The Construction of Campus Network Public Opinion Analysis Model Based on T-GAN Model

Jianan Zhang
School of Education Science, Nantong University, Nantong 226019, China

***Abstract*—The advancement of information technology has made the internet and social media an indispensable part of modern life, but with it comes a flood of false information and rumors. The aim of this study is to develop a technology that can automatically identify campus network public opinion information, in order to protect student groups from the intrusion of erroneous information, maintain their mental health, and promote a clear campus public opinion environment. This study used the Scrapy framework to write web scraping scripts to collect campus public opinion data, and carried out cleaning and preprocessing. Then, a transformer based generative adversarial network (T-GAN) model was designed, combined with a multi-scale convolutional neural network (MCNN) structure, for public opinion analysis on campus networks. The results show that the accuracy of the dataset processed by the T-GAN model has been improved on LGBT, KNN, SVM, and RoBERTa, proving that the campus network public opinion analysis model based on the T-GAN model helps to automatically identify campus network public opinion, protect students' physical and mental health, and promote the healthy development of the campus network environment.**

Keywords*—Public opinion analysis; T-GAN; feature extraction; multi-scale convolutional neural network; campus network

I. Introduction

In this era of information explosion on the Internet and social media, research has discovered a new space for people to share, communicate, and influence each other. Despite the continuous innovation of network technology, which promotes communication between people and provides unprecedented convenience in connectivity, there is also the rapid spread of unverified information hidden behind it [1]. Especially in the current era where rumors and false information are rampant, these pieces of information not only disrupt people's daily lives, but also pose a threat to social stability and order [2]. The campus environment, as a special social place, has particularly complex network public opinion management [3]. Students, as important carriers of information dissemination, frequently share insights and emotions related to numerous issues online [4]. However, the convergence of negative information on the Internet may aggravate students' rebellious mood and induce expanding foam of public opinion [5]. The constantly expanding public opinion has increased the complexity of campus management and caused interference with educational activities on campus [6]. In this context, timely monitoring and analysis of campus public opinion data is crucial for adopting effective management strategies and maintaining a harmonious and stable campus environment. In response to this issue, this study proposes a Generative Adversarial Network (GAN) model constructed using deep learning technology, aiming to conduct in-depth analysis of campus public opinion data. In addition, to improve the performance of the model in sentiment classification, this study also designed an innovative generative text data augmentation method. This method can effectively balance the distribution of data and enhance the accuracy of the model's judgment on different emotional categories. Therefore, by mining and analyzing campus public opinion data, it is helpful for schools to timely grasp the growth tendency of campus public opinion, provide important reference basis for taking effective management measures, and maintain a harmonious and stable campus environment. The novelty of this study lies in its innovative combination of Generative Adversarial Network (GAN) structure and Transformer model advantages, and the development of a deep learning model specifically designed for campus network public opinion - T-GAN. Many researchers have conducted research on this issue. Yadav A's research team has designed a deep learning model based on emotion analysis using deep learning and natural language processing techniques. Testing on popular datasets has shown significant effectiveness in solving emotion analysis problems [7]. Researchers such as Nemes L have used recurrent neural networks combined with natural language processing technology to construct an emotion classification model based on recurrent neural networks, which can classify user emotions based on keywords and demonstrate extremely high accuracy [8]. Mehta P and other scholars proposed designing an emotion mining model that utilizes machine learning and Lexicon survey methods for emotion mining. The research results show that the model can effectively match in opinion mining and sensory evaluation [9]. However, the above methods mainly address the issues of sentiment mining and sentiment classification, and research on precise sentiment classification based on campus public opinion data is relatively rare. Therefore, in response to this issue, this study innovatively utilizes deep learning technology to construct a Generate Adversarial Networks (GANs) model for in-depth analysis of campus public opinion data. Meanwhile, to improve the accuracy of the model in sentiment classification in public opinion data, a generative text data augmentation method has been studied and designed, which can expand the corpus with uneven data distribution, thereby achieving a balance in data distribution [10]. Therefore, in order to solve how to automatically identify and filter negative public opinion information in campus networks, and protect the physical and mental health of students, the establish of a campus network public opinion analysis model based on the Transformer-based Generate Adversarial Networks (T-GAN) model is studied to improve the accuracy of the model in sentiment classification and better conduct in-depth analysis of campus public opinion data. Although Yadav A's research team has successfully designed an emotion analysis deep learning model by combining deep learning and natural language processing techniques, and has demonstrated significant effectiveness in solving emotion analysis problems on popular datasets; Researchers such as Nemes L have also used a combination of recursive neural networks and natural language processing techniques to create an emotion classification model. This model classifies user emotions based on keywords and demonstrates extremely high accuracy; Mehta P and other scholars have proposed an emotion mining model that combines machine learning and dictionary research methods, and the research results show that this model is effective in opinion mining and perceptual evaluation. However, these methods mainly focus on the general issues of emotion mining and emotion classification, and there is little research on fine emotion classification based on campus public opinion data. In response to this research gap, our article aims to innovatively use deep learning techniques to establish a Generative Adversarial Networks (GANs) model, deeply analyze campus public opinion data, and explore the underlying factors that affect student emotions. Meanwhile, in order to enhance the accuracy of the model in sentiment classification of public opinion data, this study also designed a generative text data augmentation method. This method achieves data distribution balance by expanding the corpus with uneven data distribution. Through this approach, we hope that the model can more accurately understand and classify emotional tendencies in campus public opinion, provide an effective emotional analysis tool for campus managers, help them identify and respond to emotional dynamics in student groups in a timely manner, and thus maintain a healthy and harmonious campus environment. Overall, the main objective of this article is to construct a generative adversarial network model for analyzing campus public opinion data using deep learning techniques. Design and implement a text data augmentation strategy to balance data distribution and improve the accuracy of sentiment classification. Verify the effectiveness of the model on campus public opinion data and explore its potential positive impact on the campus environment. The overall structure of the entire article is divided into the following parts: Section I is the introduction, which outlines the background, importance, and purpose of the research. Emphasis was placed on the impact of the information age on the mental health and value development of students, as well as the necessity of automatically identifying campus public opinion information. Section II gives details about the design of a T-GAN based campus network. Section III delves into the verification of a campus network and Section IV concludes the paper.

