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Research Article

Emotion Classification Method of Financial News Based on Artificial Intelligence

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With the continuous development of economy, the economic development model is constantly changing. Especially since China's entry into WTO, the scale of economic development has reached a new height. The continuous development of economy makes the financial news module evolve towards specialization. However, with the emergence of Internet of Things technology, a large number of data appear in the network, which brings some difficulties to the classification and analysis of data economy. Emotion classification refers to the complexity and diversity of people's emotions. It can be classified from different observation angles. Because the core content of emotion is value, human emotion should be classified mainly according to the different characteristics of the movement and change of value relationship it reflects. This paper is aimed at studying the emotional classification method of financial news based on artificial intelligence and expecting to use artificial intelligence technology and classification method to classify financial news. It allows more people to know the implied information of financial information and promotes economic development. Artificial intelligence is a branch of computer science. It attempts to understand the essence of intelligence and produce a new intelligent machine that can respond in a similar way to human intelligence. This paper mainly summarizes the topic selection characteristics and subdivision topic selection characteristics of financial data news through quantitative and qualitative methods and explores the classification of financial news. In this paper, a simplified classification algorithm based on convolution function is proposed for the classification of traditional financial news networks. The experimental results show that the classification accuracy of artificial intelligence method is improved by 4% compared with the traditional emotion classification method, and the classification accuracy of positive emotion is lower than that of negative emotion by 2%.

1. Introduction

News is a channel to transmit information to the outside world. Basically, each industry has its own news media. With the popularization of Internet of Things technology, network news has become an emerging way and an indispensable source of information. The rapid development of economy provides the material basis for the rise of financial news. Financial news transmits information to everyone with the help of Internet of Things technology. However, the Internet of Things is mixed with many negative information, which affects the dissemination of correct news. Therefore, we need to classify the news according to the news content and correctly identify the incorrect information. With the characteristics of freedom, virtuality, and concealment, the Internet of Things makes more and more people willing to express their views through the network. It obtains the necessary information, which provides conditions for the dissemination of false information. This paper uses artificial intelligence technology to classify the emotion of financial news and transmit positive and healthy financial information.

Through this research, this paper strives to achieve a comprehensive, objective, and comprehensive grasp of the

data reform of financial news. To some extent, it fills the gap in this research field. By analyzing the emotional tendency of network news, this paper can grasp the proportion of positive and negative news for a period of time and the positive and negative aspects of news hot events. This is very important for public opinion analysis. Through the study of emotion classification, we can timely understand the people's views and views on a government policy or news event, so as to take corresponding measures. It is of great significance to social stability and policy implementation.

Financial news is an important source for people to understand financial information, which provides an important basis for people to make decisions. Therefore, the emotional classification of financial news is very important. The experimental research shows that when the news theme word is 6, the accuracy rate of positive emotion is 69%, and the accuracy rate of negative emotion is 78%, and the accuracy rate is the highest. It shows that in the emotional classification of financial news, the more subject words, the better.

2. Related Work

As the existing offline communication mode has been transferred to the Internet, a variety of multimedia services are emerging. Unlike in the past, these jobs are a huge source of opinions and attitudes. In particular, various opinions and comments published on the Internet in real time can help the company or the country determine the policy direction. In this context, Park et al. have developed a machine learning-based emotional classifier for environmental problems, so as to understand how people identify climate change problems related to the environment from the comments issued below the news. Machine learning is a special study of how computers simulate or realize human learning behavior in order to obtain new knowledge or skills. It reorganizes the existing knowledge structure to continuously improve its performance. Based on this research, they applied machine learning technology SVM (support vector machine) and Naive Bayes to construct emotion classification algorithm. They compared different network information by using CNN (convolutional neural network) and BI—the deep learning technology vigorously studied recently, and compared their advantages and disadvantages [1]. Emoji is a graphic symbol that expresses things in the form of images. With emoji, they can read and understand the text according to its meaning. Among the things mentioned at that time, the researchers studied the classification of Twitter content according to the use of emoticons. Sendari et al. aimed to determine the emotional use of Twitter over a period of time. Each tweet on the Twitter timeline contains text and emoticons, which will be classified according to several categories. Naive Bayesian algorithm calculates the probability of emoji tweets to obtain text classification with emoji. The characteristic of Bayesian method is to combine a priori probability and a posteriori probability, that is, it avoids the subjective bias of using only a priori probability and the overfitting phenomenon of using sample information alone. The results show that the "happiness" category has become the emotional trend of Twitter users, in which emojis are dominant [2]. Due to the increase in the number of applications and their use in various fields, the research of text emotion classification has been growing steadily in the past few years. When making certain decisions in business analysis, stakeholders must understand users' emotions. Saranya and Jayanthy classified emotions with ontology and process ambiguous sentences with machine learning algorithm (SVM). Each emotion is mapped hierarchically according to its depth level, and each emotion is associated with weight. POS marker is used to split sentences into words corresponding to their part of speech. Anew thesaurus is used to provide the ranking of emotional words obtained from part of speech tagging in the form of three dimensions. Due to the use of ontology, the insertion of new emotion as a concept and the mapping of its attributes become simple. This ontology-based machine learning technology for text emotional classification has proved to be efficient and performs better [3]. Kuchibhotla and Niranjan focused on the classification of various acoustic emotional corpuses with frequency domain characteristics using feature subset selection methods. The number of speech emotion samples available for training in the corpus is less than the number of features extracted from the speech samples, which is called dimension disaster. Because of this high-dimensional eigenvector, the efficiency of the classifier is reduced and the computation time is increased. To further improve the efficiency of the classifier, it requires an optimal feature subset, which is obtained by using the feature subset selection method. This will improve the performance of the system, increase efficiency, and reduce the calculation time. Experiments have shown that SFFS enhances the performance of the classifier because it eliminates the nesting effect suffered by SFS. The results also show that the best subset of features is a better choice for classification rather than a complete set of features [4]. They used electroencephalogram (EEG) signals to more accurately identify human emotional states than nonverbal and verbal signals, because emotions are psychological and physiological processes associated with personality, motivation, mood, and temperament. Imah and Rahmawati used an adaptive multilevel generalized learning vector quantization algorithm to identify mood states based on EEG signals. The emotional condition for its categorization is price, that is, low price and high price. DEAP datasets are characterized by data imbalance. One of the advantages of AMGLVQ algorithm is to handle classification under imbalanced data conditions. The test results show that AMGLVQ has better performance [5] than random forest (RF) and support vector machine (SVM). In recent years, a lot of research has been done on emotional recognition in Parkinson's disease (PD). EEG signals have been found to be helpful in identifying the relationship between emotional status and brain activity. Rejith and Subramaniam used four features and two classifiers to analyze the classification of emotional recognition in Parkinson's disease based on electroencephalogram. For each EEG signal, they obtained alpha, beta, and gamma band frequency characteristics for four different feature extraction methods (entropy, energy entropy, spectral entropy, and spectral

