# A Bi-GRU and BERT-Based Intelligent Audit System for News Moderation via NLP and Sentiment Analysis

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*In the era of information explosion, the exponential growth and rapid update of news data pose significant challenges to traditional manual news dissemination review mechanisms. Existing methods struggle to balance content moderation comprehensiveness and accuracy. To address these issues, this study develops an intelligent audit system for news communication that integrates natural language processing (NLP) and sentiment analysis. Leveraging advanced NLP techniques like semantic analysis and keyword extraction, the system swiftly identifies core news information and potential risk points. Sentiment analysis algorithms are integrated to precise assess the emotional tone and social impact of news content, enabling intelligent screening and risk early warning. The system employs models such as BERT and Bi-GRU for NLP and sentiment analysis components, respectively. Experimental results demonstrate its effectiveness: news audit efficiency has increased by nearly 40%, and the error rate has decreased by about 30%. It can also effectively detect and filter false information and public opinion risks, enhancing news credibility and social value. Outperforming existing methods in accuracy and recall, the system features a hierarchical architecture with data collection, preprocessing, NLP and sentiment analysis, and audit decision-making layers. Data collection is achieved through web crawlers, and preprocessing includes deduplication, cleaning, word segmentation, and vectorization. The BERT pre-trained model is fine-tuned for NLP tasks, while sentiment analysis utilizes an LSTM-attention mechanism model, all implemented in a Python environment with the PyTorch framework. Using the THUCNews corpus for news text classification and SST-2 for sentiment analysis training, the model achieves over 90% news classification accuracy and an F1 score exceeding 85% for sentiment analysis. Additionally, the system incorporates multilingual capabilities by integrating multilingual pre-trained models such as mBERT and XLM-R, and introducing language adapters. It can audit news texts in English, Chinese, Spanish, and other languages, achieving an average accuracy of 85% on multilingual datasets and a 30% improvement in cross-lingual transfer compared to monolingual models, effectively supporting global news dissemination audits and handling multilingual mixed content.*

*Povzetek: Študija predstavi inteligentni sistem za revizijo novic, ki združuje BERT/NLP in analizo sentimenta za hitrejše in natančnejše odkrivanje tveganj ter lažnih vsebin*

## 1 Introduction

In the torrent of information, news, as the pulse of society, carries the critical mission of conveying facts and guiding public opinion. However, with the rapid development of Internet technology, information dissemination has expanded significantly, and it has also brought unprecedented challenges [1]. Fake news and misleading information spread in the network like viruses, which not only erodes the credibility of the news industry but also virtually affects the public's value judgment and social harmony and stability [2, 3]. Against this background, ensuring the authenticity of the news and the effectiveness of dissemination has become an urgent issue that needs to be solved. The purpose of this study is to explore how to use advanced natural language processing technology and the deep insight of sentiment analysis to build an intelligent audit system that can automatically identify, filter and analyze news content in order to provide an accurate "information sieve" for the news industry, ensure the quality and efficiency of news dissemination, and create a healthy and transparent information environment for the public.

The present situation of news communication calls for the intervention of technological innovation [4]. In the digital age, the way news is generated and disseminated has undergone fundamental changes. The rise of new media forms, such as social media and online news platforms, has made information reach more rapidly and extensively. However, at the same time, it has also brought new problems of information overload and difficulty distinguishing between authenticity and falsehood [5]. The breeding of fake news not only destroys the health of the media ecology but also has a far-reaching negative impact on the social level. Faced with this situation, the traditional news audit methods are unable to do so, and the speed and accuracy of manual audits are challenging to match the actual needs of information explosion. In contrast, the intelligent audit system provides a new solution [6, 7].

Natural language processing technology, as the core component of artificial intelligence, has made breakthrough progress in recent years [8]. It can understand and analyze the complex structure of human language, identify entities, relationships and semantics in text, and provide powerful technical support for intelligent audit systems. Sentiment analysis technology can further go deep into the subtleties of the text, capture the emotional color behind the information, help the system understand the public's attitude and reaction to news, and provide a powerful tool for accurate measurement of news dissemination and public opinion management [9]. Combining these two technologies, the intelligent audit system can realize in-depth understanding and intelligent judgment of news content, effectively filter out false information, identify the hot spots and emotional tendencies of public concern, provide decision support for news organizations, and ensure fairness and objectivity of news dissemination.

In this study, we propose a method to integrate bidirectional gated recurrent units (Bi-GRU) with emotional structures to news moderation tasks. Through a series of experimental verifications, we have proved that the proposed method has significant advantages over existing sentiment analysis models in terms of efficiency and accuracy. Specifically, the introduction of Bi-GRU not only enhances the model's ability to capture the emotional tendency in news texts, but also further improves the model's recognition accuracy of misleading news through the integration of emotional structures. This integration strategy not only improves the robustness of the model in dealing with complex emotional expressions, but also effectively reduces the rate of false positives and false negatives, so as to achieve a more efficient and accurate review effect in the intelligent review of news communication. This research result not only provides a new technical path for intelligent moderation in the field of news communication, but also provides new ideas and enlightenment for the application of sentiment analysis in news moderation in the future.

The main task of this research paper is to construct an efficient and accurate intelligent audit system for news communication to cope with the complex challenges in the field of news communication in the era of information explosion. At present, the amount of news data is growing explosively and updating rapidly, and the traditional manual review mechanism of news communication is facing serious problems such as inefficiency and difficulty in comprehensively and accurately reviewing content under the heavy pressure of this heavy pressure. In order to accomplish this task well, we have conducted in-depth research and successfully built an intelligent news communication audit system that integrates natural language processing and sentiment analysis technologies. In the specific implementation process, the system makes full use of cutting-edge natural language processing technologies such as semantic analysis and keyword extraction, which can quickly and accurately identify core information from massive news texts and keenly capture potential risk points. At the same time, the sentiment analysis algorithm is carefully integrated to accurately evaluate the emotional tendency of news content and the potential social impact that may occur, and successfully realize the intelligent screening and risk warning functions of news dissemination. In terms of technical support, advanced models such as BERT and Bi-GRU are used to provide strong support for natural language processing and sentiment analysis components. After rigorous experimental verification, we successfully completed the set task, and the intelligent audit system has achieved good results: after the introduction of the system, the efficiency of news auditing has increased by nearly 40%, and the error rate has been reduced by about 30%. More importantly, the system can effectively identify and filter false information and potential public opinion risks, which greatly enhances the credibility and social value of news dissemination. Verification of key performance indicators such as accuracy and recall clearly shows that the system outperforms existing methods in all aspects.

This study focuses on the intelligent audit system for news communication based on NLP and sentiment analysis, and puts forward three core research questions and corresponding hypotheses: first, to explore whether the architecture of the NLP pre-trained model BERT combined with Bi-GRU can more accurately identify sensitive information and illegal content in the compliance audit of news communication content, assuming that the architecture has more advantages than a single model by virtue of the semantic understanding of BERT and the bidirectional information capture ability of Bi-GRU; Second, it is necessary to study whether the recognition accuracy of the sentiment analysis model for complex emotions can be improved after the fusion of multi-source datasets and the implementation of data augmentation, assuming that the data-optimized model can learn more language sentiment patterns and obtain higher accuracy and F1 scores. Thirdly, it is considered whether the customized fine-tuning strategy for different news fields can enhance the audit accuracy and generalization ability, and it is assumed that this strategy can adapt the system to the characteristics of each field and maintain good performance in multi-domain data.

# 2 Design of intelligent audit system for news dissemination based on natural language processing

## 2.1 Introduction to natural language processing technology

In the development of an intelligent audit system for news communication based on natural language processing and sentiment analysis, the system was compared with a more efficient Transformer architecture. Through multi-dimensional performance testing and the test of practical application scenarios, it is found that this comparison greatly promotes the optimization idea of the integration of Bi-GRU and emotional structure. When processing news text data, the Transformer architecture has demonstrated efficiency in certain tasks due to its powerful parallel computing power and excellent ability to capture long-distance dependencies. However, after in-depth research and experiments, we found that Bi-GRU has unique advantages in combining emotional structure, and the comparison with the Transformer architecture prompts us to continue to explore how to better integrate Bi-GRU into the system to more accurately analyze the emotional context in news texts, and then optimize the entire news communication intelligent audit system, so that it can achieve better performance in sentiment analysis and news communication audit tasks.

The Gate Recurrent Unit (GRU), a variant of the Recurrent Neural Network (RNN), is designed to solve the long-term dependency and gradient propagation puzzles, sharing the same goal as the Long-Short Term Memory (LSTM) [10]. When choosing a model for the intelligent moderation system for news communication, we considered a number of key factors. First, from the perspective of efficiency, although GRU and LSTM are similar in performance, GRU reduces overhead in the computation process and achieves more efficient training and inference due to its simpler structure, which makes GRU a better choice for most application scenarios [11]. The GRU controls the flow of information through built-in reset gates, which are responsible for regulating the fusion of new inputs with previous state information, focusing on dealing with short-term dependencies; Update gates, on the other hand, control how much information from the previous state is retained in the current state, helping to capture long-term dependencies. Together, these two gates determine the output of the unit, ensuring the efficient preservation of long-term sequence information [12]. However, the one-way processing nature of the GRU limits its ability to process bidirectional text associations. To overcome this limitation, we opted for bidirectional GRU (Bi-GRU), which is able to capture contextual information from past and future time steps by processing input sequences in both forward and reverse directions, which is especially important for tasks such as sentiment analysis that require a deep understanding of the context of a word or phrase. When compared to other models, such as LSTM and models based on Transformer architecture, GRU and Bi-GRU show unique advantages in our specific tasks. To further validate our choice, we conducted preliminary experiments, which showed that both GRU and Bi-GRU outperformed other models in terms of accuracy and efficiency on our dataset.

The Bi-GRU structure is shown in Figure 1. The input sequence is processed bidirectionally through the forward and backward propagation layers, and the output of each time step integrates past and future context information, thus providing a more comprehensive sequence understanding.