II. Design of a T-GAN-Based Campus Network Public Opinion Analysis Model

The GAN model is the foundation of subsequent research in this paper. This chapter focuses on the collection and enhancement of campus network public opinion data based on the T-GAN model, and embeds a mixed MCNN structure in the network model for public opinion data analysis. The model is validated through experiments.

A. Collection and Enhancement of Campus Network Public Opinion Data Based on T-GAN Model

In the methodology section of this study, the reason for choosing to use a combination of Generative Adversarial Network (GAN) structure and Transformer model is multifaceted. Firstly, this combination fully utilizes the ability of GAN to generate authentic data and the powerful performance of Transformer in processing sequential data, making it particularly suitable for processing text data. Secondly, the current focus of research is on automatically identifying public opinion emotions in campus networks, which typically involve data in the form of text [11]. The Transformer model excels in understanding text sequences. In addition, campus public opinion data often suffers from class imbalance, and the generation ability of GANs can effectively enhance the sample of niche categories to provide richer learning materials, thereby improving the generalization ability and accuracy of the model. The participants are a group of campus network users, especially students in the cognitive development stage. Student groups are usually active in the online space, expressing opinions and feelings related to their personal life and learning experiences, which reflect their true emotions and may have an impact on others. Therefore, collecting data from it is representative and rich in valuable information such as user emotions and attitudes.

The data type to be collected in the study will mainly be public opinion information in text format, such as posts, comments, Weibo, etc. The characteristics of the required data collection include: 1. Text content: specific user statements and comments. 2. Timestamp: The time information of a speech, used to analyze public opinion dynamics. 3. User information: Basic information of the speaker, such as registration time, historical speeches, etc. (subject to privacy and regulatory restrictions).

In order to complete data collection and processing, the following tools will be used in the study: 1. Crawler tools, such as Scrapy, are used to automatically crawl target text data from online platforms and social media. 2. Data preprocessing tools: including text cleaning, denoising, word segmentation, and encoding, to prepare data formats suitable for model input. 3. Deep learning frameworks, such as TensorFlow or PyTorch, are used to construct and train T-GAN and MCNN models. 4. Evaluation and analysis tools: such as Sklearn, used for evaluating model performance and statistical analysis of results. Through this comprehensive method and corresponding tools, this study will be able to accurately capture and analyze emotional public opinion in campus networks, provide a basis for subsequent intervention measures, and thus maintain a healthy online environment.

Currently, the most commonly used social comment platform for students is Weibo, and many schools also set up official accounts on Weibo to post school related information [12]. Therefore, this study will focus on collecting public opinion data from Weibo platforms. Due to the complexity of online comment data, efficient data collection methods are needed. Traditional manual data collection methods are inefficient, so this study utilizes crawler technology to quickly collect data [13]. Through crawler technology, text data can be automatically crawled from Weibo platforms. The specific process of crawling text data is expressed in Fig. 1.

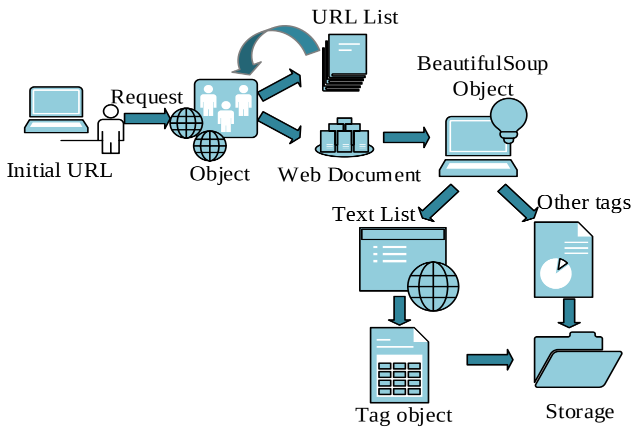

Fig. 1. The specific process of crawling text data.

From Fig. 1, when using crawler technology to crawl campus comment data, the first step is to initialize the Uniform Resource Locator (URL) to send the request. This study uses the Scrapy framework to write crawler scripts, starting from Weibo websites, and automatically accessing URL links after splitting to obtain Hyper Text Markup Language (HTML) resources in comment pages. Next, the Xpath parser is utilzied to quickly locate the target node in the web page text data, and save the HTML text attributes that need to be parsed as BeautifulSoup objects through regularization matching. This step helps to parse and manipulate complex HTML documents, saving the crawled text information in Excel or Csv format for subsequent data analysis [14]. After obtaining the crawled text information, it is necessary to clean and preprocess it for subsequent manual annotation and production of test datasets.

The crawled Weibo comment text data contains meaningless text such as emoticons, images, and punctuation marks, which need to be cleaned and deleted to improve the quality of the text data [15]. Regular matching method is an efficient, convenient, powerful, and flexible matching algorithm with good cross platform performance. Therefore, this study uses regular matching method to batch delete and preprocess the remaining text information, including removing stop words and segmenting Chinese text. During word segmentation, new words that ware not included in the vocabulary may be encountered. Therefore, this study collects 183 new words from online platforms and enters them into the vocabulary library. In addition, this study also utilizes a hidden Markov model to analyze the possible idioms composed of Chinese characters, and calculates the paths through Viterbi. Comment texts on online platforms often appear in the form of short dialogues, which contain non-standard words such as oral language and internet buzzwords. Therefore, it needs to pay attention to these characteristics during the word segmentation process [16]. By analyzing the possible idioms composed of Chinese characters using hidden Markov models, new words and idioms in comment texts can be more accurately identified, improving the accuracy and precision of text segmentation. Preprocessed text data can be transformed into data that computers can recognize and operate on using text representation technology. The Word2Vec model is an associated model that can generate word vectors and can be utilized for training to reconstruct linguistic word texts. By training the Word2Vec model, words can be mapped into vector space for computation and data analysis. The structure of the Word2Vec model is indicated in Fig. 2.

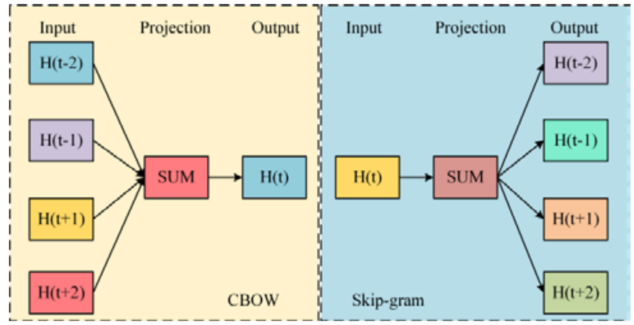

Fig. 2. The structure of the Word2Vec model.