energy entropy). Then, they associated the extracted features with different control signals and develop two different models (Probability Neural Network and K-Nearest Neighbors algorithm) to observe the classification accuracy of these four features. Experiments show that the proposed energy entropy feature is uniform for all six moods. Compared with other features, the accuracy rate is more than 80%, while different features with classifiers produce different results for a few emotions, with the highest accuracy rate exceeding 95% [6]. Although these theories describe financial news, they do not effectively process the data in financial news, so this paper expects to use artificial intelligence technology to process related data.

Artificial intelligence (AI) is an important technology to support daily social life and economic activities. It has made a great contribution to the sustainable development of the economy and has solved various social problems. Although recently developed AI technologies do perform well in extracting certain patterns, they also have many limitations. Most ICT models are overly dependent on large data and lack self-conceiving capabilities. Lu et al. developed a new concept of general intelligent cognitive technology called Beyond AI. Its core functions include computer vision, machine learning, natural language processing, robot, and speech recognition. Specifically, the plan to develop an intelligent learning model called Brain Intelligence (BI). The model uses imaginative artificial life to generate new ideas about events without experiencing them. This model will demonstrate the BI intelligent learning model developed in autodriving, precision medical, industrial robots, etc. [7]. The fields of neuroscience and artificial intelligence (AI) have a long and interwoven history. Recently, however, communication and cooperation between these two areas have become less common. Hassabis et al. believed that a better understanding of the biological brain can play a crucial role in building intelligent machines. They investigated the historical interactions between AI and neuroscience and highlighted the current advances in AI. These advances have been inspired by neurocomputational studies in humans and other animals. Finally, they highlighted common themes that may be key to future research in these two areas [8]. Although these theories introduce artificial intelligence, they are less practical to combine with financial news.

3. Emotional Classification of Financial News in Artificial Intelligence

3.1. Financial News. With the development of Internet of Things technology, various kinds of information appear in life, financial news is no exception, and in many cases financial news appears in the form of data news [9, 10]. Data news provides a new possibility by combining the traditional news narrative ability and sensitivity with massive data information. It is a way of news work based on the collection, analysis, and presentation of data information. The general track of China's economic news development is from economic information to economic news to financial news. In fact, financial news has been attached great importance and is closely related to China's entry into the WTO [11]. The emergence of financial news has promoted the evolution of financial media toward specialization [12]. The research objects of financial media mostly focus on professional financial media and comprehensive paper media. There are many studies on financial reports in comprehensive paper media. Figure 1 shows the basic system structure of financial news:

Before discussing the relevant content of financial news, we need to give a brief explanation of the concept of financial news. From the appearance time of financial news, the development time of financial news is not long, so there is no recognized concept [13, 14]. First of all, from the coverage, financial news refers to financial and other macroeconomic fields related to the state and government behavior. It is primarily related to financial aspects. From a macro perspective, financial news includes information about the whole society and the global economic situation, analysis, and prediction of economic development trend [15, 16]. The micro financial news focuses on smaller individuals, including enterprises, families, and individuals. It uses vivid cases to reflect social and economic life.

With the development of economy, news is gradually close to the public, and this trend also appears in financial news [17]. The audience of financial news is increasing. The audience of financial news is widely distributed in all corners of society, but it cannot be understood that every member of society is the audience of financial news [18, 19]. Among them, the real financial news audience refers to the part that has long adhered to and paid attention to the financial information on the news media. Their work is often closely related to the economic field, and they need to obtain a large amount of financial information from various channels in daily production and life [20]. The improvement of education also provides conditions for the popularization trend of financial news. Financial news has the characteristics of positioning and service in the trend of popularization. It includes the civilian selection of topics, the closeness between the theme and real life, the popularization of language, and the diversification of forms.