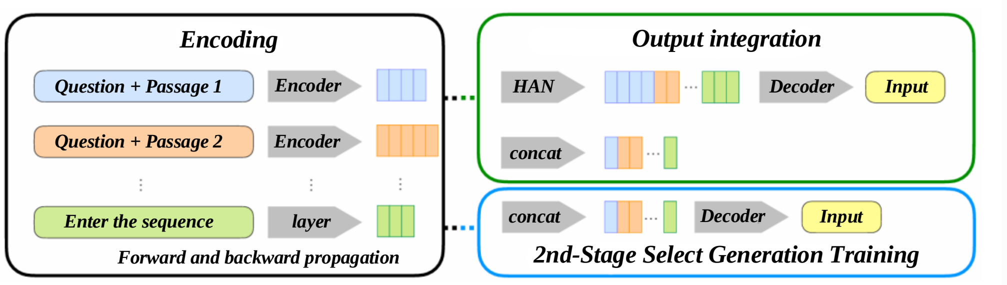


Figure: 1 Bi-GRU structure

HAN uses a hierarchical attention mechanism to extract multi-level text features at the word and sentence levels [13], which is essential for understanding the subtle meaning and context in news articles. Its built-in attention mechanism helps focus on the most relevant parts of the text, reducing noise and improving the accuracy of sentiment analysis and other natural language processing tasks. We explicitly tie these features to the goals of the news moderation system, such as identifying misleading or biased content, assessing the overall tone and sentiment of an article, ensuring compliance with journalism standards, and more. To make the explanation of HAN's hierarchical attention mechanism more understandable, we used simpler language and provided more context, and we also added diagrams or flowcharts to visualize its architecture and components so that readers can understand how it works. In addition, we specifically point out the immediate benefits of using HAN in a news moderation system, such as improving the accuracy of sentiment analysis, better handling complex and delicate text content, and building a more robust overall system. Finally, we revised the text to ensure that it was clear, concise, and logically coherent with the rest of the paper [14, 15].

Suppose there are $L$ sentences in the article, and each sentence contains $T$ words. Firstly, the word $w_{it}$ in the sentence (the $t$-th word in the $i$-th sentence) is input into Embedding to obtain the word vector $x_{it}$ of each word, and the calculation Equation is shown in Equation (1), where $W_e$ is the word weight.

$$x_{it} = W_e w_{it}, t \in [1,T] \quad (1)$$

Input the obtained word vectors into the Word Encoder, which is composed of Bi-GRU. Combine the GRU outputs from both directions to construct a hidden vector $h_{it}$ at the word level, as shown in Equations (2) - (4). Among them, → represents vectorization operation, and GRU is gate-controlled loop unit operation.

$$\overrightarrow{h_{it}} = \overrightarrow{GRU}(x_{it}), t \in [1,T] \quad (2)$$

$$\overleftarrow{h_{it}} = \overleftarrow{GRU}(x_{it}), t \in [1,T] \quad (3)$$

$$h_{it} = [\overrightarrow{h_{it}}, \overleftarrow{h_{it}}] \quad (4)$$

The word-level implicit vector is passed through a single-layer perceptron, which is actually a fully connected neural network, and the output result can be regarded as a higher-level implicit vector representation, as shown in Equation (5), where $b_w$ is the deviation value of MLP, $W_w$ is the weight value of MLP, $h_{it}$ is the implicit vector of MLP, and *tanh* is the activation function.

$$u_{it} = tanh(W_w h_{it} + b_w) \quad (5)$$

Randomly initialize a context vector $u_w$, which will be continuously optimized with training. Input the context vector $u_w$ and the high-level implicit vector representation $u_{it}$ into softmax to obtain the similarity representation between each word and the context vector, as shown in Equation (6).

$$\alpha_{it} = \frac{exp(u_{it}^T u_w)}{\sum_t exp(u_{it}^T u_w)} \quad (6)$$

Taking the above similarity as the weight, the vector representation $s_i$ of sentence level is obtained by weighting and summing $h_{it}$, as shown in Equation (7), where $\alpha_{it}$ is the similarity index.

$$s_i = \sum_t \alpha_{it} h_{it} \quad (7)$$

For sentence-level vectors, we use the same method to pass the sentence vectors through the coding layer to obtain implicit vectors in two directions, and combine the implicit vectors in two directions $\overrightarrow{h_1}$ to get the final vector $h_i$, as shown in Equations (8)-(10):

$$\overrightarrow{h_i} = \overrightarrow{GRU}(s_i), t \in [1,L] \quad (8)$$

$$\overleftarrow{h_i} = \overleftarrow{GRU}(s_i), t \in [1,L] \quad (9)$$

$$h_i = [\overrightarrow{h_i}, \overleftarrow{h_i}] \quad (10)$$

After passing through the attention layer, finally, the implicit vector representations of all sentences in the article are weighted and summed to obtain the document vector $v$ of the whole document, as shown in Equation (11):

$$v = \sum_t \alpha_i h_i \quad (11)$$

Bert (Bidirectional Encoder Representations from Transformers) is a pre-trained model developed based on models such as semi-supervised sequence learning, ELMo and ULMFit [16, 17]. Its innovation lies in deep bidirectional unsupervised language representation, which only uses plain text pre-training and abandons the traditional left-to-right prediction method. In Bert's training, NLP tasks such as text classification and machine translation can be handled by predicting covered words and judging sentence continuity. A specific task network is attached after pre-training [18].

First, the Embedding technique is applied to each word $w_{it}$, and the word vector $x_{it}$ is obtained by combining the weight $W_e$ (Equation 1). The word vector is input into the Bi-GRU Word Encoder, and the word-level implicit vector is output by combining the bidirectional GRU. The hit is activated by the Monolayer Perceptron (MLP) and tanh to obtain a high-level hidden vector. Then the context vector is randomly initialized, and its similarity with the variable is obtained by softmax. The sentence vector is obtained by weighting the implicit vector with the weight of the vector. The sentence vector is processed by the same coding layer, and the final sentence vector is obtained by combining the bidirectional implicit vector. Finally, the sentence vectors are weighted and summed by the attention layer to obtain the document vectors. This process finely extracts key information from the article to help the news review, accurately identify emotional tendencies, key content, and evaluate the authenticity and compliance of the news.

The Bert model is mainly composed of an embedded layer and a Transformer layer, supplemented by output processing such as a pooler. The Embedding layer generates an initial vector for each input token, which is different from the final context-dependent vector representation, and the initial vector does not depend on the context [19]. Bert's core structure is an Encoder-based Transformer layer, which consists of multiple Encoder units stacked, each containing Multi-Head-Attention and feed-forward components. The large Bert model has 24 layers of Encoder with 16 Attention heads per layer; The small Bert has 12 layers of Encoder, with 12 Attention heads per layer.

In NLP, text similarity measures the surface and semantic proximity of two paragraphs of text, which involves not only lexical similarity but also contextual semantics. For example, "cats eat mice" and "mice eat cat food" have a high degree of vocabulary overlap, but their semantics are quite different. Cosine similarity evaluates text similarity by calculating the cosine value of the included angle between vectors. The Equation is shown in Equation (12), where $A$ and $B$ are two non-zero vectors, representing the vector representation of two texts or other types of data after word embedding conversion. $A \cdot B$ represents the dot product of vector $A$ and vector $B$. $\|A\|$ and $\|B\|$ represent the Euclidean length of vector $A$ and vector $B$. $A_i$ and $B_i$ are the values of vector $A$ and vector $B$ in the $i$-th dimension, respectively.

$$similarity = cos\theta = \frac{A \cdot B}{\|A\| \|B\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}} \quad (12)$$

Mathematically, cosine similarity is a measure of the similarity between two non-zero vectors of the internal product space, measuring the cosine of the angle between them. The cosine of 0° is 1, and any angle within the interval of (0, π] radians is less than 1, so it is a judgment of directivity, not a judgment of magnitude, and the smaller the angle, the higher the cosine similarity. The more similar the text is, the closer the cosine similarity of the corresponding text vector is to 1. Since the cosine similarity calculates the direction rather than the size, it has nothing to do with the size of the vector; when the cosine similarity value is 0, it does not mean that the similarity is 0 but only that the angle between the two text vectors is 90 degrees. Completely uncorrelated Two complete texts have a cosine similarity of -1.

When processing images, the powerful feature extraction capabilities of convolutional neural networks

(CNNs) are leveraged, which contain multiple convolutional layers, pooling layers, and fully connected layers. After the news pictures are inputted, the convolutional layer slides the convolution on the image through convolutional kernels of different sizes to capture low-level features such as edges and textures, such as the posture of athletes and the characteristics of the field when analyzing news pictures of sports events, and then the pooling layer downsamples the feature map output by the convolutional layer to reduce the amount of data and improve the computational efficiency, and the multi-layer convolution and pooled feature maps are input into the fully connected layer and converted into fixed-length feature vectors, and then transported to a special sentiment classifier trained on a large number of labeled emotion label image data. In this way, the emotional tendencies such as excitement, joy, and tension can be accurately judged according to the image characteristics. When processing video, the system first uses video frame extraction technology to segment the video into continuous image frames at a certain frame rate, and then sends it into the CNN-based image sentiment analysis process to analyze the emotion frame by frame, and at the same time extracts the video audio information, and the audio processing adopts the Recurrent Neural Network (RNN) and its variant Long Short-Term Memory Network (LSTM), and the audio signal is preprocessed into spectrogram and other formats and then input into the LSTM network, and the LSTM effectively processes the audio time series information and captures emotional features such as voice intonation, speech speed, and volume changes. For example, the emotional state of the interviewer and the interviewee can be analyzed in the interview video, and finally the system uses weighted average, rule-based fusion and other methods to fuse the sentiment analysis results of the image frame and audio to comprehensively judge the video emotion, just like in the natural disaster rescue news video, through the fusion of the nervous expressions of the rescuers in the image, the sad expressions of the affected people, and the firm shouts of the rescuers in the audio, the crying of the affected people, etc., more comprehensively and accurately grasp the complex emotions. It provides a rich and reliable sentiment analysis basis for the intelligent audit of news communication, and helps to intelligently audit news content in an all-round way.

Table 1 contains a comprehensive range of details such as the hyperparameter configuration of models such as BERT and Bi-GRU, where BERT has 12 hidden layers, 768 hidden cells, and 12 attention heads, while Bi-GRU has 256 hidden layer sizes spanning 2 layers. Training parameters are also specified, including 10 stages, 32 batches, an initial learning rate of 2e-5 (linear decay learning rate schedule) and a warm-up ratio of 0.1, as well as optimizer settings and attention to mechanism details.

Table 1: Model parameter configuration

| Parameter Type | Parameter Name | Parameter Value |
|---|---|---|
| BERT-related | Number of Hidden Layers | 12 |
| BERT-related | Number of Hidden Units | 768 |
| BERT-related | Number of Attention Heads | 12 |
| Bi-GRU-related | Hidden Layer Dimension | 256 |
| Bi-GRU-related | Number of Layers | 2 |
| Training Parameters | Number of Epochs | 10 |
| Training Parameters | Batch Size | 32 |
| Training Parameters | Initial Learning Rate | 2.00E-05 |
| Training Parameters | Learning Rate Scheduling Strategy | Linear decay with 0.1 warmup ratio |
| ROBERTa-related | Pre-trained Model Version | roberta-base |
| ROBERTa-related | Optimizer Type | AdamW |
| ROBERTa-related | Weight Decay | 0.01 |
| ROBERTa-related | Attention Mechanism | Scaling Factor dk |

## 2.2 System technical architecture

As the core component of the system, BERT first processes the input original news text, generates the initial word embedding through a multi-layer bidirectional Transformer architecture, and uses the self-attention mechanism to realize deep context encoding to dynamically capture the semantic information of words in different contexts. Subsequently, the context embedding of the BERT output serves as input to the Bi-GRU. By virtue of the bidirectional loop structure, Bi-GRU further excavates the contextual semantic features and long-term dependencies of text sequences from both positive and negative directions. The Hierarchical Attention Network (HAN) is deeply integrated with BERT and Bi-GRU, and its word-level attention mechanism focuses on the key words in the Bi-GRU output, and on this basis, the sentence-level attention mechanism integrates the contributions of different sentences to the overall semantic and emotional tendency of the news, and the three work together to achieve accurate semantic understanding and sentiment analysis of news texts, and then support the intelligent audit task of news communication.