In Fig. 2, the structure of the Word2Vec model includes two parts: Skip gram and CBOW. The Skip gram model can predict the $H(t-1), H(t-2), H(t+1), H(t+2)$ of the preceding and following text with the known head word $H(t)$. This model's goal is to infer the current word through contextual information [17]. In contrast, the CBOW model adopts the opposite approa ch, which can infer the central word from known contextual words. The training of CBOW model can be seen as a language model task, predicting the central word through a large amount of text corpus to preserve important semantic information of the text. The Skip gram and CBOW models together form a bidirectional language model that can help better understand and process natural language. The objective function expression of Skip gram is shown in Eq. (1).

$$O_{Skip} = \frac{1}{T}\sum_{t=1}^{dk}\sum_{-c\le j\le c, j\neq 0}\log P_{Skip}(H_i|H_{i+1}) \tag{1}$$

In Eq. (1), O_{skip} represents the objective function of Skip gram, and T represents time, c means the context window's size during model training. d_k represents the dictionary's size. H_i represents the word vector. $P_{Skip}(H_i|H_{i+1})$ represents the path probability of the word vector in the Skip gram model. The expression is shown in Eq. (2).

$$P_{Skip}(H_i|H_{i+1}) = \frac{\exp(< v_i, v_{i+j} >)}{\sum_{k=1}^{dk}\exp(< v_k, v_i >)} \tag{2}$$

In Eq. (2), v_i, v_k represent the output and input vectors, respectively. The objective function expression of the CBOW model is shown in Eq. (3).

$$O_{CBOW} = \frac{1}{T}\sum_{t=1}^{dk}\sum_{-c\le j\le c, j\neq 0}\log P_{CBOW}\left(H_i|H_{i+j}\right) \tag{3}$$

In Eq. (3), O_{CBOW} represents the objective function of the CBOW model, $P_{CBOW}(H_i|H_{i+1})$ represents the path probability of the word vector in the CBOW model, as shown in Eq. (4)

$$P_{CBOW}\left(H_i\middle|H_{i+j}\right)=\frac{\exp\left(<v_i, v_{i+1}>\right)}{\sum_{k=1}^{dk}\exp\left(<v_k, v_{i+j}>\right)} \tag{4}$$

The word vector generated by the Word2Vec model is static, meaning that for the same word, its vector representation remains the same regardless of the context. In contrast, the word vectors generated by the BERT model are dynamic, meaning that the vector representation of the same word may change in different contexts [18]. This is because that the BERT model utilizes a large number of self-attention mechanisms, which can adaptively focus on different words in different contexts, thereby generating different word vectors. In addition, the BERT model differs from traditional temporal networks in that it does not emphasize the order relationship between words. In the BERT model, the vector representation of each word is independent of other words, making it more flexible to handle text data. The mathematical expression of the BERT model is denoted in Eq. (5).

$$\begin{cases} E_{(pos,2i)} = \sin\left(\dfrac{pos}{1000^{\frac{2i}{emb_{\dim}}}}\right) \\ E_{(pos,2i+1)} = \cos\left(\dfrac{pos}{1000^{\frac{2i+1}{emb_{\dim}}}}\right) \end{cases} \tag{5}$$

In Eq. (5), $E_{(pos,2i)}$ and $E_{(pos,2i+1)}$ represent odd and even position matrices, respectively, and $emb_{\dim}$ represents the embedding dimension [19].

The technology used in this article - the T-GAN model that combines Generative Adversarial Networks (GAN) and Transformer models - has the following advantages: 1) Data augmentation ability: GAN's unique data generation ability can expand and balance the dataset by generating realistic text data, which is particularly beneficial for handling imbalanced data distribution and insufficient training data. 2) High text processing performance: The Transformer model has excellent sequential data processing capabilities, making it particularly suitable for analyzing text data. Its self-attention mechanism can capture long-distance dependencies and enhance the model's understanding of context. 3) High model accuracy: Compared to traditional deep learning and machine learning models, T-GAN demonstrates higher accuracy and recall in text sentiment classification tasks, indicating superior classification performance of the model. 4) Strong generalization ability: Due to the combination of two powerful neural network models and extensive testing on multiple datasets, T-GAN exhibits good generalization ability, which means it can adapt to different types of text data analysis tasks. 5) Real time analysis capabilities: T-GAN is suitable for real-time data analysis, helping managers monitor and respond to emotional fluctuations in the network in a timely manner. It is particularly valuable for environments that require quick response, such as campuses. 6) Improving user experience: Automated sentiment classification tools can reduce the burden of manual review, improve information supervision efficiency, and thus improve the user experience on campus network platforms. 7) Contribution to social management: This technology can analyze and identify emotional tendencies in a large amount of online public opinion data, providing strong technical support for social public opinion analysis and crisis prevention.

B. *Public Opinion Data Analysis Based on Hybrid Embedded MCNN Structure*

GAN is a powerful generation model that can generate new sentences related to a given corpus topic [20]. This newly generated sentence is closer to real data, while ensuring data security while also preserving the smoothness of the original data as much as possible. This characteristic enables GAN to effectively improve the classification performance of the network. However, traditional GAN models mainly rely on the LSTM layer as a generator in structure, which has some limitations, such as high computational costs and a lack of interactivity between information. To address these limitations, a self-attention-based autoencoder Transformer is studied to replace the LSTM layer. Transformer, due to its ability to learn long-term dependencies, can effectively address the aforementioned limitations. The structure of the T-GAN model is expressed in Fig. 3.

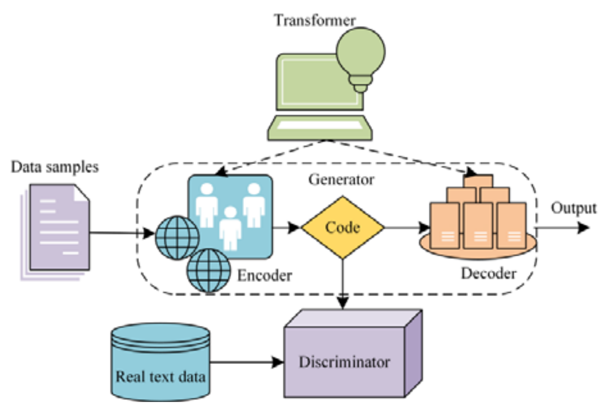

Fig. 3. The structure of T-GAN model.