3.2. Artificial Intelligence. In recent years, with the development of artificial intelligence technology, a series of intelligent fields have emerged, and emotion classification is one of them. News is a kind of text. To deal with the text, we need to analyze the text elements.

$$A = (a_1, a_2, \cdots a_t). \tag{1}$$

V represents the vector, and t represents the components of the text.

$$S = (g_1, g_2, \cdots g_t). \tag{2}$$

The document S corresponds to the t dimension vector.

$$g_h = \frac{k}{w}. \tag{3}$$

h represents the corresponding position of the text, k

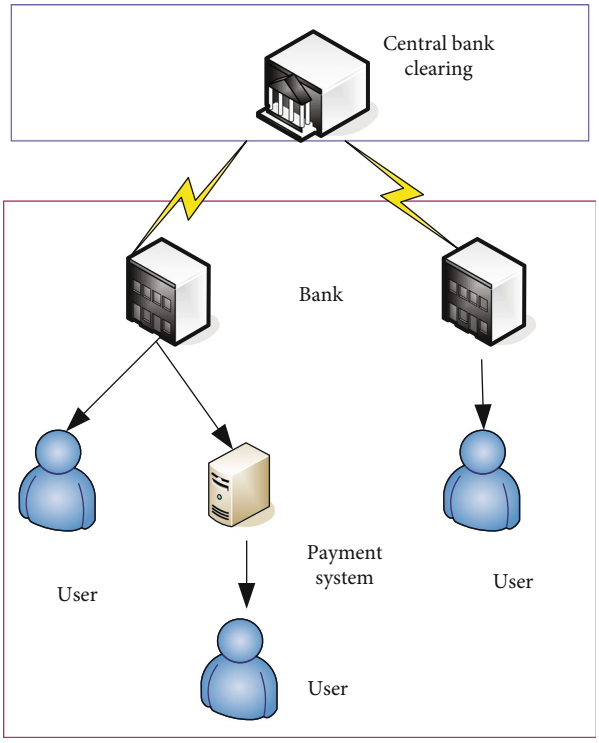

Figure 1: Basic system structure of financial news.

represents the occurrence of text elements, and w represents the total vocabulary of the text.

$$zx_{ab} = \frac{w_{ab}}{\sum h^{w} hb}. \tag{4}$$

b represents a part of the news document, a represents vocabulary, w represents the total vocabulary of the text, and k represents the occurrence of text elements. Figure 2 shows a common model of document structure

$$ruy_a = 1\log\frac{|Q|}{|(\ln_a \in u_l)|}. \tag{5}$$

$$p = \frac{1}{f}\sum_{j}^{f}\log g\left(h_j \middle| h_{j-f}, \cdots h_{j+f}\right). \tag{6}$$

h_j represents whitening words, and f represents several words after j. When the model is solved by convergence, the vocabulary of the whole news can be obtained. The model structure is shown in Figure 3.

Neuron is an important part of neural network. A large number of neurons are connected with each other to form a neural network adaptive dynamic system. The system can be multi-input and single output, and its structure mode is

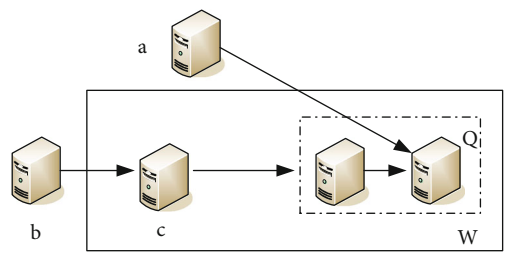

Figure 2: Document structure model.

shown in Figure 4.

$$\begin{aligned} h_a &= \eta_a + g_a, \\ \eta_a &= \sum_t \beta_o u_t, \\ k_a &= r\left(\sum_t \beta_o u_t + g_a\right). \end{aligned} \tag{7}$$

η_a represents the strength of the neural network, g_a represents the deviation, u_t represents the information input, and $r(*)$ represents the distance function.

By synthesizing the evidence of the recognition framework, the following expression can be obtained:

$$y(S) = y_1 \oplus y_2 = 0\begin{cases} \sum_{h,j} & y_1(S_h)y_2(A_j) \\ & \dfrac{S_h \cap A_j}{1-u} \\ & 0 \end{cases}, \forall S \subset \varphi, A \neq \varphi. \tag{8}$$

Among them, u reflects the degree of conflict between various evidences, which we call conflict factor.

$$Q(j(a)) = \frac{1}{l}\sum_{1}^{l} j(a)\beta(a). \tag{9}$$

Among them, $\beta(a) = y(a)/w(a)$.

$$w(a) = w_1(a_1)w_2(a_2|a_1)\cdots w_c(a_c|a_1\cdots a_c). \tag{10}$$

a represents scalar or vector.

Convolutional neural network can solve the parameter problem on the model. Using this model can reduce the relevant parameters to be collected and improve the performance of the algorithm. Convolutional neural network can be connected locally, which greatly reduces the parameters of the network. Weight sharing is used to control the number of parameters. Downsampling in space or time gradually reduces the spatial size of data and the number of parameters in the network. It not only reduces the consumption of computing resources but also can effectively control over fitting.

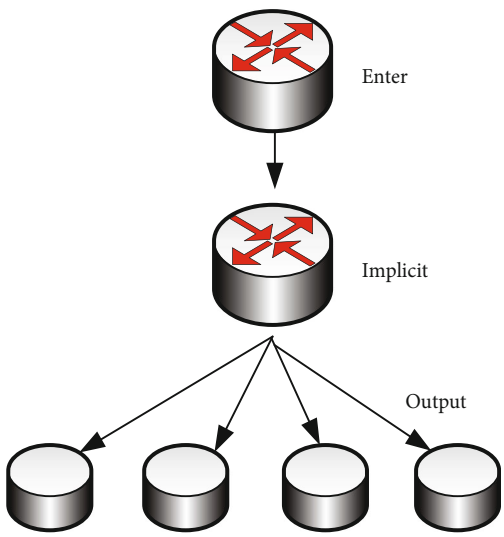

Figure 3: Convergence model structure diagram.