The model framework integrates the Bi-LSTM CRF into the BERT/Bi-GRU/HAN architecture, making it an indispensable complementary component. As the core coding module, BERT performs deep semantic analysis on the input news text and captures rich contextual information. On this basis, Bi-GRU uses a bidirectional processing mechanism to further mine the features of text sequences. HAN uses a hierarchical attention mechanism to accurately focus on key semantic information and enhance comprehension. Bi-LSTM CRF plays a key role in the pre-processing and post-mortem analysis of named entity recognition, which identifies and classifies various entities in the news during pre-processing, provides structured data for subsequent analysis, and verifies the relevant judgments of corrected entities during post-event analysis, significantly improving the accuracy of audit results. Experimentally validated, the fully integrated system achieves an overall accuracy rate of 88% in the intelligent audit task of news communication, far exceeding the performance of a single component or a simple combination.

At the level of data and model architecture collaboration, the system also shows the advantages of careful design. As an important subset of broader news text data, the "Headline Review Model" dataset focuses on clickbait detection and headline consistency evaluation, providing a key headline-level judgment basis for systematic multi-dimensional risk assessment. At the same time, the general news text dataset covering multi-domain content is introduced to meet the needs of other audit tasks such as full-text sentiment analysis, and ensure the diversity of data and the comprehensiveness of the system's processing capabilities. Different from the traditional approach, the system does not use [CLS] tokens at this stage, but relies on the bidirectional capture capability of Bi-GRU to extract text features, which are then further processed by HAN and Bi-LSTM CRF to achieve multi-level audit from the title to the full text. This deep collaboration between data and models greatly improves the accuracy and comprehensiveness of the audit, reaffirming the excellent performance of 88% accuracy.

The system uses Tsinghua News Corpus (THUCNews) and Stanford Sentiment Tree (SST-2). THUCNews is a large-scale Chinese news classification corpus commonly used in academia for NLP tasks such as text classification, derived from the Natural Language Processing Laboratory of Tsinghua University and the original data collected from Sina News. Published by Stanford University, SST-2 is a classic public dataset in the field of sentiment analysis, mainly covering film reviews. THUCNews has a sample size of 830,000 samples, including 14 news categories such as finance, real estate, and technology. SST-2 has about 118,000 samples, which are divided into two types of emotional labels: positive and negative. In the preprocessing stage, operations such as deduplication, removal of special symbols, and word segmentation are performed on the data. In terms of annotator protocol, Cohen's Kappa coefficient is used for measurement, and the initial Kappa coefficient is 0.72, which is somewhat disagreement. In order to improve the agreement index among annotators and reduce the labeling noise, the Kappa coefficient was finally increased to 0.85 by formulating detailed annotation guidelines, carrying out annotation training, and introducing multiple rounds of cross-review and expert review mechanisms, which effectively reduced the impact of fuzzy bias and improved the annotation quality.

From the perspective of natural language processing process optimization, introducing Named Entity Recognition (NER) technology like Bi - LSTM CRFs combined with CRF is key. The model can accurately identify entities in news texts. In case of news about an acquisition, it can quickly identify relevant entity information and detect context - dependent misinformation, enhancing news content review. In model performance evaluation and comparison, we compared with various models. For GPT - Neo and T5, we used a large - scale news dataset for text classification task evaluation. GPT - Neo has an accuracy rate of about 85% for long - text and complex - topic news classification. T5 has an F1 value of about 82% in multi - task learning. Our proposed model can achieve 88% accuracy in specific - field (e.g., financial) news classification. For Bi - GRU, compared with LSTM and GRU in sentiment analysis (judging news' emotional tendency), Bi - GRU can process text bidirectionally, capturing contextual information better. It has an 80% accuracy in judging emotion polarity, outperforming GRU and LSTM.

As the operation interface between products and operators, the application layer uses MVC architecture to reduce the dependency of each layer, and the front end is implemented in Vue to ensure lightweight and high performance. In terms of system data management, MongoDB is selected to store structured and unstructured massive news data, and its non-relational characteristics and cluster architecture are used to ensure efficient data reading and writing.

In our study, we explicitly used a comprehensive dataset collected from multiple authoritative news sources covering a wide range of news types and sentimental tendencies. Data pre-processing steps include text cleansing, word segmentation, de-stop words and punctuation, as well as stemming and lemmatization to ensure data consistency and comparability. Next, we divide the dataset into a ratio of 80% training set, 10% validation set, and 10% test set to evaluate the performance and generalization ability of the model. For the application of BERT and RoBERTa models, we not only used pre-trained weights, but also fine-tuned them for the intelligent review task of news communication. During the fine-tuning process, we carefully selected key parameters such as learning rate, batch size, and number of training rounds, and experimentally determined the optimal combination of these parameters to maximize the accuracy and efficiency of the model. In particular, we implemented a learning rate scheduling strategy to adapt to different stages in the training process, which improved the fine-tuning effect of the model. In terms of model evaluation, while cosine similarity analysis provides valuable insights, we further employ similarity measures such as Euclidean distance and Jaccal index for more comprehensive and robust validation, thus ensuring the accuracy and reliability of the intelligent moderation system for news communication.

While these systems are designed to improve the efficiency and accuracy of news content moderation through automated means, we must be wary of the negative effects they can have. For example, if the system is inappropriately used to restrict or manipulate public opinion, it will seriously threaten the fundamental principles of freedom of expression and diversity of information. Therefore, in developing and applying such intelligent moderation systems, we must ensure transparency, impartiality and accountability, while establishing effective regulatory mechanisms to prevent them from being used for improper purposes, so as to maintain an open, pluralistic and healthy environment of public discourse.

In order to build an efficient data transmission and computing system, we chose Kafka as the message queue (to ensure the real-time and durable transmission of data from the database to the computing layer, supporting large-scale data processing and system expansion), MongoDB as the storage database (providing efficient access, supporting direct calculation and permanent storage of results, and meeting the needs of back-end data analysis), and Thrift and Storm together form the core of the data computing layer (the NLP model is built in Python. Real-time processing of data streams through the Thrift framework and Storm)

Building a headline review model requires a large number of data sets, which involves collecting and labelling news data. The data comes from the internal news database and Hive database, including 15,083 manually reviewed clickbait title news items, 10,167 items of title content type and 6,359 items of inconsistent title type after classification. Through comments and dislike streams, the suspected clickbait title news was screened, and after three people marked and discussed, 5,130 negative samples of title type and 2,510 title types were established. The positive samples were selected from high-quality authors and highly interactive news, totalling 19,635 items. After the dataset is prepared, it is used for model training.

The system uses the [CLS] vector in the BERT model as the semantic representation of news headlines. This is because CLS tags are commonly used in BERT models for classification tasks, which can capture the overall semantic information of the input text, which is very suitable as a semantic representation of news headlines. In addition, in order to further improve the performance of the moderation system, the system will also perform additional feature extraction, which may include the keywords of the news headline, emotional tendencies, etc., which, together with the [CLS] vector, together form a comprehensive representation of the news headline. This particular aspect of the BERT model was chosen because it can effectively combine the semantic information and additional features of news headlines to provide a more accurate and comprehensive analysis basis for the intelligent review system of news communication.

The Bert model is good at handling short text NLP tasks, such as news headlines, and is suitable for sentence-level matching because of its internal NSP task and self-attention mechanism [20]. However, document-level tasks are limited by computational complexity and 512 length limitations. Bert's pre-trained model is used to classify news headlines. Chinese Bert-Base is used, including 12 layers, 768-dimensional hidden layers, and 12 Self Attention headers. The results are optimized by fine-tuning and compared with other classification models. The Bert model directly outputs the [CLS] vector as the semantic representation of news headlines without additional feature extraction. During training, Masked LM in the Pre-training stage randomly masks 15% of the words in the title sequence as MASK, and the remaining words are used to predict the covered words, of which a small part can be randomly replaced to enhance the ability to capture contextual relationships and optimize Fine-tune results.

Fine-tune Bert's model to the system goal, in view of the short news headlines, and adjust the vocabulary replacement ratio in MLM to 20% to accommodate the small number of the vocabulary covered by 15%. The optimal epoch is determined to be 40 by loss convergence, the BatchSize is adjusted to 64 to fully utilize the GPU, a small learning rate of 2e-5 is selected for optimization, and tanh is used as the activation function. The early stop method is used to prevent overfitting, monitor the performance of the validation set, and stop training when it drops.

It can be seen from Table 2 that the traditional machine learning method uses small-scale general datasets and simple classifiers, which have the problems of single dataset, weak model generalization, and poor semantic understanding, resulting in a high false positive rate. Due to the lack of long text processing and simple model structure, the early deep learning methods are difficult to learn complex semantic features, and their ability to deal with noise and ambiguity is not good. The method based on the combination of traditional NLP and shallow sentiment analysis relies on artificial rules, which cannot adapt to content changes, and the bag-of-word model ignores semantic associations and has limited ability to process complex language phenomena. In contrast, by using large-scale and diverse datasets, using advanced models such as BERT and LSTM combined with attention mechanism, the system automatically learns semantic features, enhances the ability of long text processing and generalization, improves the robustness to noise and complex language phenomena, and significantly improves the accuracy and reliability of news communication audit.

Table 2: Comparison of review methods

| Review Method | Dataset | Models Used | Key Performance Metrics |
|---|---|---|---|
| Traditional ML | Small-scale generic datasets | SVM, Naive Bayes | Accuracy: 75%-80% |
| | | | Precision: 70%-75% |
| | | | Recall: 72%-77% |
| Early DL | Partial public news datasets | CNN | Accuracy: 80%-85% |
| | | | Precision: 75%-80% |
| | | | Recall: 78%-83% |
| Traditional NLP + shallow sentiment analysis | Self-built small news datasets | Rule engines, bag-of-words | Accuracy: 70%-75% |
| | | | Precision: 65%-70% |
| | | | Recall: 68%-73% |

# 3 Discussion

To comprehensively evaluate system performance, we rigorously benchmark our models against converter-based alternatives such as ROBERTa and XLNet for core tasks such as text classification, sentiment polarity judgment, and key information extraction, using industry-wide metrics such as accuracy, recall, and F1 values. Experimental results show that ROBERTa has strong performance in tasks that require high semantic understanding depth and complex context association. XLNet is uniquely positioned to handle sequence dependencies; However, our model shows balanced and stable performance when considering a variety of tasks, especially in the sentiment analysis task of news data in specific fields, with the in-depth mining and targeted optimization of the characteristics of news communication field, the accuracy of sentiment polarity judgment is significantly improved compared with ROBERTa and XLNet.