In Fig. 3, the structure of the T-GAN model includes two main parts: a generator and a discriminator [21]. The generator can randomly generate vectors from space as input, generating pseudo samples with the same dimensions as real samples. The discriminator can use real and pseudo samples for training and predict a binary value to determine whether the input sample is real [22]. The T-GAN model adopts an alternating optimization method during the training process, which trains the generator network and discriminator network alternately to solve the maximum minimum game problem until both networks reach a convergence state. The mathematical expression of the maximum minimum game is expressed in Eq. (6).

$$\underset{G}{Min}\,\underset{D}{Max}\,V(G,D)=F_{x\sim Pdate(x)}[\log D(x)]+F_{z\sim noise(x)}[\log(1-D(G(z)))] \tag{6}$$

In Eq. (6), G, D denote the generator and discriminator. x represents the real sample. $D(x)$ expresses the real data. z means the noise vector sample. $G(z)$ refers to the generated sample. $F_{x\sim Pdate(x)}$ indicates the discriminator that follows the real data, and $F_{z\sim noise(x)}$ represents the generator and discriminator that follows the random data [23]. The Transformer architecture is embedded with a VAE module, which consists of two sub modules: encoder and decoder. The mathematical expression of the encoder is denoted in Eq. (7).

$$z \sim Enc(x) = q(z|x) \tag{7}$$

In Eq. (7), $q(z|x)$ represents the encoding space, and $z \sim Enc(x)$ represents encoding the sample x into the sample z. The mathematical expression of the decoder is expressed in Eq. (8).

$$x \sim Dec(z) = p(x|z) \tag{8}$$

In Eq. (8), $p(x|z)$ represents the decoding space, and $x \sim Dec(z)$ represents the decoding of sample z to sample x. The attention mechanism in the Transformer architecture identifies and highlights key values by adjusting weight values, and the process of finding key values is denoted in Eq. (9).

$$O = Attention(Q, K, V) \tag{9}$$

In Eq. (9), O represents the output of the attention mechanism. Q represents the query vector. V represents the key value. K represents the key value. Due to the use of multi head attention mechanism in the Transformer architecture, the three vectors Q, K, V will be projected into different subspaces, as shown in Eq. (10).

$$MH(Q, K, V) = concat(H_1, H_2, ..., H_n)W^0 \tag{10}$$

In Eq. (10), MH represents the multi head attention mechanism. H represents the subspace. n represents the degree. W^0 represents the initial matrix. By calculating the self-attention function in different subspaces, the projection output of each subspace can be obtained. Then, these output results are concatenated and the final output is obtained through projection, as shown in Eq. (11).

$$O_{MH} = Attention(QW_i^Q, KW_i^K, VW_i^V) \tag{11}$$

In Eq. (11), O_{MH} represents the projection output processed by the multi head attention mechanism. W_i^Q, W_i^K, W_i^V represents the linear projection of the corresponding response Q, K, V vector. The generator structure in the T-GAN model enhances the language model by introducing an LSTM layer to improve the attention mechanism of the decoder [24]. The generator structure of the T-GAN model is shown in Fig. 4.

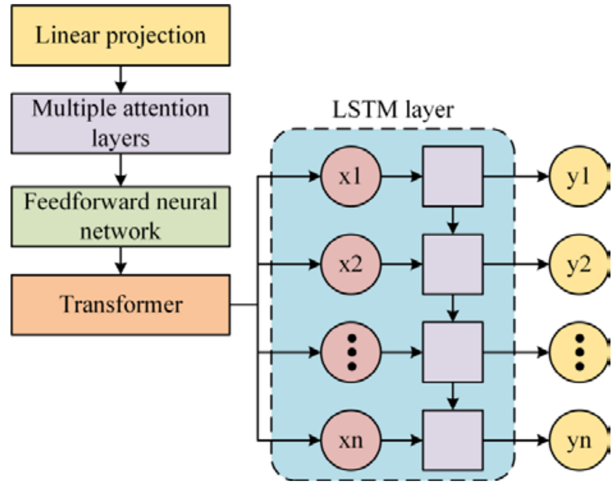

Fig. 4. The generator structure of T-GAN model.

As shown in Fig. 4, in the generator structure of the T-GAN model, the output results generated by the Transformer decoder are input into the LSTM layer for language model enhancement. This design enables the model to better focus on more advanced semantic and stylistic features, thereby generating more realistic and natural samples. The data text enhanced by the T-GAN model requires the use of MCNN for feature extraction [25]. In this process, the data text is mixed and embedded as input to add more forms of representation from the feature extraction level, thereby improving model performance. The structure of mixed embedded MCNN is shown in Fig. 5.

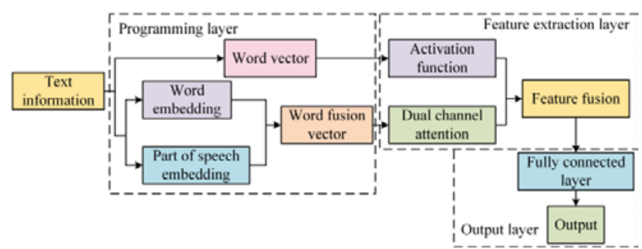

Fig. 5. The structure of mixed embedded MCNN.

As shown in Fig. 5, the structure of hybrid embedded MCNN consists of three parts: encoding layer, feature extraction layer, and output layer [26]. In the encoding layer, multi-channel input is used to improve the representation ability of short dialogue text [27]. And through part of speech embedding and word embedding, the association of parts of speech in the text is strengthened to generate mixed word vectors. The expression of the mixed word vector is shown in Eq. (12).

$$\begin{cases} w_{pi} = w_i \oplus pos_i \\ W_p = [w_{p1}, w_{p2}, ..., w_{pm}]^T \end{cases} \tag{12}$$

In Eq. (12), w_{pi} represents the mixed word vector. W_p represents the mixed word vector channel. m represents the embedding sequence [28]. The feature extraction layer performs feature extraction in the form of dual channels, as shown in Eq. (13).