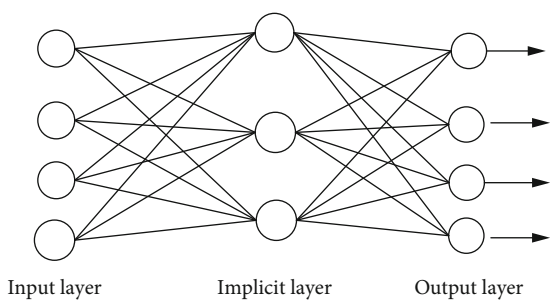

Figure 4: Neural network structure diagram.

The Gaussian distribution method is required to optimize the training parameters in the neural network model, and its function expression is as follows:

$$u = \sqrt{\frac{9}{y_i + y_{i+1}}}. \tag{11}$$

y_i, y_{i+1} represents the size of hidden layer before and after parameter optimization.

$$a_u = d_u(s_{u-1u}a_{u-1} + e_{u-1}). \tag{12}$$

Formula (12) represents the implicit output of the model. When $d = 1$, it can be obtained that the model vector is 0.

$$a_o = d_o(s_{o-1o}a_{o-1} + e_{o-1}). \tag{13}$$

Formula (13) represents the output data of each layer of the neural network.

$$\beta = \frac{1}{3}\sum_{h}^{d}(p_u - r_j). \tag{14}$$

Formula (14) represents the error range of model training, p_u represents the output value of the last layer.

$$u = 0.6\sum_{1}^{A}\sum_{1}^{B}(t^o - y^o)^3 = \sum_{o=1}^{A} u_o. \tag{15}$$

It first considers the weight change of the output layer of u.

$$\beta(a) = \frac{w(a) = w_1(a_1)w_2(a_2|a_1)\cdots w_c(a_c|a_1\cdots a_c)}{y(a) = y_1(a_1)y_2(a_2|a_1)\cdots y_c(a_c|a_1\cdots a_c)}. \tag{16}$$

The weight (16) represents the importance formula; among them,

$$\beta_j(a_j) = \beta_{j-1}(a_{j-1})\frac{y_j(a_{j-1})}{w_j(a_{j-1})}. \tag{17}$$

The forward relay formula of convolution layer is as follows:

$$u_n^x = f\left(\sum_c u_x^{x-1} \times W_L^x + C_n^x\right). \tag{18}$$

n represents the subscript, W_L represents the set of $x-1$ layers connected with L feature maps of x layer, and C represents the convolution window.

3.3. Overview of Emotion Classification. With the rise of Internet technology, the relationship between people and people is becoming closer and closer. More and more people express their attitudes on the Internet. However, the information on the Internet of Things is too complicated, which also makes it difficult to sort out all kinds of information. Emotion classification is an integral part of emotion analysis, and emotion classification is a special text classification. Based on financial news, this paper mainly focuses on the classification of emotional tendency of text. The analysis of emotional tendency of financial news is our ultimate goal. News is a description of facts, which should abide by the "principle of authenticity." News narration generally shows the characteristics of "low subjectivity." Because the subjective characteristics of news are not obvious, it is not easy to carry out emotional analysis.

Sentence level emotion classification is a fine-grained emotion classification. For a given piece of text data, it first does sentence segmentation and locates to the level of sentence group or sentence block, then classifies the emotion of the sentence group or sentence block, and finally outputs the emotional tendency of the sentence group or sentence block. If efficiency is considered when classifying, the length of sentences needs to be considered.

When classifying the emotion of news, we need to consider the emotional words of subject sentences. After finding emotional words, they use relevant classification algorithms to calculate them. By counting the number of commendatory and derogatory words in the sentence, we can judge

the emotional tendency of the sentence, so as to determine the emotional attitude of the whole news. Figure 5 shows the system structure of emotion classification using artificial intelligence method:

4. Emotion Classification Experiment of Financial News

4.1. Financial News Data. With the development of Internet of Things and information technology, the data scale is developing rapidly. Efficient integration of all kinds of data is conducive to improving the utilization of resources. Since China's entry into WTO, financial information from all over the world has poured in. The correct classification and interpretation of financial news is conducive to grasp the economic law and improve the accuracy of decision-making for the audience.

According to the data in Table 1, we have investigated 130 financial news in the surrounding areas and simply classified them. According to the survey data, there are 33 articles on macroeconomy in the news, accounting for 25.3%. 36 articles explored industrial economy in the news, accounting for 27.7%; 21 articles explored financial development in the news, accounting for 16.2%; 27 articles explored the development of market economy in the news, accounting for 20.8%. 13 articles explored policies and measures in the news, with a proportion of 10%. According to the data, there are more news on macroeconomy and industrial development in financial news. It shows that people pay more attention to industrial economy in the current economic development. Among all the report categories, the policy news is the least, which is consistent with the actual situation of the introduction of the policy. It is noteworthy that the proportion of such news is increasing, indicating that people have paid more attention to the financial industry in recent years. This also shows the importance of classifying financial news.