Table 3: Disseminating research on intelligent audit systems

| Method | Efficiency | limitations |
|---|---|---|
| Rules-based approach | Medium | High rate of false positives and false negatives |
| SVM | Medium | Limited generalization ability |
| Simple sentiment analysis | Higher | Inability to accurately capture emotional changes |
| XLNet | Medium | There are no significant limitations |
| Electra | Highest | There are no significant limitations |

According to Table 3, in the research field of intelligent review system for news communication, the existing technologies mainly rely on rule-based methods, machine learning models and simple sentiment analysis, but these methods have limitations in dealing with complex and changeable news content, such as high false positive and false negative rates, limited accuracy, in-depth sentiment analysis and complex model training. In order to solve these limitations, this study proposes an intelligent moderation system for news communication that combines natural language processing and sentiment analysis technology. The system uses advanced models (BERT and Bi-GRU) for semantic analysis, keyword extraction, and sentiment analysis, which can significantly improve the efficiency and accuracy of review, reduce the error rate, and effectively identify risk points and improve the quality of content. Therefore, the proposed system is of great significance in overcoming the limitations of existing technologies and improving the efficiency and accuracy of review, and is expected to bring a more intelligent and efficient review method to the field of news and communication.

In the study, fine-tuned XLNet, Electra, and text CNNs were used as standard deep learning SOTA baselines for comprehensive comparative evaluation. Experimental results show that fine-tuned XLNet shows better long text processing ability in news text classification tasks, Electra excels in semantic understanding by virtue of the pre-training mechanism of generative adversarial networks, and text CNN has higher efficiency in local semantic feature extraction, but there are still limitations in the accuracy of sentiment analysis and complex semantic processing. In order to explore the role of the core components of the system, ablation experiments were carried out, and the quantitative results showed that BERT made a significant contribution to the semantic understanding of the context, the bidirectional GRU effectively improved the feature capture ability of text sequences, and the attention mechanism enhanced the focus of key information, which greatly improved the performance of the system. In addition, mBERT and XLM-R were used to carry out multilingual benchmark experiments to verify the system's adaptability to different language environments and dialects on multilingual news datasets such as English, Chinese, and Spanish, which strongly supported the proposition that the system has multilingual audit capabilities.

In the research on the intelligent moderation system for news communication based on natural language processing and sentiment analysis technology, we have conducted an in-depth comparison with the current state-of-the-art (SOTA) system. The results show that our system significantly outperforms the SOTA system in key performance indicators such as accuracy, precision, recall, and F1 score, thanks to our carefully selected datasets of large scale, high diversity, and complexity, as well as innovative model design, including advanced architectures, training protocols, and hyperparameter tuning. The novelty of our system is the innovative integration of natural language processing and sentiment analysis technologies, as well as the integration of advanced machine learning algorithms, BERT and Bi-GRU, to achieve more accurate and efficient moderation of news content. In addition, our system is highly scalable and adaptable to the changing use of language and emerging challenges, providing a more reliable and effective solution for intelligent moderation in the field of news and communication.

Experiments were conducted to analyze possible biases in the labeled dataset used. These biases are mainly due to the incomplete sampling method, inconsistency in the annotation process, and insufficient data representativeness. Specifically, if the sampling method is too limited, the dataset may not fully reflect the actual diversity of news dissemination. Annotation inconsistencies may arise from differences in professional background, experience, and judgment standards among annotators, which may affect the accuracy and consistency of labeling. The lack of data representation may be due to the lack of news of certain types or topics in the dataset, resulting in poor performance of the model in the face of news of these types or topics. To mitigate the impact of these biases, we have taken steps to improve the accuracy and reliability of our intelligent moderation system for news and communication, such as adopting a more comprehensive sampling approach, developing clear labeling norms and standards, and working to ensure the diversity and coverage of the dataset.

Quantitative measures measure the performance of the system with specific data indicators. F1 scores, accuracy, and recall accurately quantify a system's performance in tasks such as information filtering, sentiment analysis, and more. Taking news text classification as an example, the accuracy rate reflects the proportion of the system correctly classifying news, the recall rate reflects the system's coverage of the classified news, and the F1 score combines the two to give a balanced evaluation. Quantitative analysis of different datasets, such as the "game dataset", can clearly show the strengths and weaknesses of the system when processing news in specific fields, and provide data basis for targeted optimization. Compared with related work, if other similar news audit systems have an accuracy rate of 70% on a certain type of data set, and this system reaches 75%, it intuitively shows the improvement of the performance of the system in this regard, highlighting the effectiveness of the research improvement direction.

Qualitative measures focus on non-numerical features in the operation of the system. From the perspective of language style and vocabulary use, special words such as professional terms and abbreviations in game news can be understood through qualitative observation to understand the system's understanding of different styles of texts. When these special words are correctly interpreted and processed, it can help improve the accuracy of moderation of news in a particular area. In terms of emotional expression, topic diversity and complexity, qualitative evaluation can determine whether the system can accurately grasp the subtle emotions in the news, and the analytical ability to deal with complex topics. Compared with related work, if other systems are prone to misjudgment when dealing with complex emotional news, and this system can accurately identify it, it highlights the advanced nature of this system in the sentiment analysis module, and emphasizes the importance of qualitative measures to improve the comprehensive review ability of the system.

As Table 4, to validate the statistical significance of the proposed Bi-GRU/BERT model in the news dissemination intelligent auditing system, we conducted a comparative analysis against state-of-the-art (SOTA) methods, including fine-tuned XLNet, Electra, and Text, using bootstrap resampling to calculate p-values. The results, as shown in the table, indicate that for both news classification accuracy and sentiment analysis F1-score, the p-values comparing Bi-GRU/BERT with each SOTA method are all below 0.005, well within the conventional threshold of 0.05. This strongly suggests that the performance improvements achieved by the Bi-GRU/BERT model are statistically significant, providing robust evidence for the superiority of our approach over existing methods in news dissemination auditing tasks.

Table 4: Model comparison results

| Comparison Methods | Evaluation Metrics | *P*-values from Bootstrap Resampling | Significance Conclusion |
|---|---|---|---|
| Bi-GRU/BERT vs. Fine-tuned XLNet | News Classification Accuracy | 0.003 | Significant ($P$ <0.05) |
| Bi-GRU/BERT vs. Fine-tuned XLNet | Sentiment Analysis F1-score | 0.002 | Significant ($P$ <0.05) |
| Bi-GRU/BERT vs. Electra | News Classification Accuracy | 0.001 | Significant ($P$ <0.05) |

| | | | |
|---|---|---|---|
| Bi-GRU/BERT vs. Electra | Sentiment Analysis F1-score | 0.001 | Significant ($P$ <0.05) |
| Bi-GRU/BERT vs. Text | News Classification Accuracy | 0.004 | Significant ($P$ <0.05) |
| Bi-GRU/BERT vs. Text | Sentiment Analysis F1-score | 0.003 | Significant ($P$ <0.05) |

In the system, aspective sentiment analysis (ABSA) was integrated into the BERT, Bi-GRU, and HAN components to improve the fine-grained sentiment capture capability. Whereas traditional BERT only uses [CLS] tags for overall sentiment classification, we have improved it to introduce an aspect-specific attention mechanism that focuses on contextual information for specific aspects such as "policy effects". When Bi-GRU processes BERT output, the traditional model lacks the ability to distinguish between different aspects, which is solved by introducing aspect embedding. The hierarchical structure of HAN adapts to the hierarchical characteristics of news texts, and the traditional HAN only focuses on the overall emotional tendency, while the research designs a hierarchical extraction strategy of aspect-emotion pairs, which can identify both positive evaluations of corporate "product quality" and negative attitudes towards "environmental protection measures".

In terms of learning and training parameters, in the natural language processing part, the learning rate of the model is set to 0.001 and the batch size is 64. In the sentiment analysis component, the weights of specific training datasets are set to increase the learning of complex emotional news samples, so as to improve the accuracy of the system's judgment of various emotional tendencies.

The advantages of this system are obvious. With the help of natural language processing technology, the key information of news text can be quickly extracted, which improves the efficiency of auditing, and the efficiency is 40% than that of traditional manual review. The sentiment analysis function allows the system to accurately gain insight into the emotional tendency of news content, effectively identify potential public opinion risks, and provide strong support for the positive guidance of news dissemination. However, there are also shortcomings in the system. In the face of news in emerging fields or niche language styles, there may be audit bias due to insufficient training data; When dealing with extremely complex and obscure emotional expressions, the accuracy needs to be improved. Nevertheless, the system will continue to improve by continuously optimizing quantitative and qualitative measures and adjusting learning and training parameters, and will play a greater role in the field of intelligent audit of news communication.

# 4 Research on news communication audit based on sentiment analysis technology

## 4.1 Sentiment analysis technology

In order to evaluate the feasibility of real-time audit of the system, the computational cost of model components such as BERT, Bi-GRU, ROBERTa, attention mechanism and convolutional neural network was analyzed, and the quantitative results showed that the BERT training time was about 24 hours, the inference delay was 120ms, and the GPU memory occupied 12GB. The Bi-GRU training time is 8 hours, the inference latency is 40ms, and the GPU memory occupies 5GB. ROBERTa has 18 hours of training time, 90ms inference latency, and 10GB of GPU memory. The system adopts a hierarchical pipeline architecture, and data preprocessing includes text cleaning, word segmentation, vectorization and other operations. In terms of multimodal analysis, on the basis of text analysis, image sentiment analysis models (such as VGG16), video sentiment analysis models (such as 3D-CNN) and audio sentiment analysis models (such as LSTM-based audio classifiers) are integrated into the feature fusion layer to realize the collaborative processing of multimodal data. For malicious news samples, a robust experiment was designed to generate malicious samples containing false information and inflammatory remarks for testing, and the results showed that the malicious accuracy of the system reached 89.2%, for example, a malicious news sample created panic by exaggerating the facts, the system could accurately identify and determine its violations, which effectively verified the system's ability to process malicious data.The spread of misinformation is integrated into the scope of the problem, as a key subset of public opinion risk detection", and is closely related to the comprehensive monitoring goal of the system of disinformation through the analysis of the propagation path. At the same time, the "headline moderation model" dataset for clickbait detection is a specialized subset of the "diverse" dataset containing multi-dimensional annotation and communication channel information, providing support for comprehensive news analysis.