$$\begin{cases} Vc = Conv(c) \\ vc = GMP(Vc) \end{cases} \tag{13}$$

In Eq. (13), Vc represents the feature vector obtained after convolution operation. c represents the word vector. GMP represents global maximum pooling. vc represents the feature vector obtained after global maximum pooling operation. The feature vectors of words and mixed words obtained through two channels are shown in Eq. (14).

$$\begin{cases} V_\alpha = \sum_{i=1}^{m} \alpha c_i \times Vc \\ V_\beta = \sum_{i=1}^{m} \beta c_i \times Vc \end{cases} \tag{14}$$

In Eq. (14), V_α, V_β represents the feature vectors of the word and the feature vectors of the mixed word, respectively. These two feature vectors are concatenated in the output layer, then input into the fully connected layer for fusion, and then processed using a Softmax classifier to obtain the classification probability as shown in Eq. (15).

$$P = soft\max\left(\omega\left[V_\alpha \oplus V_\beta\right] + \mu\right) \tag{15}$$

In Eq. (15), P represents the classification probability of the output. ω represents the weight transformation matrix. $\oplus$ represents the connection operation. μ represents the bias vector [29].

III. Verification of Campus Network Public Opinion Analysis Model Based on T-GAN Model

To experimentally validate the T-GAN-based campus network public opinion analysis model, this chapter first set the experimental environment and parameters, and analyzed the impact of experimental parameters on the performance of the model [30]. Finally, the performance of the T-GAN model was verified.

A. Experimental Environment and Parameter Settings

All experiments in this article were conducted in the Python 3.6.7 environment. The dataset used was Senti Large, with 20% of the data samples used as the test set and the other 80% used as the training set. The Senti Large dataset is an enhanced dataset generated through T-GAN based on publicly available Sentiment datasets. The Sentiment dataset is mainly used for sentiment analysis, which is a natural language processing technique aimed at identifying and extracting subjective information from text. This type of information may include the author's emotions, emotions, or opinions on a specific topic or product, which can be positive, negative, or neutral. The Sentiment dataset mainly focuses on text data, as the core of sentiment analysis is to understand and analyze emotions or emotions in the text. Therefore, this type of dataset does not contain image data. The main application scenarios of this dataset include product review analysis, social media sentiment tracking, and public opinion research. Overall, the Senti Large dataset is an enhanced text dataset for sentiment analysis, utilizing advanced T-GAN technology to expand the original Sentiment dataset to improve model performance and generalization ability. To evidence the generalization ability of the model, the study also added a manually calibrated Weibo data sample set as a pure test set. The careful setting of experimental parameters will directly affect the training effect of the model and the final classification results. To optimize the effectiveness of the model, the following parameters were set in the experiment based on the characteristics of the T-GAN model. The experimental environment configuration and parameter settings are indicated in Table I. As shown in Table 1, in order to conduct this experiment, corresponding parameters need to be configured in a specific environment. Firstly, the experiment should be conducted on the Windows 10 operating system to ensure sufficient memory capacity. Here, 64GB was chosen as it can effectively handle large datasets and run deep learning models. The graphics processor used in the experiment is NVIDIA's TITAN BLACK GPU, which can accelerate the training and prediction of deep learning models. Meanwhile, the study chose Intel Core i5-4460 as the central processing unit. PyTorch 1.8.1 was chosen as the deep learning framework in terms of software, and the CUDA11.1 platform and API were utilized to fully utilize NVIDIA GPU for computation. In terms of parameter settings, research has set vector spaces with dimensions of 30 and 300 for part of speech vectors and word vectors, respectively. The learning rate is set to 0.002, the number of convolutional kernels is 256, and the batch size is 16. In order to prevent overfitting of the model, the study set the Dropout ratio to 0.5, which means that half of the neurons will be randomly ignored during the training process. These configurations will ensure the smooth progress of the experiment and the accuracy of the results.

TABLE I. EXPERIMENTAL ENVIRONMENT CONFIGURATION AND PARAMETER SETTINGS

Experimental environment	**Configuration**	**Parameter Description**	**Paramete r value**
OS system	Windows10	Part of speech vector dimension	30
Memory	64GB	Word Vector Dimension	300
GPU	NVIDIA TITAN BLACK GPU	Learning rate	0.002
CPU	Intel(R)Core(TM)i 5-4460	Number of convolutional kernels	256
PyTorch framework	PyTorch 1.8.1	Batch size	16
CUDA Framework	CUDA11.1	Dropout rate	0.5

B. *The Effect of Experimental Parameters on Model Performance*

To delve deeper into the impact of parameter dropout rate on model prediction results, the experiment set the dropout rate range between $[0.1, 0.2, 0.3, 0.4, 0.5]$. After training, the impact of different dropout rates on prediction performance is shown in Fig. 6. From Fig. 6 (a), when the discard rates were 0.5 and 0.2, the accuracy reached the highest of 90.1% and the lowest of 81.8%, respectively. From Fig. 6 (b), when the discard rates were 0.1 and 0.2, the recall rates reached the highest of 89.9% and the lowest of 78.8%, respectively. From Fig. 6 (c), when the discard rates were 0.5 and 0.2, the F-value reached the highest of 90% and the lowest of 78.3%, respectively. Overall, when the discard rate was 0.5, all performance indicators of the model reached the optimal state.

The batch size is the amount of data input into the model at once when training the corpus, and the setting of this parameter has a huge impact on the training efficiency of the model. If the batch size is set too large, overfitting may occur, increasing training costs, while if the batch size is set too small, it may reduce training efficiency. Therefore, choosing an appropriate batch size is crucial. The range of batch size parameters selected for the experiment was $[4, 8, 16, 32]$, and the impact of batch size on accuracy obtained through training is shown in Fig. 7. From Fig. 7, when the batch size was 16, the accuracy of the model reached its highest value, at 90%. In contrast, when the batch size was 4, 8, and 32, the accuracy of the model was 84.8%, 89.1%, and 82.3%, respectively, which increased by 5.2%, 0.9%, and 7.7% compared to the accuracy of the batch size of 16, respectively. Overall, the most suitable value for the batch size parameter was 16. This setting could effectively improve the accuracy of the model while ensuring its training efficiency.

In the learning process of neural networks, parameter learning rate plays a crucial role. The learning rate can help update the weight of the model through backpropagation, thereby achieving reasonable adjustment of the weight. To deeply explore the influence of learning rate on the loss function, the experiment plotted the influence of parameter learning rate on the loss function as shown in Fig. 8. From Fig. 8, when the learning rate was less than 0.002, the value of the loss function showed a significant downward trend as the learning rate increased. When the learning rate was 0.002, the decline rate of the loss function was the fastest. This observation indicated that when the learning rate was 0.002, the model could more effectively optimize weights, thereby achieving a better level of loss function.