According to the data in Table 2, we have investigated the publishing institutions of financial news. According to the survey, the news released by colleges and universities is 4, and the proportion is 3%. Caixin's news is 20, with a proportion of 15%. The news of official institutions is 30, with a proportion of 23%. The number of news released by enterprise organizations is 33, accounting for 26%. The news released by other media is 17, with a proportion of 13%. The number of news released by sorting out public materials was 26, accounting for 20%. According to the data, the proportion of financial news released by enterprise organizations and official institutions is large, which is very different from other types of news. In financial news, the data is mainly financial related information. Compared with other institutions, enterprises are easier to obtain and the data is true. For this reason, financial news is mostly reported by enterprises and official institutions. In addition, it is worth paying attention to the relevant financial news reported through public data. This kind of news is equivalent to the integrated release of data and information, and there are many such reports. It shows that people need to integrate financial information, which is also in line with today's fast pace of life.

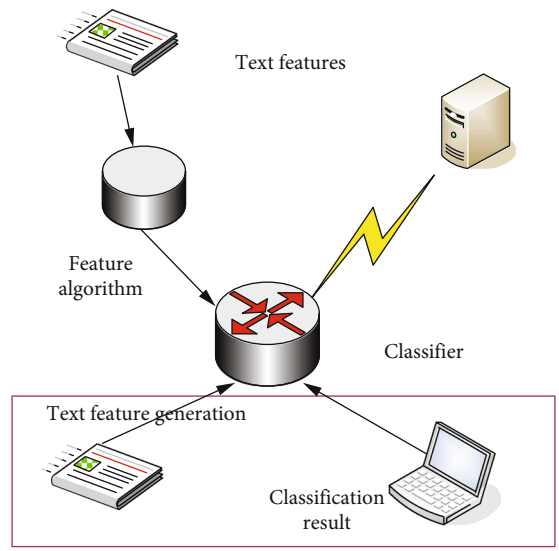

Figure 5: System structure of artificial intelligence method for sentiment classification.

4.2. News Classification Test. News is news that everyone can see. Everyone has his own opinion. Based on this situation, the same news will have different comments with different attitudes. Sentence level emotion classification is a fine-grained emotion classification. For a given piece of text data, it first does sentence segmentation and locates it at the level of sentence group or sentence block. It then classifies the emotion of the sentence group or sentence block and finally outputs the emotional tendency of the sentence group or sentence block. In order to classify the emotion of financial news, we have explored different algorithms, as shown below:

According to the data in Table 3, we have classified the financial news above. In the calculation and comparison, we select three reference models. Firstly, we use traditional methods to classify emotion types, in which the accuracy rate of single word classification is 94.7%, the recall rate is 94.3%, and the V value is 94.5%. The accuracy rate of random vocabulary classification was 86.3%, the recall rate was 86.5%, and the V value was 86.43%. The correct rate of word pair vector classification is 92.6%, the recall rate is 92.66%, and the V value is 92.57%. According to the data, under the calculation of traditional methods, the word vector generated by running a single word is the best, and the effect of random words is the worst. Therefore, when using word2vec for experiments, the optimal feature processing method is to use a single word vector.

According to the data in Table 4, when classifying emotions, we also use artificial intelligence method for comparative analysis. Under artificial intelligence technology, the accuracy rate of single word classification is 93.2%, the recall rate is 93.3%, and the V value is 93.27%. The accuracy rate of random vocabulary classification was 90.6%, the recall rate was 90.64%, and the V value was 90.61%. The correct rate

Table 1: Survey data analysis of financial news selection categories.

Category	Length	Proportion
Macroeconomics	33	25.3
Industry	36	27.7
Finance	21	16.2
Market	27	20.8
Policy	13	10

Table 2: Analysis of financial news sources survey.

Category	Length	Proportion
Efficient institutions	4	3
Caixin	20	15
Official institutions	30	23
Corporate organizations	33	26
Other media	17	13
Public information collation	26	20

Table 3: Traditional model test situation.

Category	Correct rate	Recall rate	V
Individual vocabulary	94.7	94.3	94.5
Random words	86.3	86.5	86.43
Word pair vector	92.6	92.66	92.57

Table 4: Artificial intelligence model test situation.

Category	Correct rate	Recall rate	V
Individual vocabulary	93.2	93.3	93.27
Random words	90.6	90.64	90.61
Word pair vector	94,4	94.66	94.57

of word pair vector classification is 94.4%, the recall rate is 94.66%, and the V value is 94.57%. According to the data, under the algorithm of artificial intelligence, the word vector generated by word pair vector is the best, and the effect of random vocabulary is the worst.

5. Result of Emotion Classification

5.1. Emotion Classification. In a complete news, the vocabulary involved is very large. News is a description of facts, which should abide by the "principle of authenticity." News narration generally shows the characteristics of "low subjectivity." Because the subjective characteristics of news are not obvious, it is not easy to carry out emotional analysis. However, words other than nonobjective descriptions will be collected in the overview of the whole news. We can classify the news according to these words.

According to the data in Figure 6, we made a comparative analysis on the emotional classification of news under the same conditions in the experiment. Firstly, we use artificial intelligence technology to analyze the overall situation. First, when the news theme word is 1, the accuracy of positive emotion is 48%, and the accuracy of negative emotion is 57%. When the news theme word is 3, the accuracy of positive emotion is 0%, and the accuracy of negative emotion is 59%. When the news theme word is 6, the accuracy of positive emotion is 52%, and the accuracy of negative emotion is 66%. When the news theme word is 9, the accuracy of positive emotion is 41%, and the accuracy of negative emotion is 44%. When the news theme word is 12, the accuracy of positive emotion is 33%, and the accuracy of negative emotion is 37%. According to the data, when the subject word is 6, the accuracy of emotion analysis is the highest.