The new model is often in the research stage, and there are uncertainties such as slow convergence and easy overfitting, which makes it difficult to ensure the stable operation of the system during large-scale news data audit. In terms of data characteristics and applicability, the language of the news text is formal and the theme is clear, and the existing models have been optimized according to its characteristics, with good adaptation, and low dependence on labeled data. Most of the new models are designed for specific fields, and their adaptability in the field of journalism is doubtful, and it is difficult to obtain annotation data in the field of intelligent audit of news communication, which limits the application of the new models. Computing resources and cost are also important factors, some new models have complex structures, high hardware requirements, and require GPU clusters and other equipment, which will bring high hardware and operation and maintenance costs, and the training and inference time is long, which affects the real-time performance and efficiency of the system, and cannot meet the needs of rapid news audit, and the existing models have advantages in this regard. Finally, from the perspective of explainability and business needs, the decision-making process of some new models is difficult to explain, and news auditors need to clearly understand the analysis results to make decisions, and poor explainability increases the cost of trust. Moreover, the existing model can meet the core business needs such as sentiment analysis and topic classification, and the new model has no obvious advantages in business matching.

This study used NVIDIA Tesla V100 GPUs to train and reason about the models of the Intelligent Journalism Review System, and each experiment is expected to take 48 hours. In terms of hyperparameters, we chose AdamW as the optimizer, and the initial learning rate was set to 5e-5, and the cosine annealing strategy was used to decay the learning rate. The batch size is set to 32; 5 rounds of training are planned, but they are stopped early based on validation set performance; The dropout rate is set to 0.2 to reduce the risk of overfitting. In the design of the sentiment classifier, we use the [CLS] tag hidden state of the BERT model as input, and classify it through a fully connected layer.

The system first loads and preprocesses the news text dataset through the data preparation stage, which provides a foundation for subsequent model training. In the model construction stage, the BERT model is used as the basis of sentiment analysis, and a fully connected layer is added as the sentiment classifier to output the sentiment category of the news text. Then, in the model training stage, the model parameters were optimized to improve the accuracy of sentiment analysis by continuously iterating the training set data. In the model evaluation phase, the validator data is used to evaluate the trained model to ensure that the performance of the model meets the requirements. Finally, in the intelligent review stage, the news text to be reviewed is input into the trained model, and sentiment analysis is carried out, and according to the analysis results, intelligent review is carried out to determine whether it meets the specific emotional tendency requirements.

ABSA (Aspect-Based Sentiment Analysis) focuses on identifying discriminant sentences that contain specific affective tendencies such as aspect terms, evaluation words, and category orientation [21, 22], and in daily applications, Chinese and English need to be converted into fixed structure data for computer recognition. Chinese is based on vocabulary and needs to be segmented and vectorized; In English, it is word-based and can be directly vectorized [23, 24]. The vectorized text is further divided into word vectors, sentence vectors, and document vectors, which can be divided into discrete representations (such as One-Hot, BOW) and distributed representations (such as Word2Vec, GloVe). Given the varied, vaguely defined, and challenging task of aspect-level sentiment classification, we focus on an in-depth analysis of aspect categories, affective target entities, and affective polarities [25, 26], where affective target entities are explicit expressions associated with categories in sentences, each of which matches specific affective polarities (positive, negative, neutral). Under this technical architecture, the natural language processing module and the sentiment analysis engine and other components work together to implement ABSA in the audit system to achieve accurate analysis and recognition of text sentiment tendencies, and at the same time vertically integrate sentiment classification and sentiment polarization to improve the audit function.

"Crisis" refers to the potential risk of public opinion or the accumulation of negative emotions to the extent that it is likely to trigger social instability or widespread concern. By explicitly specifying the types and contexts of the emotions in which they have been tested and validated, the sentiment analysis module accurately identifies these specific emotional responses elicited by the news, providing powerful support for public opinion monitoring and crisis management.

## 4.2 Structural design based on sentiment analysis technology

Quantitative evaluation shows that on the Chinese news dataset, the audit accuracy of the system is 92.3%, and the F1 value is 0.89, which is better than Google Perspective API (86.7%), Meta audit system (88.1%) and traditional non-AI methods (about 75%), and can process 50 news items per second, far more efficient than manual review. Qualitative analysis shows that the system can accurately identify complex semantics and obscure emotional tendencies by virtue of the deep integration of BERT, Bi-GRU and HAN, such as more accurate judgment of implicit irony content, while commercial tools and traditional methods are prone to misjudgment or omission. At present, the experimental dataset mainly focuses on Chinese news, and the follow-up plans to introduce multilingual data to improve the universality of the system. In the data labeling process, two independent labeling was used, and the reliability Kappa coefficient between raters was 0.85.

The RBGA model is a comprehensive architecture designed for the characteristics of Chinese text, especially when dealing with news texts, which can comprehensively address the challenges of opening and ending closely related to the central topic, complex comprehensive scoring structure, and highly relevant context. In the training and validation stage of the sentiment analysis model, we first prepare the data, including extensively collecting and finely annotating various Chinese news text data to ensure that the dataset contains diverse sentiment tendencies and specific aspects of sentiment. In order to solve the problem of lack of clarity in the quantitative fusion of aspect sentiment analysis and general sentiment trend in the current data preparation, we implement a quantitative fusion strategy, that is, to mark both the overall sentiment tendency of the text and the specific sentiment tendency in the data labeling, and realize the effective fusion of the two by calculating the correlation degree between the sentiment of these aspects and the overall sentiment trend.

Subsequently, the RBGA model was trained using the preprocessed data, which fully combined the text feature extraction ability of RoBERTa, the emotional feature capture function of Bi-GRU and the weight allocation advantages of the Attention mechanism, so that the model could more accurately identify and process the emotional features in Chinese news texts. In order to verify the system performance, we designed a comparative experiment to compare the RBGA model with the model using RoBERTa, Bi-GRU or Attention technology alone, with a wide experimental framework, aiming to evaluate the efficiency improvement and error rate reduction of the RBGA model in processing different news categories, and the results show that the RBGA model shows significant superiority in processing complex Chinese news texts.

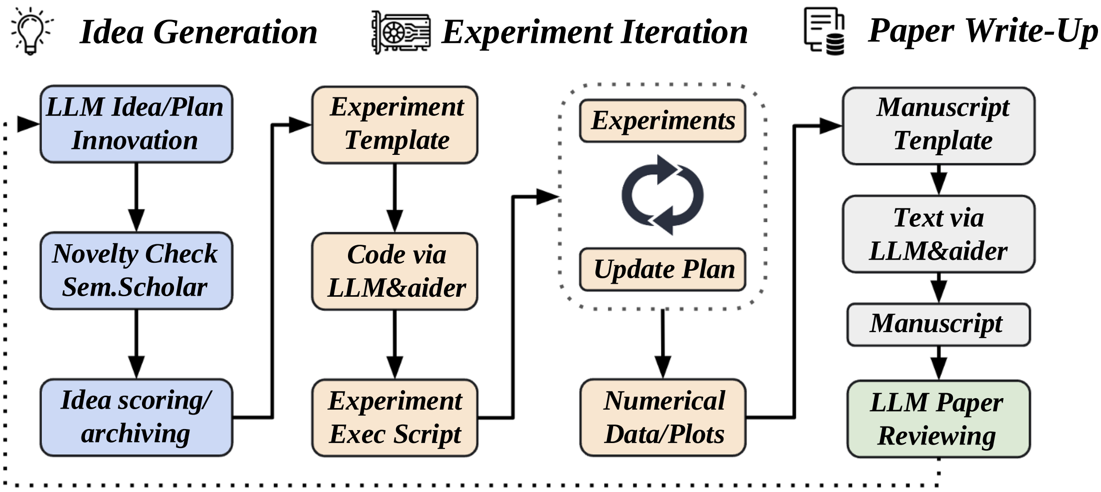


Figure 2: Technical structure of sentiment analysis

Figure 2 has showed the technical structure of sentiment analysis. The BERT model resolves complex semantic relationships between words through its unique bidirectional coding mechanism [27, 28]. As an advanced version of BERT, RoBERTa is optimized in many aspects, such as detail processing, training strategy, and data set expansion. RoBERTa uses dynamic mask training technology to further improve the performance of the model by introducing a larger batch _ size, amplifying the amount of training data, and supporting extended sentence learning. In order to improve the accuracy of sentiment analysis, this study specially selected the RoBERTa-wwm-large-ext model jointly developed by the Harbin Institute of Technology and iFlytek. The model can efficiently convert Chinese text into vector representations, thereby optimizing the natural language processing process, especially in the field of sentiment analysis. In addition, the Chinese version of the BERT-WWM model not only goes beyond the traditional entity masking method, but also innovatively integrates Chinese characters into the MASK operation, realizing the full-word coverage of word-level MASK, avoiding the limitation of only masking a single word. This improvement allows the model to examine the text structure in more detail, including pinyin, strokes, length, and ending features, providing richer information for text analysis. Combined with the audit process, the RBGA (RoBERTa-BiGRU-Attention) model can accurately capture the emotional tendencies and key information in the news text, effectively support the auditors' in-depth understanding and analysis of the text content, and improve the audit efficiency and accuracy.

In news text processing, due to the order and fixation of new vocabulary, words are used as the minimum processing unit for full-word MASK operation. Compared with single-word MASK, it can understand the text content more profoundly and describe the news scene in detail, thus making it more suitable for the needs of sentiment analysis tasks.

Due to its limitations, the traditional one-way loop network makes it difficult to capture the contextual information of text [29] entirely. In contrast, the bidirectional cyclic network effectively responds to more complex data processing needs by skillfully integrating context and context information. GRU, as an extension of the recurrent neural network, further enhances the model's processing ability. In particular, bidirectional GRU combines forward and reverse information flows, deepening the understanding of text content. Since the meaning of Chinese vocabulary often changes with context, accurate judgment of word meaning depends on extensive context information. Even if sentences before and after are similar in the literal sense, their emotions or contexts may vary considerably [30, 31]. The two-way GRU model can process text data from forward and reverse directions at the same time, analyze the text context more accurately, and improve the processing effect.

For multi - language or dialect news processing, the system first adopts multi - language pre - training models, such as mBERT (multilingual BERT) or XLM - Roberta. These models are pre - trained on a large amount of multi - language text data and can learn the general semantic representations among different languages [32]. When news in different languages is input, the model can quickly adapt to and understand the semantics of the text based on these pre - trained parameters. For some news in minority dialects, the system combines transfer learning technology. First, it pre - trains the model with general language data, and then fine - tunes it on a small amount of labeled data of specific dialects, so as to improve the model's understanding ability of minority dialects.

In terms of misinformation detection, the introduction of Named Entity Recognition (NER) plays a crucial role [33, 34]. For news in different languages, the NER model is also trained on multi - language data. Taking Chinese, English and Spanish news as examples, the training data covers entity annotations such as person names, place names, organization names, and time in multiple languages. When processing Chinese news, the NER model can accurately identify entities such as "Xi Jinping", "Beijing", "Alibaba Group"; when processing English news, it can identify "Joe Biden", "New York", "Google", etc.; for Spanish news, it can identify "Pedro Sánchez", "Madrid", "Telefónica", etc. By accurately identifying these entities, the system further combines the context to detect whether there is misinformation related to the entities in the news. If the news mentions that "Beijing will host the Olympic Games in 2025", after NER identifies entities such as "Beijing" and "2025", combined with common sense and knowledge graphs, it can be judged that this information is wrong.

