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Abstract: Traditional social media platforms have low accuracy in identifying false information. Therefore, a method based on multi-modal feature fusion is proposed to recognise false information within social media platforms. This method processes false information data on social media platforms by calculating noise during transmission, and utilises multi-layer management to establish correlations between multi-modal point cloud data. By designing modal grouping and calculating similarity, we integrate information from the three dimensions of time, space, and attributes to supplement the shortcomings of the data. By utilising multi-modal feature fusion algorithms, accurate recognition of false information on social media platforms can be achieved. The experimental results show that using this method can effectively improve the training accuracy of the model and have the ability to resist false data injection attacks, achieving high recognition accuracy.

Keywords: multi-modal feature fusion; social media platform; false information; recognition methods.

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1 Introduction

With the popularisation and development of social media, the spread of false information has become one of the serious social problems. As one of the main channels of information dissemination (Sierra et al., 2022; Osei-Frimpong et al., 2022), social media platform not only provides convenience for users to obtain and share information, but also provides opportunities for malicious users to spread false information (Manca et al., 2022). False information not only disturbs the public's judgment and decision-making, but also may cause great influence and loss to society (Fazli-Salehi et al., 2022; Wright et al., 2022). At present, the recognition of false information has become one of the research focuses. However, because false information has diversified forms of expression and dissemination, traditional text analysis methods often cannot accurately recognise false information. In order to solve this problem, scholars began to pay attention to the methods to improve the accuracy and reliability of false information recognition.

Li et al. (2022) puts forward an evolutionary game analysis of spreading false information by multiple parties after major emergencies. Firstly, a three-party game model is constructed by using the relevant knowledge of evolutionary game theory: regulators, opinion leaders and ordinary netizens. Then solve the model equation and analyse the evolutionary stability strategies of all parties in different situations. Finally, the evolution trend under different strategy combinations and different parameters is numerically simulated. The results show that the probability of each player making an ideal decision is positively related to the punishment degree of the supervision institution to the opinion leader who publishes false information, the reward of the supervision institution to the opinion leader who publishes positive information, the participation and satisfaction of netizens who adopt positive information, the richness of the real content published by the opinion leader and the psychological identity of netizens to the opinion leader. However, the similarity between the dataset generated by this method and the actual data is low, which cannot effectively improve the accuracy of data training by the model. Zhang and Guo (2022) proposes a method for recognising false identity information of social network users based on preference logic. Firstly, the preference logic system is used to deal with the preferences of social network users. At the same

time, a logistic regression model is constructed to recognise and establish new connections, and new matching users are placed in the collection as seed nodes based on user information attributes, so as to realise false identity recognition of social network users. The experimental results show that the recognition rate and practicability of this method are high. However, this method cannot accurately recognise the false information in the social media platform, and the recognition effect is not good. Zhang (2021) puts forward a method to recognise the characteristics of false health information in social media. Through the analysis of 1,004 social media health big data, the false health information in social media is extracted by programming code and classified. Discover the main features of medical fake news in social media, and form a feature list of social media fake news. Through the statistical analysis of social media, it is found that the characteristics of false health news in social media can be divided into representation characteristics, semantic characteristics and source characteristics, including 11 basic characteristics and 29 small characteristics. However, this method has low recognition accuracy.

On the basis of the above research, this paper proposes a research on false information recognition of social media platforms based on multimodal feature fusion. Multi-modal feature fusion refers to the effective combination of features from different modes, including text, images and videos, in order to obtain more comprehensive and accurate information. In social media platforms, false information is often presented in various forms. Therefore, the method of multi-modal feature fusion can better capture the features of false information and improve the accuracy of recognition. The purpose of this study is to explore the recognition of false information on social media platforms based on the method of multi-modal feature fusion. The significance of this study is to provide a new method to solve the problem of false information recognition on social media platforms. By using the method of multi-modal feature fusion, false information can be recognised more comprehensively and accurately, thus protecting the public from misleading and harm caused by false information. The specific scheme of the content studied in this article is as follows:

- 1 Data pre-processing: Calculate the noise in the transmission process according to the instantaneous value probability of noise signal, and pre-process the false information data of social media platform to make it more suitable for subsequent processing.
- 2 Multi-layer management establishes correlation: Multi-layer management is introduced to establish correlation between multi-modal point cloud data. This helps to extract information from different dimensions and comprehensively consider the relationship between them.
- 3 Modal grouping design and similarity calculation: Through modal grouping design and similarity calculation, the information of time, space and attributes is integrated to make up for the defects of false information data.
- 4 Multi-modal feature fusion algorithm: Multi-modal feature fusion algorithm is adopted, and various information features are comprehensively considered to obtain the final false information recognition result.