In addition to the analysis of the full text, we also analyze the topic sentences. According to the data, when the news theme word is 1, the accuracy of positive emotion is 67%, and the accuracy of negative emotion is 76%. When the news theme word is 3, the accuracy of positive emotion is 68%, and the accuracy of negative emotion is 76%. When the news theme word is 6, the accuracy of positive emotion is 69%, and the accuracy of negative emotion is 78%. When the news theme word is 9, the accuracy of positive emotion is 60%, and the accuracy of negative emotion is 70%. When the news theme word is 12, the accuracy of positive emotion is 56%, and the accuracy of negative emotion is 65%. According to the comparison of the two groups of data, the accuracy of using topic sentences to analyze financial news is higher, and it also reaches the highest level when the topic word is 6.

In the experiment, we not only analyzed the emotional accuracy but also analyzed the positive and negative meanings. According to the data in Figure 7, we also conducted experiments on the full text and topic sentences. First of all, from the effect of the full text, when the news theme word is 1, the accuracy of positive emotion is 67%, and the accuracy of negative emotion is 78%. When the news theme word is 3, the accuracy of positive emotion is 65%, and the accuracy of negative emotion is 74%. When the news theme word is 6, the accuracy of positive emotion is 60%, and the accuracy of negative emotion is 68%. When the news theme word is 9, the accuracy of positive emotion is 51%, and the accuracy of negative emotion is 59%. When the news theme word is 12, the accuracy of positive emotion is 43%, and the accuracy of negative emotion is 54%. According to the data, when analyzing the positive and negative emotions of the full text, the more the number of topics, the lower the accuracy, and the decline rate of positive emotions is greater than that of negative emotions.

From the analysis of the positive and negative meanings of the topic sentence, when the news topic word is 1, the accuracy of positive emotion is 73%, and the accuracy of negative emotion is 74%. When the news theme word is 3, the accuracy of positive emotion is 74%, and the accuracy of negative emotion is 78%. When the news theme word is 6, the accuracy of positive emotion is 76%, and the accuracy of negative emotion is 80%. When the news theme word is 9, the accuracy of positive emotion is 68%, and the accuracy of negative emotion is 75%. When the news theme word is 12, the accuracy of positive emotion is 64%, and the accuracy of negative emotion is 70%. According to the data, when

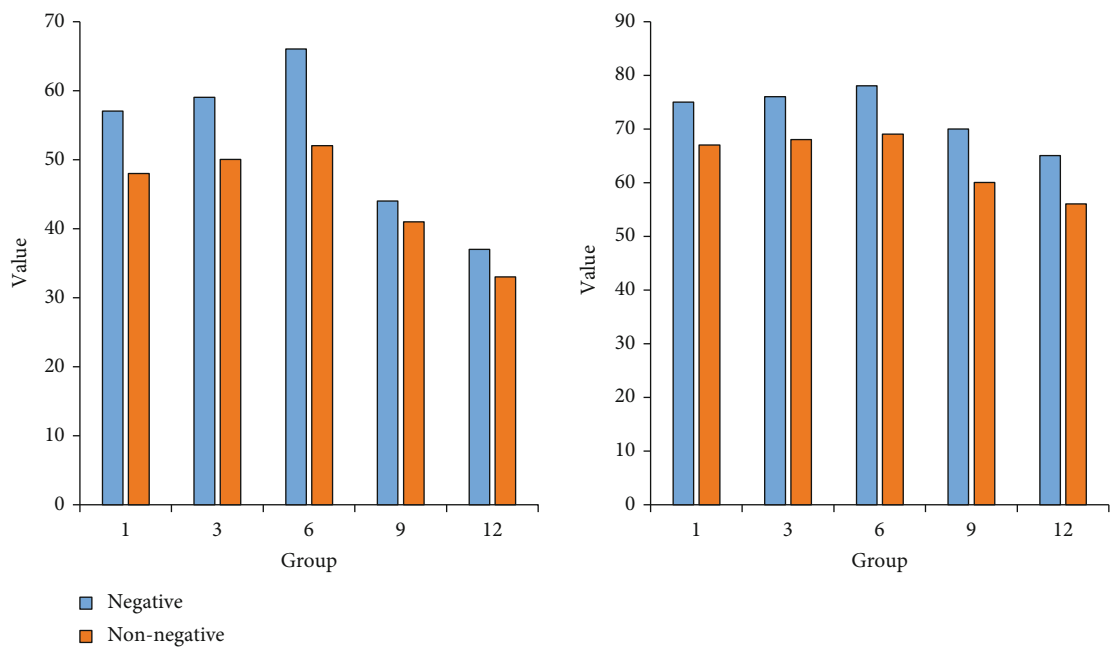

Figure 6: Prior knowledge and accuracy analysis.