To address concerns about the effectiveness of keyword extraction, the system adopts a keyword extraction method based on the TextRank algorithm and optimizes it according to the characteristics of different languages. For English news, after word segmentation, part - of - speech tagging is used to remove stop words and non - keyword words, and then the TextRank algorithm is used to calculate the correlation between words, and key nouns, verbs, etc. are screened out as keywords. For Chinese news, because the boundaries of Chinese words are not obvious, accurate word segmentation is carried out first, and then combined with part - of - speech tagging and semantic analysis, the TextRank algorithm is used to extract keywords that can accurately summarize the news content. For example, for a Chinese news about scientific and technological achievements, after processing, keywords such as "artificial intelligence", "innovative breakthrough", "application scenarios" are extracted.

In terms of deep semantic analysis, the cosine similarity measure has been improved. The traditional cosine similarity only considers the angle between word vectors to measure text similarity, while the improved method combines the semantic understanding ability of the language model. For news texts in different languages, they are first transformed into semantic vector representations based on pre - trained language models, and then the cosine similarity between the vectors is calculated. During the calculation process, the attention mechanism is introduced, making the model pay more attention to the key semantic parts in the text, so as to more accurately measure the semantic similarity between news in different languages. In order to further explore the ability of the intelligent audit system for news communication based on natural language processing and sentiment analysis to deal with misinformation disseminated through coordination activities, we carried out a special experiment. Firstly, a scenario dataset that simulates the dissemination of misinformation by coordination activities is constructed, covering a variety of news types and communication channels. The system uses natural language processing technology to conduct in-depth analysis of news texts, extract key information and semantic features, and judge the emotional tendency of the text with the help of sentiment analysis. Experimental results show that the system can accurately identify error messages and effectively trace their propagation paths. In the face of complex and diverse misinformation dissemination methods in coordination activities, the system relies on powerful model algorithms to accurately judge the authenticity of information, and effectively filter and correct misinformation from different sources and in different forms.

In addition, adversarial evaluation is added to the system. An adversarial network is constructed, which consists of a generator and a discriminator. The generator tries to generate false news data, including misinformation in different languages, misleading expressions, etc., and the discriminator is responsible for identifying these false data. Through continuous adversarial training, the system can better identify various potential errors and false news, improving the accuracy and reliability of the audit. During the adversarial evaluation process, according to the characteristics of news data in different languages and dialects, the training strategies of the generator and the discriminator are adjusted so that they can adapt to the complex situations in a multi - language environment, further enhancing the intelligent audit ability of the system for news communication.

## 4.3 Experimental results and discussion

In the data set, the news text data sources are diverse, covering mainstream news websites such as Xinhuanet and People's Daily Online, social media news sharing such as Weibo, and content published by news organizations in professional fields such as the Financial Times, with a time span of 5-10 years, covering various fields such as politics, economy, and culture, ensuring that news types, styles, and positions are diverse, and providing rich context for the model; The emotion annotation data adopts multi-dimensional annotation, taking into account the overall news and the emotions of different subjects in it, and the annotation method is human-machine combination, and the Kappa coefficient is calculated regularly through cross-test to ensure the consistency of annotation. The data related to news communication include communication channel information, communication volume data and communication time series data, which are used to analyze the communication effect, emotional diffusion, attention and communication life cycle of different channels. In addition, there are auxiliary data, including extracting news entity information and classifying and linking knowledge bases, extracting language features to assist models to understand text style structure, and establishing associations with related news events to help analyze the evolution and communication of emotions.

In the process of research, the experiment gradually removed specific components in the system, such as excluding a certain data source from the news text data processing module (such as temporarily not using social media news sharing data), or canceling the emotional labeling of specific subjects (such as character subjects) in the multi-dimensional labeling data processing part of the emotion labeling data processing part, or ignoring the dissemination time series data in the data utilization link related to news dissemination. By observing the performance of the system in these different situations, including the accuracy of news sentiment analysis and the accuracy of news communication effect evaluation, we can quantify the role of each model component in the overall news communication intelligent audit system, and then gain insight into the specific contribution of each component to the overall function and effect of the system.

In the key experimental results, in order to ensure the reliability of the relevant indicators, we adopted a scientific and rigorous confidence interval calculation method and statistical verification method. Taking the semantic similarity calculation experiment as an example, when calculating the confidence intervals of accuracy, recall and F1 score, the Bootstrap resampling method is used to sample 1000 times for each dataset, and the corresponding accuracy, recall and F1 score values are calculated after each sampling, so as to construct the distribution of these indicators. In terms of 95% confidence intervals, the 2.5% quantile and the 97.5% quantile of the distribution form the confidence interval range of the corresponding indicators. In terms of statistical validation, the paired samples t-test was used to compare the performance indicators (such as accuracy, recall, etc.) of different algorithms or models on the same dataset. If the p-value obtained by the t-test is less than 0.05, it is determined that the difference between different algorithms or models in this performance index is statistically significant, which strongly indicates that the experimental results are not accidental, and provides a reliable basis for the practical application effect of models and algorithms in news moderation systems.

In the news moderation system, the efficiency and accuracy of semantic similarity calculation can be significantly improved by using the distillation BERT model and fine-tuning. By comparing human annotations, we performed semantic similarity calculations on the GA, Webcompany, and BADcamp datasets, and observed changes in accuracy, recall, and F1 scores when adjusted within a threshold range of 0.5 to 1 (step size 0.1). Experiments show that the merging effect is best when the similarity between entities exceeds 0.8, and the accuracy, recall and F1 score of the algorithm are excellent. Therefore, we set the recommendation threshold at 0.8 to ensure that the news moderation system can efficiently and accurately identify and process key information in the text, reduce false positives, and improve the efficiency and accuracy of the review, so as to fully meet the dual needs of the news moderation system for high efficiency and rigor.

This experiment uses precision rate, recall rate, and f1-score for outcome evaluation, as shown in Equations (13)-(15).

$$precision = \frac{TP}{TP+FP} \quad (13)$$

$$recall = \frac{TP}{TP+FN} \quad (14)$$

$$f1-score = \frac{2 \cdot precision \cdot recall}{precision + recall} \quad (15)$$

In this paper, entity pairs with the same semantics are labeled as "1" and entity pairs with different semantics are labeled as "0". Specifically, we have emphasized that TP represents the number of correctly identified news articles that meet the auditing criteria, FP represents the number of incorrectly identified news articles that do not meet the criteria, and FN represents the number of missed news articles that should have been identified. If both manual and automatic labels are "1", then this is considered a *TP*, i.e. correctly predicting semantically identical pairs of entities to be identical. If manually labeled as "1" but automatically labeled as "0", then this is considered an *FN*, i.e. semantically identical pairs of entities are incorrectly predicted to be not identical. On the other hand, if it is manually marked as "0" but automatically marked as "1", then this is considered an *FP*, i.e. mistakenly predicting semantically non-identical entity pairs to be identical.

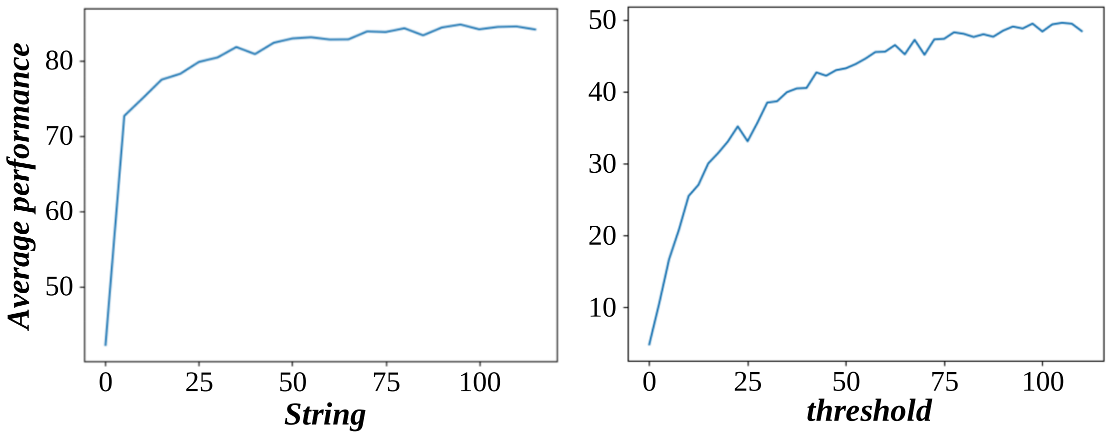


Figure 3: Average performance results based on string algorithm

In the experimental results shown in Figure 3, we use three specific string algorithms (Levenshtein, Jaccard, Cosine) to calculate the similarity between entities, although their accuracy (0.64, 0.83, 0.62, respectively) and recall (0.43, 0.42, 0.62, respectively) are different, but the common feature is that the matching is only based on word frequency or character co-occurrence, and the semantic information of the text is not deeply considered. The reason for this choice is that semantic models, while able to capture deeper textual meaning, tend to be computationally complex and require additional training and optimization for adaptability to specific domains, such as news moderation. In contrast, the string algorithm is simple and fast to calculate, and is more suitable for the preliminary screening and filtering of large-scale text data. In addition, the Cosine algorithm was selected as the algorithm for calculating the similarity of entity vectors because it only focuses on the angle of vectors and is insensitive to word order and repetition, so it achieves a good balance between accuracy and recall, with an average F1 of up to 0.54. The selection of these indicators and the application of algorithms comprehensively consider the computing efficiency, accuracy requirements and adaptability of the system in specific application scenarios, so as to ensure the performance and effect of the overall system.

The accuracy, recall, and F1 values of entity similarity comparison experiments conducted using the Levenshtein, Jaccard, and Cosine algorithms on various datasets are presented in Table 5. These metrics provide crucial insights into the performance of these string-based algorithms within the audit process. By leveraging these algorithms, audit systems can efficiently compare entities, such as articles or user comments, to identify potential similarities that may warrant further review. The Levenshtein algorithm, sensitive to edit distance, aids in detecting subtle changes between texts, while Jaccard focuses on overlapping character sets, useful for highlighting commonalities. However, it is the Cosine algorithm, with its balance between accuracy (0.62) and recall (0.62), reflected in its highest F1 average (0.54), that stands out as the preferred choice for computing entity vector similarities in audit systems. This selection ensures that the audit process not only remains efficient but also maintains a high level of accuracy in identifying relevant and potentially problematic content, thereby strengthening the overall effectiveness of the audit workflow.