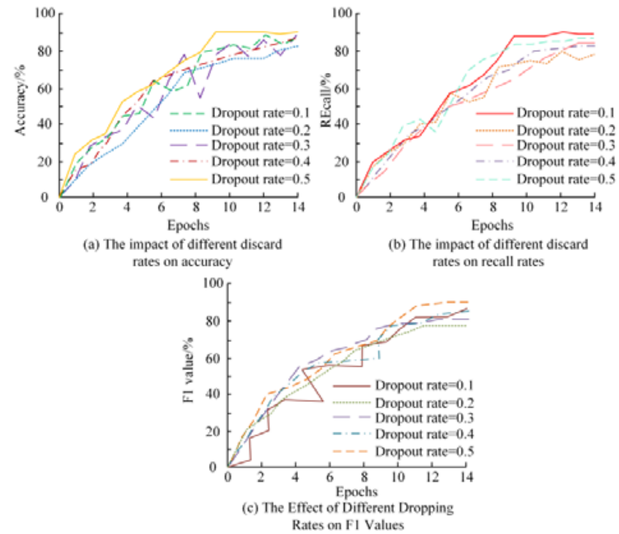

Fig. 6. The impact of different discard rates on prediction performance.

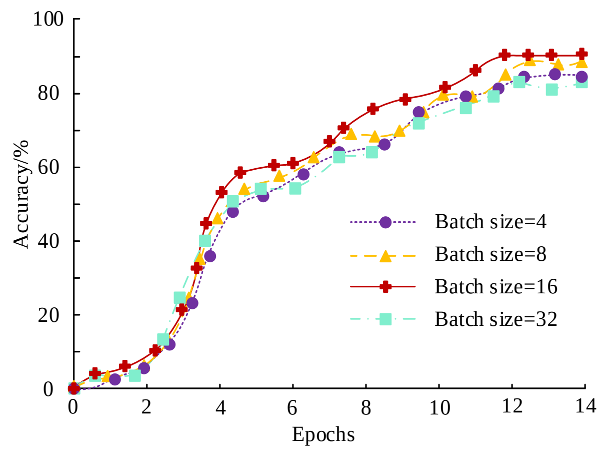

Fig. 7. The impact of parameter batch size on accuracy.

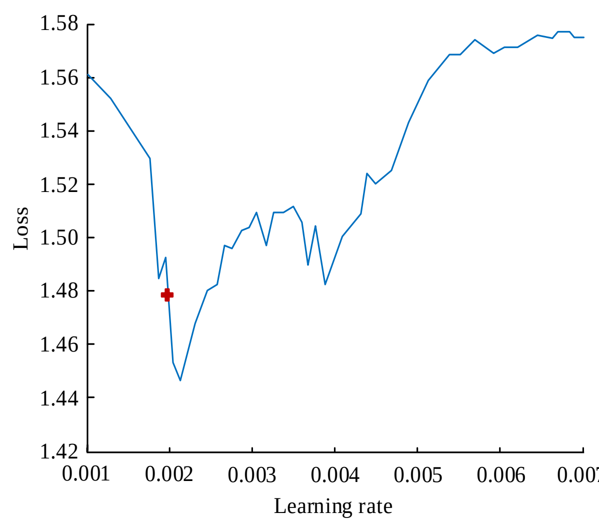

Fig. 8. The influence of parameter learning rate on the loss function.

C. Performance Verification of T-GAN Model

To visually demonstrate the performance of the T-GAN model, the new data generated by the T-GAN model was projected onto the same two-dimensional plane as the real data. The data projection is shown in Fig. 9. From Fig. 9, the new data generated by the model highly overlapped with the real data on the projection plane, which strongly proved the accuracy of the model's prediction. This phenomenon indicated that the model could capture the main features of the data and generate results that are highly similar to real data.

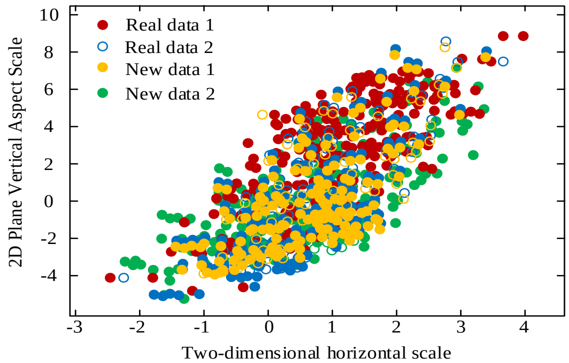

Fig. 9. Data projection map.

To prove the effectiveness of the T-GAN model, it was trained on the Senti -Large dataset and its predictive performance was evaluated. The predictive performance results of the T-GAN model are shown in Fig. 10. From Fig. 10, the T-GAN model converged rapidly on the training set, approached convergence after nearly 20 iterations, and achieved excellent predictive performance. Specifically, the T-GAN model achieved an accuracy of 92%, a recall rate of 91.8%, and an F1 value of 88.7% on the training set. These indicators all indicated that the T-GAN model performed well in predicting performance on the training set.

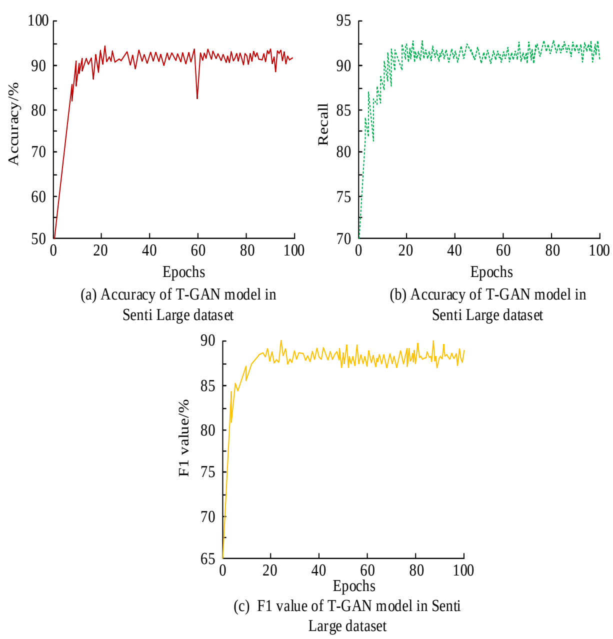

Fig. 10. Prediction performance results of T-GAN model.