Through the above innovative technical route, the method based on multi-modal feature fusion can effectively improve the training accuracy of the model, and has the ability to

resist false data injection attacks, and achieve high accuracy of false information recognition.

2 False information recognition of social media platform based on multi-modal feature fusion

2.1 Social media platform false information data pre-processing

Collecting false information data of social media platform in three-dimensional images, considering that the false information data of social media platform will be disturbed by noise in the transmission process (Upadhyay et al., 2022), in order to reduce the quality of data, the false information data of social media platform is pre-processed to remove the noise content in the data. There are some differences between noise signal and normal point cloud data signal. If noise signal is defined as d , the instantaneous probability of noise signal is:

$$p(d) = \sqrt{p_d} \times \exp\left(\frac{d}{p_d}\right) \quad (1)$$

In equation (1), p_d represents the power of the noise signal.

Because the noise signal is instantaneous, the noise of false information data on social media platform during transmission is calculated according to the instantaneous probability, and the formula is:

$$p(e) = p(d) + p(f) \quad (2)$$

In equation (2), $p(f)$ represents the power spectrum of the noise signal.

At the moment when the noise signal is generated, some false information data sequences of social media platforms will be missing (Malik, 2022). Using equation (3) to eliminate the noise of false information data of social media platforms can ensure the integrity of the sequences, namely:

$$R(a) = \alpha \times \left(h - \frac{1}{\theta}\right) + p(e) \quad (3)$$

In equation (3), α represents the average slope of noise elimination, h represents the total time of false information data collection on social media platform, and θ represents the filter function of noise elimination.

The complete false information data sequence of social media platform is still discrete after denoising (Patil and Kumar, 2021), and it needs to be fitted by least square curve fitting method, and the following results are obtained:

$$H(h) = R(a) \times Q(W) + \mu \quad (4)$$

In equation (4), $Q(W)$ represents the false information data of the original social media platform, and μ represents the fitting coefficient.

Using interpolation method to pre-process the fitted false information data of social media platform to obtain smooth false information data of social media platform, namely:

$$G_D = H(h) \times (H_i + \varepsilon) \quad (5)$$

In equation (5), ε represents the feature entropy value of false information data of social media platform, and H_i represents the information gain of the i feature.

By denoising the false information data of social media platform, the data sequence is fitted, and the pre-processed false information data of social media platform is obtained by interpolation method, which provides the basis for multi-modal fusion of false information data of social media platform.

2.2 *Multi-modal feature fusion of false information data on social media platform*

The multimodal feature fusion algorithm can integrate features from different modalities, improve classification accuracy, compensate for the limitations of features, improve the robustness and robustness of the system, expand application fields, and fuse the relationships between data. These advantages make multimodal feature fusion an important method and tool for processing complex data tasks. The pre-processed false information data of social media platform lacks the correlation between attributes and semantics, and it needs to be multi-modal fusion to realise the significant feature interaction of false information data of different social media platforms.

Multi-layer management is introduced to establish the correlation between multi-modal point cloud data (Kara, 2021; Potts et al., 2023). In order to accurately describe this relationship, it is necessary to design the structure of each layer as a matrix in which point cloud data nodes are connected with each other. Through multi-modal grouping design, the node set and total node set of point cloud data are given as follows:

$$X = \sum_{i=1}^m \frac{x_i}{X_A} \quad (6)$$

$$Z = \sum_{i=1}^m \frac{z_i}{Z_A} \quad (7)$$

In equation (6) and equation (7), X_A represents the node probability of point cloud data A , Z_A represents the total node probability of point cloud data A , x_i and z_i represent the gray level occurrence probability, and m represents the network grouping of multimodal point cloud data.