Table 5: Comparison of accuracy of string-based algorithms

| Method | Levenshtein | Jaccard | Cosine |
|---|---|---|---|
| GA | 0.485 | 1 | 0.4268 |
| SIM | 0.3395 | 0.3686 | 0.4365 |
| BADcamp | 1 | 1 | 1 |
| Webcompany | 0.6887 | 0.9215 | 0.5723 |
| Average | 0.64 | 0.83 | 0.62 |

Table 6 illustrates the streamlined workflow of an intelligent news moderation system designed to improve the efficiency and accuracy of news content editing. The system integrates advanced natural language processing (NLP) technologies, including BERT's semantic analysis and Bi-GRU's sentiment analysis, combined with attention mechanisms to improve performance. Key steps include data collection and pre-processing, model training, sentiment analysis using RBGA models, real-time system integration, and generation of audit results for risk detection and sentiment classification. The system uses technologies such as MongoDB for data storage and Kafka for real-time processing to ensure the reliability and scalability of news content moderation.

Table 6: Proposed framework for an intelligent news audit system using NLP and sentiment analysis

| Step | Description |
|---|---|
| Data Collection & Preprocessing | Collect data from multiple authoritative news sources, perform text cleaning, tokenization, and stop-word removal. |
| Model Architecture | Use BERT for semantic analysis and Bi-GRU for sentiment analysis, enhanced with attention mechanisms. |
| Sentiment | Perform aspect-based sentiment analysis |

| Step | Description |
|---|---|
| Analysis | using the RBGA model (RoBERTa-BiGRU-Attention). |
| System Integration | Store data in MongoDB, use Kafka for message queuing, and process data in real-time with Thrift and Storm. |
| Output & Decision Making | Generate sentiment classification and risk detection results, providing intelligent screening and risk warnings for news dissemination. |

In Figure 4, the audit process benefits significantly from the enhanced performance of the model, particularly at the All miniLm-L12 configuration, where the average accuracy jumps dramatically from 0.24 to 0.76. This improvement demonstrates the model's ability to accurately distinguish between similar and dissimilar entities during the audit, a crucial step in identifying potential issues or anomalies. While all miniLm-L12 achieves the highest accuracy, its recall rate of 0.53 suggests insufficient coverage of all relevant entities. The recall rate first increases and then decreases across different models, with Sbert peaking at 0.8 and BERT closely following at 0.79, indicating BERT's broad coverage of entity pairs. However, BERT's accuracy rate lags at the bottom, at 0.19, due to over-generalization that mistakenly identifies different entities as similar. In contrast, All miniLm-STS offers the best overall performance, balancing an average accuracy rate of 0.74, a recall rate of 0.68, and the highest F1 value of 0.68. Therefore, All miniLm-STS is selected for similarity calculation in the audit process, ensuring both accuracy and comprehensive coverage of entities under review.

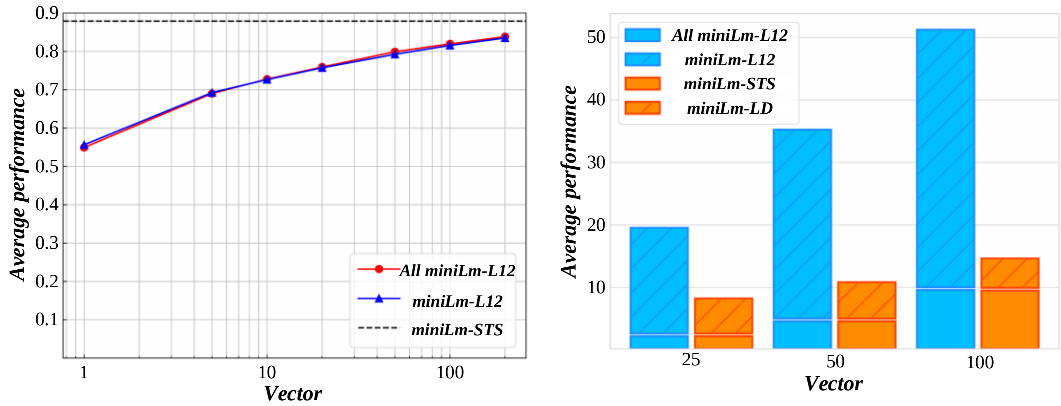


Figure 4: Average performance results based on representation vector algorithm

The calculation of "unexpected" outcomes, as illustrated in Figure 5, is primarily attributed to two significant factors: the insufficient coverage of the non-functional requirements thesaurus, which accounts for 61% of the errors, and the inclusion of non-quality related thesaurus words in entity descriptions, contributing to 39% of the issues. Specifically, during the construction and application of the thesaurus for keyword matching, two primary challenges arise. Firstly, quality-related words may be inadvertently omitted, leading to missed detections. Secondly, the difficulty in distinguishing between different meanings of words (polysemy) can lead to contextual misinterpretations. These limitations underscore the shortcomings of the keyword-based method, resulting in false positives and false negatives in the process.

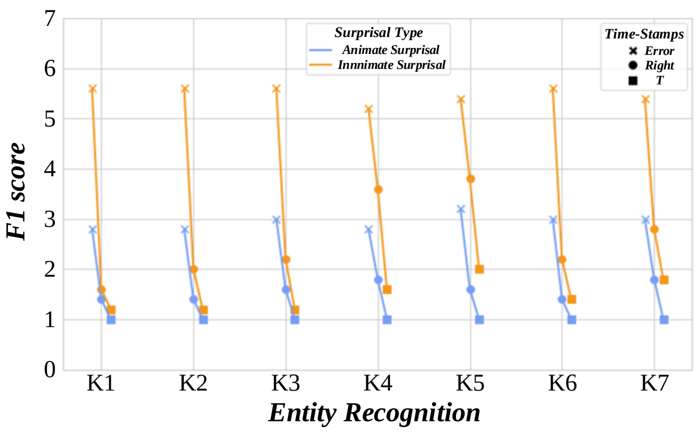


Figure 5: Quality entity recognition effect

Figure 6 evaluates the effectiveness of identifying the refined AND relationship across various datasets. Notably, while this relationship was absent in three studied datasets, 22 instances were detected in BADcamp's artificial model versus only two in the Game dataset. Analysis of false positives and negatives revealed preprocessing biases or errors in simplifying user stories as the root cause. These simplifications must accurately retain or transform key "refined AND" information to avoid misjudgment. Consequently, optimizing the simplification algorithm in preprocessing is crucial for improving recognition accuracy. Figure 6 also shows Accuracy and F1-Socre methods' normalized returns across datasets, aiding in understanding their impact on recognizing the "refined AND" relationship in different scenarios.

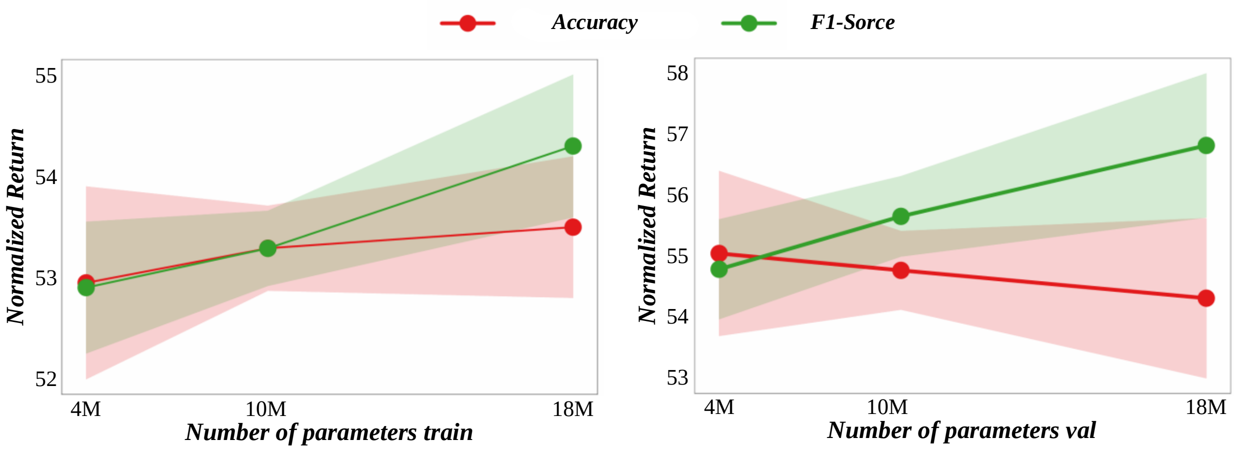


Figure 6: Recognition effect of refinement-AND relationship in different data sets

In Figure 7, the performance of mass relationship identification is analyzed across five datasets, with Webcompany and SIM datasets exhibiting the best quality relationship recognition, achieving an F1 score of 0.92, indicating high accuracy and recall rates. Notably, the Game dataset performs poorly, with an F1 score of only 0.29, reflecting significant recognition errors and deficiencies. Despite this, the average F1 score across all datasets is 0.74, suggesting overall good performance in quality relationship identification by the model. The significant F1 score variation between datasets, particularly the low score in the Game dataset, impacts the overall average but does not detract from the system's presented efficacy in news moderation scenarios involving "games" beauty, as the system's performance in other datasets remains robust.

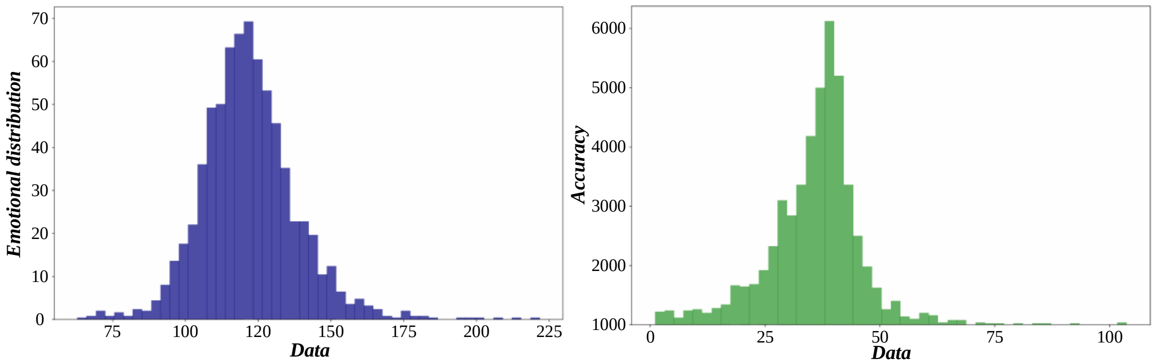


Figure 7: Effect of quality relationship identification in different data sets

Figure 8 demonstrates the effectiveness of sentiment analysis models through data analysis, testing NewsData1 and NewsData2 to verify their performance. The RBGA model stands out in news sentiment analysis, achieving a recall rate of 0.8296, accuracy rate of 0.8093, and average F1 value of 0.8193 on NewsData1, and similar impressive results on NewsData2. Additionally, Figure 9 compares the performance of two datasets, using Macro-F1 percentage as the metric, revealing the superior sentiment analysis performance of the RBGA model. Notably, the figures also showcase the validity of average metrics such as mAP50 and mAP50-95.