In order to further verify the superior performance of the T-GAN model, state-of-the-art text feature extraction models such as LGBM, KNN, SVM, and RoBERTA [20] were used to conduct comparative experiments on the test set and training set [31]. The accuracy comparison of different models is shown in Table II. From Table II, in the training set, the accuracy of the T-GAN model was 91.56%, which was 8.89%, 6.78%, 15.87%, and 1.18% higher than models such as LGBM, KNN, SVM, and RoBERTA, respectively. In the test set, the accuracy of the T-GAN model was 92.89%, which increased by 8.93%, 8.25%, 19.01%, and 1.57% compared to models such as LGBM, KNN, SVM, and RoBERTA, respectively.

TABLE II. COMPARISON OF ACCURACY BETWEEN DIFFERENT MODELS

Model	Test set accuracy/%	Training set accuracy/%
T-GAN	92.89	91.56
LGBM	83.96	82.67
KNN	84.64	84.78
SVM	73.88	75.69
RoBERTa	91.32	90.38

In order to verify the effectiveness of the T-GAN model in physical argumentation, a series of application examples were conducted to verify its effectiveness. Taking campus cafeteria public opinion as an example, when food safety issues trigger public opinion, public opinion data mainly comes from social platforms such as Weibo, WeChat, and campus forums. The study utilized the T-GAN model to conduct in-depth public opinion analysis on the text data of these platforms, and successfully extracted internet buzzwords closely related to campus cafeteria public opinion. The extraction of campus cafeteria public opinion text using the T-GAN model is shown in Fig. 11. From Fig. 11, it can be seen that the model has successfully extracted five key network buzzwords: food safety, hygiene issues, poisoning incidents, inadequate supervision, and school responses. The frequency of these hot words appearing on social media platforms is 8054, 12567, 11067, 9104, and 11972, respectively. This data fully demonstrates that the T-GAN model performs well in extracting text information closely related to campus cafeteria public opinion. Through comprehensive analysis, it can be found that the text content extracted by the T-GAN model is highly consistent with the actual campus cafeteria public opinion. This further validates the superior performance of the T-GAN model in practical applications, proving that it can effectively extract key information closely related to food safety public opinion from massive text data.

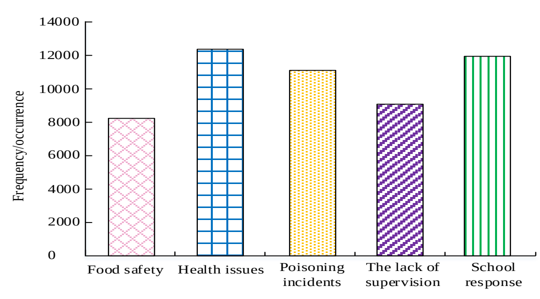

Fig. 11. Extracting public opinion text from campus canteen using T-GAN model.

IV. CONCLUSION

As the speed growth of network technology, the problem of spreading rumors and false information on social media is becoming increasingly prominent. To effectively and automatically identify and filter negative public opinion information in campus networks to protect students' physical and mental health, this study innovatively constructed a T-GAN model by combining the advantages of GAN network structure and Transformer model. At the same time, a hybrid embedding method using MCNN was used to conduct in-depth research on public opinion data as the analysis object. The results showed that when the discard rate was 0.5, the accuracy of the model reached the highest level of 90.1%, and the recall rate also reached the highest level of 89.9%. In addition, when the batch size was 16, the accuracy of the model also reached its highest value, at 90%. This indicated that the performance of the model was relatively stable for different discard rates and batch sizes. In the Senti-Large dataset, the accuracy of the T-GAN model reached 92%, the recall rate was 91.8%, and the F1 value also reached 88.7%. In the training set, the accuracy of the T-GAN model was 91.56%, which improved by 8.89%, 6.78%, 15.87%, and 1.18% compared to models such as LGBM, KNN, SVM, and RoBERTA, respectively. In the test set, the accuracy of the T-GAN model was 92.89%, which increased by 8.93%, 8.25%, 19.01%, and 1.57% compared to models such as LGBM, KNN, SVM, and RoBERTA, respectively. In summary, the T-GAN model performs best when the discard rate is 0.5 and the batch size is 16. Meanwhile, compared to other models, the T-GAN model has shown certain advantages in accuracy. These results indicate that the T-GAN model studied has good generalization performance and adaptability, and is worthy of further research and application. However, the research only analyzed the Chinese text, and the results are not comprehensive enough. This aspect still needs further improvement. Given the improvement in accuracy of the model compared to other models, we can look forward to further development of this model in future related research and applications. For example, in practical applications, the T-GAN model has the potential to serve as an important tool for campus public opinion supervision, accurately identifying negative public opinion, intervening in a timely manner, and ensuring the health of the campus network environment. In addition, its outstanding performance also provides strong reference value for expanding the model to multilingual public opinion analysis in the future.

REFERENCES

[1] A. P. Pandian, “Performance evaluation and comparison using deep learning techniques in sentiment analysis,” J. Soft Comput. Paradigm, vol. 3, no. 2, pp. 123-134, 2021.

[2] A. Mitra, “Sentiment analysis using machine learning approaches (Lexicon based on movie review dataset),” J. Ubiq. Comput. Commun. Technol., vol. 2, no. 03, pp. 145-152, 2020.

[3] J. Wang, Z. Yang, J. Zhang, Q. Zhang, and W. T. K. Chien, “AdaBalGAN: An improved generative adversarial network with imbalanced learning for wafer defective pattern recognition,” IEEE T. Semiconduct. M., vol. 32, no. 3, pp. 310-319, 2019.

[4] S. Kench, and S. J. Cooper, “Generating three-dimensional structures from a two-dimensional slice with generative adversarial network-based dimensionality expansion,” Nat. Mach. Intell., vol. 3, no. 4, pp. 299-305, 2021.

[5] Y. He, L. Zhang, Z. Chen, and C. Y. Li, “A framework of structural damage detection for civil structures using a combined multi-scale convolutional neural network and echo state network,” Eng. Comput., vol. 39, no. 3, pp. 1771-1789, 2023.

