.702	0.692	0.716	0.712	0.713	0.718	0.735	0.735	0.733	0.729
	RF	0.791	0.607	0.686	0.715	0.793	0.634	0.704	0.738	0.800	0.648	0.714	0.738
	SVM	0.868	0.814	0.827	0.828	0.837	0.680	0.745	0.776	0.846	0.723	0.779	0.778
	XGB	0.902	0.892	**0.896**	**0.894**	0.873	0.860	0.866	0.869	0.900	0.878	0.889	0.888

P PolitiFactp; *G* GossipCop; *XGB* XGBoost; *Pre* precision; *Re* recall; *Acc* accuracy

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Declarations

Ethics Approval and Consent to Participate. Not applicable.

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