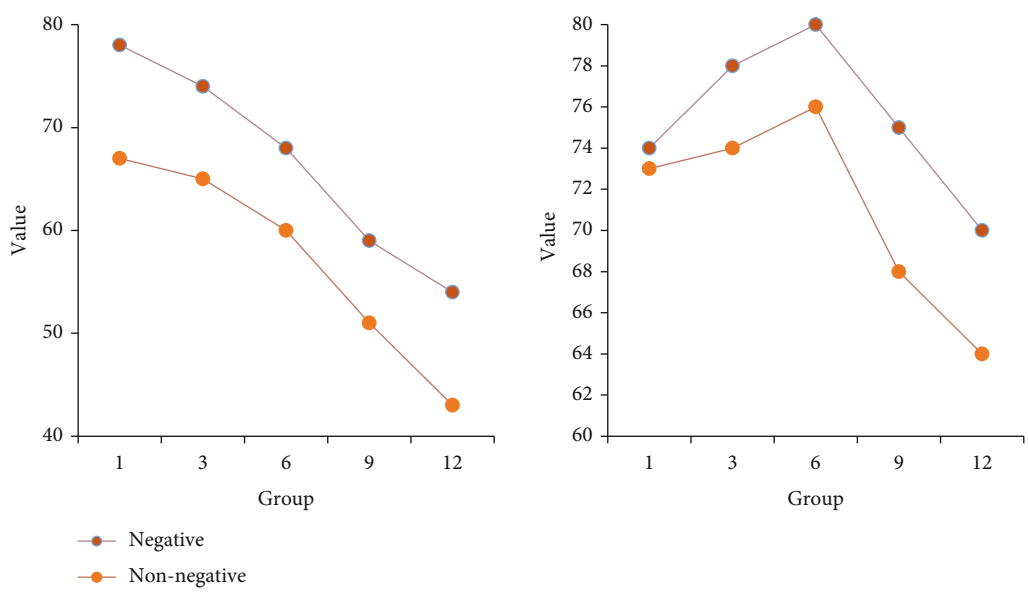

Figure 7: Analysis of emotions and attitudes toward praise and criticism.

analyzing the topic sentence, its accuracy first increases and then decreases. Although its accuracy decreases in the later stage, through the analysis and comparison of the full text, its accuracy is still high. Therefore, when analyzing the accuracy of financial news, we need to start from the subject sentence, and the subject words should not be too many.

5.2. Title Affectivity. The title includes the main title and subtitle. In many cases, we can have a general understanding of the attitude of the whole news according to the title. It is also suitable in financial news. To this end, we use artificial intelligence technology to classify the news according to the title.

According to the data in Figure 8, we have compared the full text and topic sentences, respectively. Firstly, we analyze the full text. When the news theme word is 1, the accuracy of positive emotion is 63% and the accuracy of negative emotion is 68%. When the news theme word is 3, the accuracy of positive emotion is 62%, and the accuracy of negative emotion is 69%. When the news theme word is 6, the accuracy of positive emotion is 61%, and the accuracy of negative emotion is 72%. When the news theme word is 9, the accuracy of positive emotion is 50%, and the accuracy of negative emotion is 60%. When the news theme word is 12, the accuracy of positive emotion is 44%, and the accuracy of negative

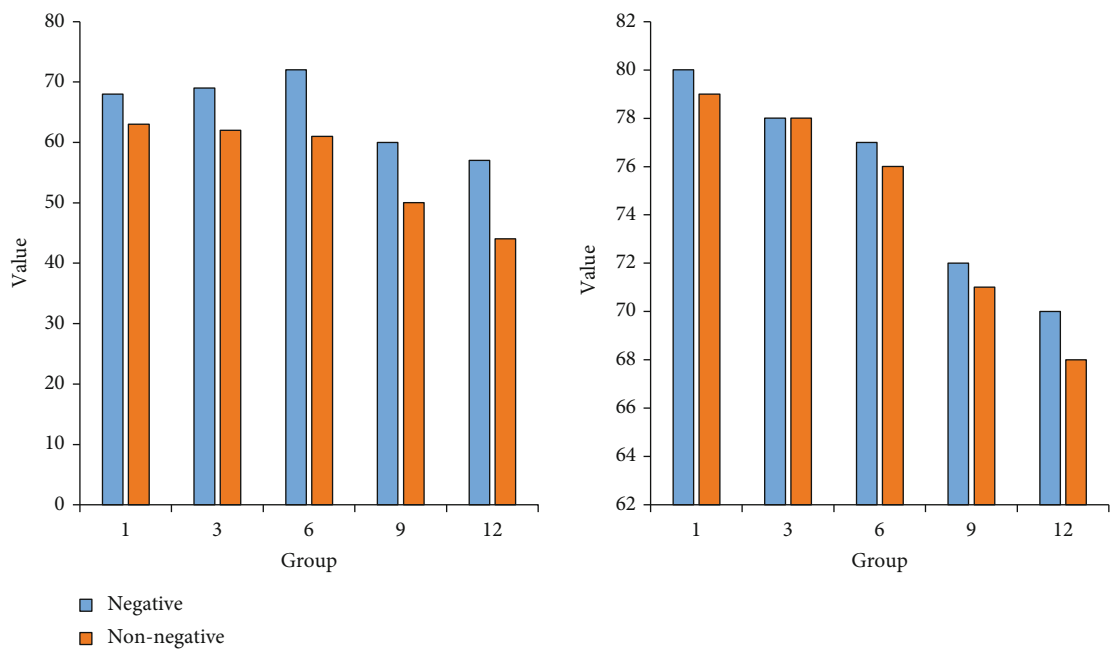

Figure 8: Title sentiment analysis.