[6] M. G. Voskoglou, “A Combined Use of Soft Sets and Grey Numbers in Decision Making,” J. Comput. Cognit. Eng., vol. 2, no. 1, pp. 1-4, 2023.

[7] A. Yadav, and D. K. Vishwakarma, “Sentiment analysis using deep learning architectures: a review,” Artif. Intell. Rev., vol. 53, no. 6, pp. 4335-4385, 2020.

[8] L. Nemes, and A. Kiss, “Social media sentiment analysis based on COVID-19,” J. Inform. Telecommun., vol. 5, no. 1, pp. 1-15, 2021.

[9] P. Mehta, and S. Pandya, “A review on sentiment analysis methodologies, practices and applications,” International Journal of Scientific and Technology Research, vol. 9, no. 2, pp. 601-609, 2020.

[10] S. Kench, and S. J. Cooper, “Generating three-dimensional structures from a two-dimensional slice with generative adversarial network-based dimensionality expansion,” Nat. Mach. Intell., vol. 3, no. 4, pp. 299-305, 2021.

[11] Z. Cai, Z. Xiong, H. Xu, P. Wang, W. Li, and Y. Pan, “Generative adversarial networks: A survey toward private and secure applications,” ACM Comput. Surv., vol. 54, no. 6, pp. 1-38, 2021.

[12] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, and Y. Bengio, “Generative adversarial networks,” Commun. ACM, vol. 63, no. 11, pp. 139-144, 2020.

[13] R. K. Al-Hamido, “A new neutrosophic algebraic structures,” J. Comput. Cognit. Eng., vol. 2, no. 2, pp. 150-154, 2023.

[14] S. Zhao, L. Yin, J.Zhang, and R. Zhong, “Real-time fabric defect detection based on multi-scale convolutional neural network,” IET Collab. Intell. Manuf., vol. 2, no. 4, pp. 189-196, 2020.

[15] Y.Fang, B. Luo, T. Zhao, D. He, B. Jiang, and Q. Liu, “ST-SIGMA:Spatio-temporal semantics and interaction graph aggregation for multi-agent perception and trajectory forecasting,” CAAI T. Intell. Techno., vol. 7, no. 4, pp. 744-757, 2022.

[16] L. L. Lemon, and J. Hayes, “Enhancing trustworthiness of qualitative findings: Using Leximancer for qualitative data analysis triangulation,” Qualitat. Rep., vol. 25, no. 3, pp. 604-614, 2020.

[17] A. I. Kadhim, “Survey on supervised machine learning techniques for automatic text classification,” Artif. Intell. Rev., vol. 52, no. 1, pp. 273-292, 2019.

[18] C. Fischer, Z. A. Pardos, R. S. Baker, J. J. Williams, P. Smyth, R. Yu, and M. Warschauer, “Mining big data in education: Affordances and challenges,” Rev. Res. Educ., vol. 44, no. 1, pp. 130-160, 2020.

[19] J. Berger, A. Humphreys, S. Ludwig, W. W. Moe, O. Netzer, and D. A. Schweidel, “Uniting the tribes: Using text for marketing insight,” J. Marketing, vol. 84, no. 1, pp. 1-25, 2020.

[20] M. Wankhade, A. C. S. Rao, and C. Kulkarni, “A survey on sentiment analysis methods, applications, and challenges,” Artif. Intell. Rev., vol. 55, no. 7, pp. 5731-5780, 2022.

[21] Y. He, L. Zhang, Z. Chen, and C. Y. Li, “A framework of structural damage detection for civil structures using a combined multi-scale convolutional neural network and echo state network,” Engineering with Computers, vol. 39, no. 3, pp. 1771-1789, 2023.

[22] S. A. Yazdan, R. Ahmad, N. Iqbal, A. Rizwan, A. N. Khan, and D. H. Kim, “An efficient multi-scale convolutional neural network based multi-class brain MRI classification for SaMD,” Tomography, vol. 8, no. 4, pp. 1905-1927, 2022.

[23] Z. Wen, Y. He, S. Yao, W. Yang, and L. Zhang, “A self-attention multi-scale convolutional neural network method for SAR image despeckling,” International Journal of Remote Sensing, vol. 44, no. 3, pp. 902-923, 2023.

[24] Y. Wang, X. Fan, S. Liu, D. Zhao, and W. Gao, “Multi-scale convolutional neural network-based intra prediction for video coding,” IEEE Transactions on Circuits and Systems for Video Technology, vol. 30, no. 7, pp. 1803-1815, 2019.

[25] X. Su, J. Xu, Y. Yin, X. Quan, and H. Zhang, “Antimicrobial peptide identification using multi-scale convolutional network,” BMC bioinformatics, vol. 20, no. 1, pp. 1-10, 2019.

[26] K. F. Chu, A. Y. S. Lam, and V. O. K. Li, “Deep multi-scale convolutional LSTM network for travel demand and origin-destination predictions,” IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 8, pp. 3219-3232, 2019.

[27] P. Zhang, G. Yu, D. Shan, Z. Chen, and X. Wang, “Identifying the Strength Level of Objects’ Tactile Attributes Using a Multi-Scale Convolutional Neural Network,” Sensors, vol. 22, no. 5, pp. 1908-1912, 2022.

[28] C. Tang, X. Liu, X. Zheng, W. Li, L. Wang, and A. Longo, “DeFusionNET: Defocus blur detection via recurrently fusing and refining discriminative multi-scale deep features,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 44, no. 2, pp. 955-968, 2020.

[29] D. Wu, C. Wang, Y. Wu, Q. C. Wang, and D. S. Huang, “Attention deep model with multi-scale deep supervision for person re-identification,” IEEE Transactions on Emerging Topics in Computational Intelligence, vol. 5, no. 1, pp. 70-78, 2021.

[30] K T. Chui, B B. Gupta, H R. Chi, V. Arya, W. Alhalabi, M. T. Ruiz, and C. W. Shen, “Transfer learning-based multi-scale denoising convolutional neural network for prostate cancer detection,” Cancers, vol. 14, no. 15, pp. 3687-3691, 2022.

[31] Z. Shen, S P. Deng, and D. S. Huang, “RNA-protein binding sites prediction via multi scale convolutional gated recurrent unit networks,” IEEE/ACM transactions on computational biology and bioinformatics, vol. 17, no. 5, pp. 1741-1750, 2019.