When the probability of false information data of the same social media platform in X and Z is greater than the threshold, it shows that there is a certain correlation between X_A and Z_A , and the matrix connecting them is defined as:

$$V = \frac{\frac{x_i}{X_A}}{\frac{z_i}{Z_A}} \times \frac{X}{Z} \quad (8)$$

Considering that the coordinate system of false information data of social media platform contains different modes, in order to calculate the distance of different modal data, it is necessary to deal with the false information data of social media platform in a unified way. Use equation (9) to calculate the similarity between modal grouping and data to be fused, and the formula is:

$$\Delta D = \frac{M_A \times E_1 + F_m \times N_m}{R \times V} \quad (9)$$

In equation (9), M_A represents the modal set of data to be fused, E_1 represents the number of false information data of social media platforms in multi-modal grouping, F_m represents the number of times that data to be fused appears in modal m , R represents the distance calculation function, and N_m represents the count of data to be fused in modal m . The modal grouping with the highest similarity can be obtained from equation (9), and the result of multi-modal fusion of false information data of social media platform in this grouping is expressed as:

$$\mathbf{x} = \frac{F(j) + F(o) + F(v)}{\Delta_D} \quad (10)$$

In equation (10), $F(j)$ represents a colour histogram; $F(o)$ represents texture features; $F(v)$ represents a shape feature; The results of multi-modal fusion need to conform to single modal grouping, which provides a basis for the recognition of false information data on social media platforms.

2.3 Realise false information recognition on social media platform

Multimodal feature fusion is the integration of features from different modalities to obtain more comprehensive and diverse information to support various tasks. It involves main features such as multi-source feature fusion, cross modal correlation modelling, feature selection and fusion strategies, multimodal conflict and consistency handling, and scale adaptability. By fusing features from different modalities, multimodal feature fusion can improve accuracy, compensate for the limitations of features, handle conflicts between modalities, and adapt to large-scale data and real-time processing needs. It has important application value in fields such as image recognition, speech recognition, sentiment analysis, and intelligent recommendation. After multi-modal fusion, the false information data of social media platform has certain relevance in terms of time, space and attributes. The similarity between the original false information data of social media platform and the data to be recognised is calculated by equation (11), and the formula is:

$$\delta = \frac{e \times o}{\mu} \times (\tau_1 + \tau_2 + \tau_3) \quad (11)$$

In equation (11), τ_1 stands for time similarity, τ_2 stands for space similarity and τ_3 stands for attribute similarity, and the three similarity indexes can be calculated by the following formula:

$$\begin{cases} \tau_1 = \frac{\delta}{\gamma \times \sigma_1} \times |b| \\ \tau_2 = \frac{\delta}{\gamma \times \sigma_2} \times |b| \\ \tau_3 = \frac{\delta}{\gamma \times \sigma_3} \times |b| \end{cases} \quad (12)$$

In equation (12), $|b|$ represents the position dimension, γ represents the attribute dimension, and σ_1 , σ_2 and σ_3 represent the normalisation factors of each dimension. Through the similarity index, the false information data of social media platform can complement each other in time, space and attribute (Mbona and Eloff, 2022), and more critical points of data can be retained, thus alleviating the situation that false information data of social media platform is missing continuous segments.

After determining the similarity index of false information data of social media platform, the subsequent critical point changes at all times, resulting in the weighted value of missing segments is not fixed (Zhukova, 2022; Lee et al., 2022; Hamdan and Sathish, 2021). When the critical point set is an empty set, the weighted value of the missing pieces of false information data of social media platform is $|L|$ (Weiss et al., 2021; Torpan et al., 2021; Singh and Banga, 2022). When the critical point set is a non-empty set, the weighted value of missing fragments can be simplified as:

$$|L| = \tau_1 \times \tau_2 \times \tau_3 \quad (13)$$

Combining multimodal feature fusion algorithm with similarity index, the recognition result of false information data of social media platform is calculated, and the formula is:

$$T_{sd} = |L| \times Y_{sd} \quad (14)$$

In equation (14), Y_{sd} represents the average of critical point sets for recognising false information data of social media platforms.

According to the similarity calculation results, the defects of false information data of social media platform in three dimensions, such as time, space and attribute, are made up. The recognition results of false information data of social media platform are calculated by using multi-modal feature fusion algorithm, and the recognition of false information data of social media platform is realised.

3 Experimental

3.1 Experimental scheme

In order to verify the false information recognition effect of social media platform based on multimodal feature fusion, a simulation experiment was carried out. A social media dataset containing real and false information is selected, which includes multi-modal data such as text, image and video. Aiming at these data, multi-modal feature extraction method is used to extract features. Specifically, text features are extracted from text, image features are extracted from images, and video features are extracted from videos. On the basis of feature extraction, feature fusion algorithm is used to combine the features of different modes to synthesise the information of each mode, so as to recognise false information more accurately. This feature fusion can use the correlation of each mode to combine and weigh the features of text, image and video, and finally get a more discriminating result of false information recognition.