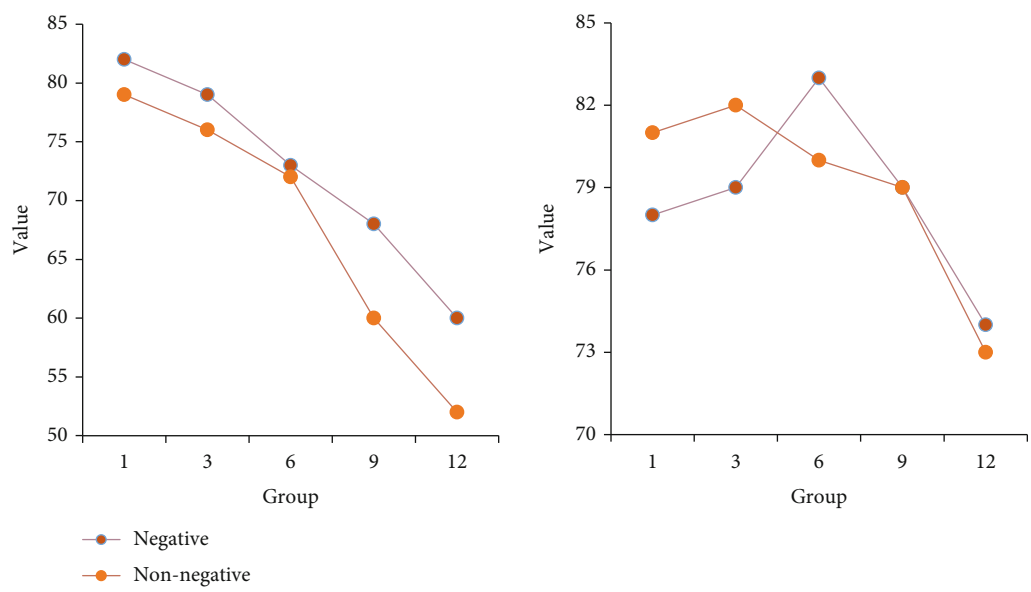

Figure 9: News comprehensive sentiment classification.

emotion is 57%. According to the data, the positive emotion analysis of the full text decreases with the increase of subject words. When the number of subject words is greater than 6, the decline is larger and larger. Therefore, it can be seen that the number of subject words should not be too large.

From the analysis of the topic sentence, when the news topic word is 1, the accuracy of positive emotion is 79% and the accuracy of negative emotion is 80%. When the news theme word is 3, the accuracy of positive emotion is 78%, and the accuracy of negative emotion is 78%. When the news theme word is 6, the accuracy of positive emotion is 76%, and the accuracy of negative emotion is 77%. When the news theme word is 9, the accuracy of positive emotion is 71%, and the accuracy of negative emotion is 72%. When the news theme word is 12, the accuracy of positive emotion is 68%, and the accuracy of negative emotion is 70%. According to the data, although the accuracy of the topic sentence is higher than that of the full text on the whole, its accuracy is declining, and there is little difference between the accuracy of positive emotion and negative emotion. It shows that the analysis of title and subject words is a more effective way.

5.3. Comprehensive Emotion Classification of News. In the above, we analyzed the emotion of news from different angles. In order to improve the comprehensiveness of the analysis, we combined the commendatory and derogatory meaning with the title for an overall analysis. The details are as follows:

According to the data in Figure 9, we analyzed the news from the full text and subject words, respectively. The accuracy rate of the full-text news is 82% when the emotion is negative, and the accuracy rate of the full-text news is 1%. When the news theme word is 3, the accuracy of positive emotion is 76%, and the accuracy of negative emotion is 79%. When the news theme word is 6, the accuracy of positive emotion is 72%, and the accuracy of negative emotion is 73%. When the news theme word is 9, the accuracy of positive emotion is 60%, and the accuracy of negative emotion is 68%. When the news theme word is 12, the accuracy of positive emotion is 52%, and the accuracy of negative emotion is 60%. According to the data, when all elements are considered comprehensively, the accuracy shows a downward trend, and the decline increases after the subject word exceeds 6. Therefore, it can be seen that the subject word needs to be reasonably selected in the comprehensive analysis.

From the analysis of emotional topic sentences, when the news topic word is 1, the accuracy of positive emotion is 81% and that of negative emotion is 78%. When the news theme word is 3, the accuracy of positive emotion is 82%, and the accuracy of negative emotion is 79%. When the news theme word is 6, the accuracy of positive emotion is 83%, and the accuracy of negative emotion is 80%. When the news theme word is 9, the accuracy of positive emotion is 79%, and the accuracy of negative emotion is 79%. When the news theme word is 12, the accuracy of positive emotion is 73%, and the accuracy of negative emotion is 74%. According to the data, the positive emotion analysis shows a downward trend, but its negative situation shows an upward trend first and then a downward trend. Therefore, when analyzing the attitude of news as a whole, we need to separate positive emotion from negative emotion and select different numbers of subject words when analyzing different emotional attitudes.

6. Conclusion

The continuous progress of the economy has forced the financial news to change to the direction of specialization, but the financial news has a short development time in China, and there are still many aspects to be improved. In order to adapt to the form of rapid economic development, it must classify financial news and provide accurate financial information for more people. This paper is aimed at studying the emotional classification method of financial news based on artificial intelligence and expecting to use artificial intelligence technology and classification method to classify financial news. It allows more people to know the implied information of financial information and promotes economic development. Although this paper has some conclusions on the classification of news, there are still deficiencies. This paper makes positive and negative classification for different news, but there is neutral news in news, which is not described in this paper.

Data Availability

No data were used to support this study.

Conflicts of Interest

There is no potential conflict of interest in this study.

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