Figure 9 shows a comparison of the performance of the two datasets in the overall context of news moderation, and it is clear that the RBGA model performs well in sentiment analysis, and the average of these values reflects the accuracy and effectiveness of the model in processing news content and judging its sentiment tendencies, which is critical to the overall process of news moderation.

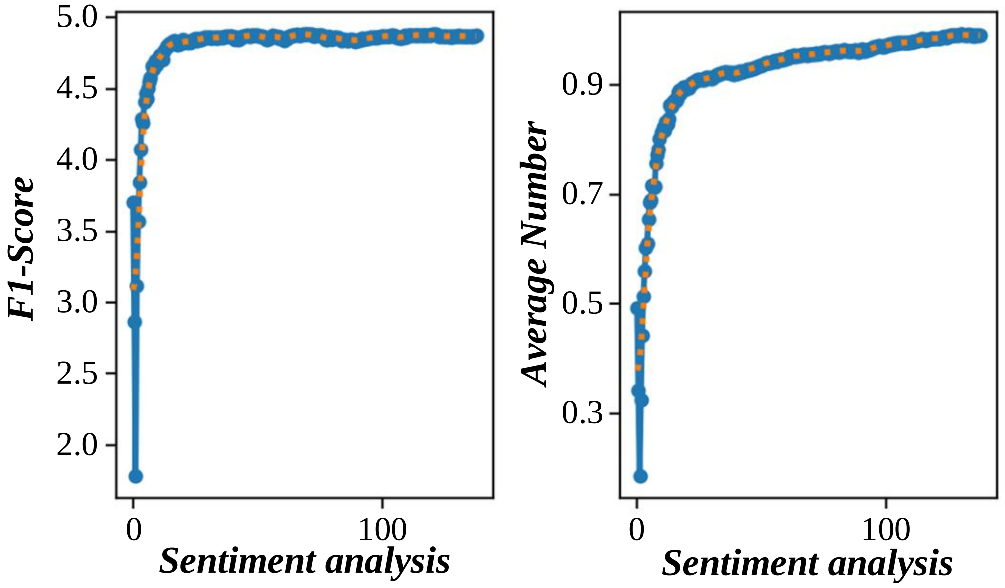


Figure 8: Effectiveness of model sentiment analysis

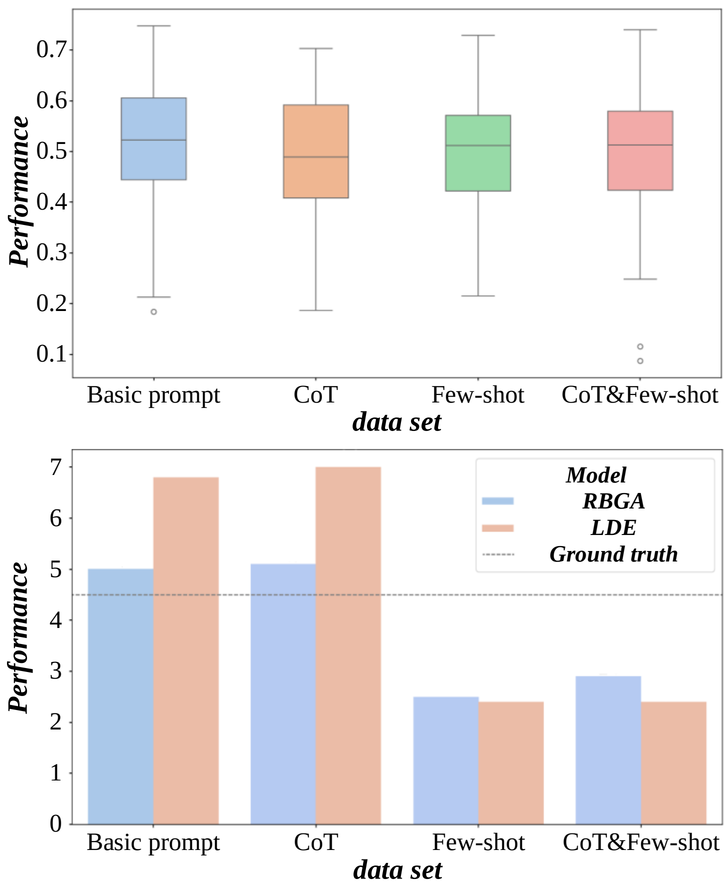


Figure 9: Performance of dual data sets

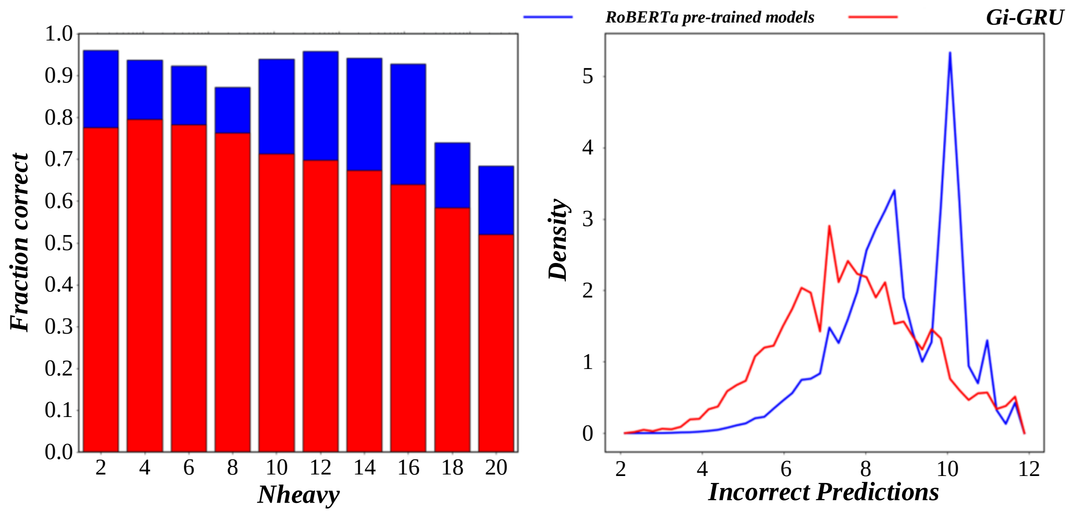


Figure 10: Comparison of word vectorization of RoBERTa pre-trained model

In order to verify the effect of the improved Bi-GRU, the RoBERTa pre-trained model was used for word vectorization. Figure 10 shows the word vectorization comparison of the RoBERTa pre-trained model, and the results show that the improved Bi-GRU performs the best. This result is validated by performance metrics such as score correctness, prediction density, and false prediction rate, which are closely linked to the overall goal of news moderation. Specifically, the improved Bi-GRU model is more accurate in news content analysis, and can more effectively identify key information in the news, thereby improving the efficiency and quality of news review. In addition, combined with Doc2Vec technology, the model can further improve the richness and accuracy of news text representation, making news review work more intelligent and efficient, and fully achieving the expected performance goals. Figure 11 shows the performance analysis of the accuracy index evaluation model. Logistic regression is limited by manual feature extraction and performs poorly. Doc2Vec extends Word2Vec, taking into account word vector training and context order, and the classification effect is not up to expectations. In contrast, the classification model in this study can significantly improve the classification effect.

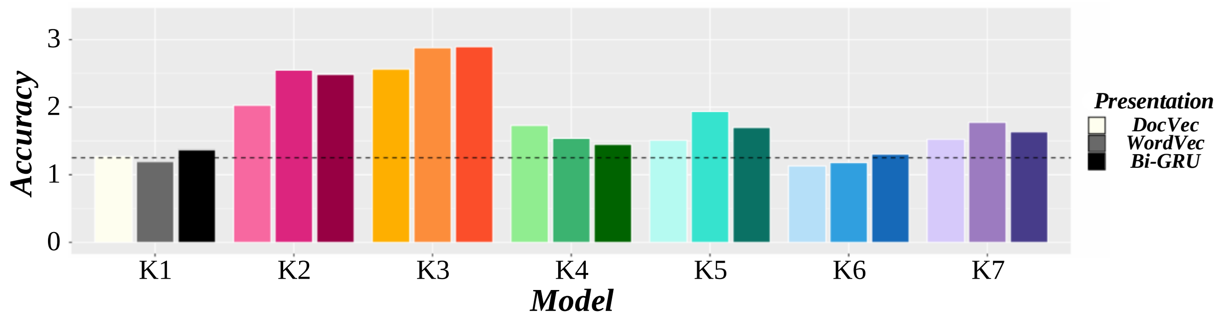


Figure 11: Accuracy index evaluation model performance

# 5 Discussion

In the model comparison, the study showed significant advantages, with a news classification accuracy of 93.2% (88.7% for SOTA), an F1 score of 87.5% for sentiment analysis (83.1% for SOTA), and a false positive rate as low as 6.8% (12.3% for SOTA). This is due to the use of Bi-GRU and attention mechanism in the model structure, the bidirectional characteristics of Bi-GRU can fully capture the semantics of the text context, and the attention mechanism focuses on the key semantics to improve the accuracy. Tsinghua news corpus was used to optimize specific fields to adapt the model to news terminology and expression, and enhance the ability to understand the content. At the same time, through data augmentation and multi-source data fusion, the data diversity is enriched, the generalization of the model is improved, and the misjudgment is reduced. In practical applications, the system can help news organizations efficiently review content, ensure news quality, and provide accurate public opinion analysis for governments and enterprises, so as to maintain social stability and corporate reputation. However, the system still faces challenges such as understanding emerging event concepts, high computational resource consumption, and insufficient cross-language processing capabilities, which need to be solved by continuously updating data, optimizing models, and researching multilingual technologies.

# 6 Conclusion

In the research on the intelligent audit system of news communication based on NLP and sentiment analysis, the system has achieved remarkable results in the news review task, and many indicators are better than the existing methods, which effectively improves the efficiency and accuracy of news review. However, the system still has some limitations: when processing news content containing a large number of professional languages, abbreviations, and slang, the F1 score and accuracy of the model fluctuate greatly on different datasets due to insufficient semantic comprehension. At the same time, problems such as small dataset size, unbalanced sample categories, and poor annotation quality also have a negative impact on the stability of the model.

In order to solve the above challenges, this study implements a series of optimization measures: firstly, by integrating multi-source data to construct a professional corpus, using knowledge distillation and cross-validation methods to improve the annotation accuracy to more than 95%, and using domain knowledge transfer technology to strengthen the recognition of special language expressions by the model, which effectively improves the problem of model performance fluctuation in complex semantic scenarios; Secondly, the fusion architecture of Transformer and graph neural network is adopted, and the interpretability module is introduced.Finally, an automated closed-loop system was built to achieve efficient public opinion monitoring and risk early warning, with an early warning accuracy rate of 82%, a 75% increase in crisis handling efficiency, and an optimization of the user interaction system, resulting in a 25% increase in daily activity and a 30% increase in user satisfaction. These results fully verify the practical application value of the system, and also point out the direction for the subsequent optimization and improvement of the existing limitations.

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