3.2 Experimental data

The dataset is divided into training set and test set according to a certain proportion, and the original data is pre-processed, which includes text segmentation and vectorisation, image feature extraction and video key frame extraction. The test environment uses a high-performance processor and computer to run the experiment, and Python programming language and tools are used for multimodal data experiment design, data processing and result analysis. In the experiment, 400 words and labels were collected and divided into two categories: training set data and test set data, each with about 200 items. Each word can be marked as ‘positive energy emotion’ or ‘negative energy emotion’ according to the attitude of comments. The database data of social media platform is divided into training set data and test set data, as shown in Table 1.

Table 1 Data type table of social media platform database

Serial number	Data type	Training set data		Test set data	
		Number	Attitude	Number	Attitude
1	Characters	50	Positive energy emotion	50	Negative energy emotion
2	Label	50	Negative energy emotion	50	Positive energy emotion

From Table 1, we can know the distribution of different data types in the social media platform database, and we can get the quantity and attitude distribution of each data type in the training set and the test set. The proposed method divides the collected data types of the social media platform database into two data types, and marks two attitudes of positive energy emotion and negative energy emotion in the form of words and labels, in which half of the training data and the test data are positive energy emotion and positive energy emotion.

3.3 Selection and calculation of performance index

In the research of false information recognition on social media platform, data similarity, recognition effect test and recognition accuracy are selected as experimental performance indicators. Data similarity refers to the similarity between different types, attitudes and data. Specifically, for literal data, including normal operation data and false data, similarity scores are calculated on the test set and training set, and listed in Table 2. For tag type data, including positive energy emotions and negative energy emotions, similarity scores are also calculated on the test set and training set, and recorded in Table 2. These similarity indicators can be used to evaluate the similarity between different data, thus helping to evaluate the performance of false information recognition models in different types, attitudes and data. It should be noted that this passage needs to be further simplified.

The recognition effect test is to judge whether the expected defence value recognised by the proposed method is consistent with the actual defence value applied on the social media platform;

Recognition accuracy is the ratio of the number of false information accurately recognised on social media platforms to the total number of recognition, and the specific formula is:

$$Z = \frac{Z_g}{Z_z} \times 100\% \quad (15)$$

In equation (15), Z_g represents the number of false information correctly recognised on social media platforms; Z_z represents the total number of false information recognised on social media platforms.

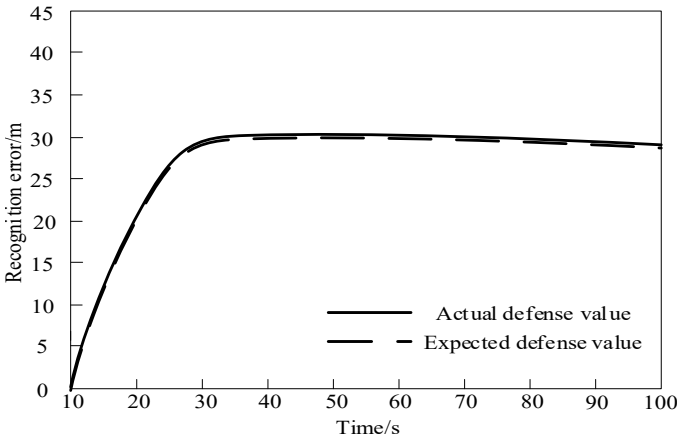
3.4 Test and analysis of performance index

Multi-modal feature fusion is used to generate social media platform data, and the test set data and training set data including normal operation data and false data are composed, and the recognition similarity scores of characters and labels are counted respectively. The comparison results are shown in Table 2.

Table 2 Comparison results of data similarity scores

Type	Attitude	Data	Similarity score	
			Normal operation data	False data
Characters	Positive energy emotion	Test set data	0.916	0.413
		Training set data	0.997	0.475
	Negative energy emotion	Test set data	0.928	0.553
		Training set data	0.993	0.568
Label	Positive energy emotion	Test set data	0.926	0.614
		Training set data	0.999	0.682
	Negative energy emotion	Test set data	0.931	0.717
		Training set data	0.993	0.792

Figure 1 Test results of recognition effect of the proposed method



According to the comparison results of data similarity scores in Table 2, for literal data, the similarity scores of normal operation data and test set data are higher, while the similarity scores of false data and test set data are lower. For the data of label type, the similarity score between positive energy emotion and test set data is higher, and the

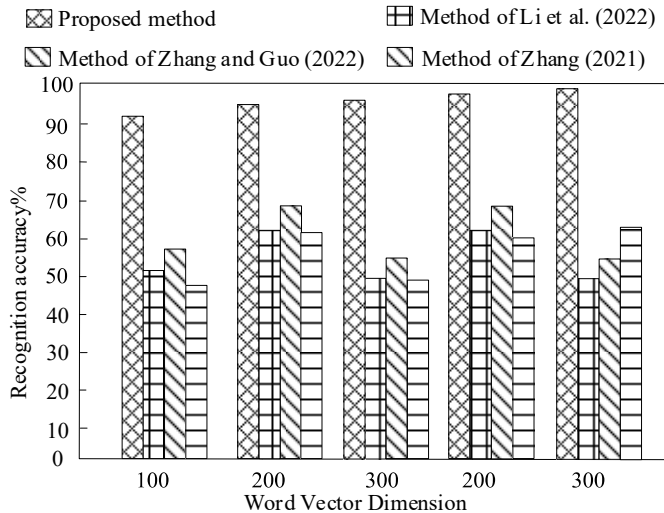
similarity score between negative energy emotion and test set data is also higher. These similarity scores can be used to evaluate the similarity between different data, with normal operation data exceeding 0.9 and false data exceeding 0.8. The dataset generated by the proposed method is similar to the actual data, which can effectively improve the accuracy of data training by the model, thus accurately detecting false data.

In order to verify the ability of the proposed method to recognise false information on social media platforms, it is tested whether the expected defence value recognised by the proposed method is consistent with the actual defence value applied on social media platforms when the social media platforms are attacked by false data injection. The test results are shown in Figure 1.

As can be seen from Figure 1, after the social media platform is attacked by false data injection, the proposed method is used to defend it, and the obtained expected defence curve is highly coincident with the actual defence curve, which verifies that the proposed method has strong anti-false data injection attack ability and can accurately recognise false information in the social media platform.

In order to further verify the application effect of the proposed method, the accuracy of false information recognition on social media platforms is tested by the proposed method, and compared with the methods in Li et al. (2022), Zhang and Guo (2022) and Zhang (2021). The four methods use word vectors in 100, 200, 300, 400 and 500 dimensions to recognise false information on social media platforms, and the comparison results of accuracy are shown in Figure 2.

Figure 2 The results of false information recognition accuracy of social media platforms in different dimensions



According to the results of Figure 2, the proposed method has higher accuracy in recognising false information on social media platforms. In different dimensions, the accuracy rate is over 90%, and it shows an increasing trend. Compared with the methods in Li et al. (2022), Zhang and Guo (2022) and Zhang (2021), the recognition accuracy of the proposed method is obviously higher, and the recognition accuracy of other methods

is lower, with a large increase or decrease. To sum up, the proposed method can accurately recognise false information on social media platforms.

4 Conclusions

Based on the method of multi-modal feature fusion, this study aims to solve the problem of false information recognition on social media platforms, and has conducted in-depth research on false information on social media platforms, and achieved certain results and gains. The following conclusions are obtained through experiments:

- 1 The dataset generated by the proposed method is highly similar to the actual data, which can effectively improve the accuracy of data training by the model, thus accurately detecting false data.
- 2 The proposed method has strong ability to resist false data injection attacks, and can accurately recognise false information in social media platforms.
- 3 The accuracy rate of the proposed method for recognising false information on social media platforms is higher, and the accuracy rate is higher than 90% in different dimensions, and it shows an increasing trend, and the recognition accuracy rate is significantly higher than other methods.

The prospect of future research needs to further explore the false information recognition of social media platforms, and the specific contents are as follows:

- 1 Further improve and optimise the multi-modal feature fusion model, improve the accuracy and robustness of false information recognition, and better capture the association information between multi-modal features.
- 2 Build a larger and more comprehensive multi-modal false information dataset, covering different social media platforms and multiple languages, and evaluate and verify the performance of the multi-modal feature fusion model more comprehensively.
- 3 The next step is to study how to apply the multi-modal feature fusion model to false information recognition across different social media platforms. Different platforms have different characteristics and user behaviour patterns, so they need to be adapted and optimised for different platforms.

Through continuous research and innovation, the false information recognition of social media platform based on multi-modal feature fusion will be able to better cope with the evolving challenge of false information dissemination and improve the credibility and user experience of social media platform.

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