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TEXT EMOTION CLASSIFICATION SYSTEM INTEGRATING VISUAL COMMUNICATION AND DEEP LEARNING FOR SOCIAL PLATFORM

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Abstract. With the development of modern information technology, social networks have become an im-portant platform for people to express, and at the same time, a large number of texts have been produced. However, the comment text has the characteristics of randomness and colloquialism in the way of expression, and also contains a lot of non-text data. Therefore, manually analyzing the emotional information in the text will consume a lot of time and the accuracy will be limited. To solve emotion classification, this study proposes a knowledge enhanced double loop emotion classification neural network model with attention mechanism. The study first preprocesses text data using a full sentence vector word vector model, then uses convolutional neural networks to recognize emotions in emoticons and emoticons in the text. Finally, the classification results are integrated using algorithms such as a dual loop sentiment classification neural network with pool-ing layers and attention mechanisms, K-nearest neighbors, and decision trees. The final compre-hensive expression recognition and text recognition results are used to obtain the text sentiment classification results. The experimental data shows that the model proposed in this study has an accuracy of 0.947 in the training set test, which is significantly better than other models. In da-tasets A and B, the accuracy of the research design model was 0.958 and 0.924, and the recall was 0.964 and 0.986, respectively. Compared to the baseline method or existing research models, the values of each indicator were significantly higher. The recall rate is the proportion of instances correctly identified as positive by the model to all actual positive instances, which can reflect the emotional classification performance of the research and design model. The higher the value, the better the performance of the model. In practical applications, the positive review rate of this model is above 0.9, which has obvious advantages compared to other models. This study utilizes deep learning techniques to classify sentiment in comment texts, providing reference for the field of text sentiment classification. In the e-commerce industry, it is possible to identify the emotions in user comments on products, further understand the product situation on the platform, and make targeted planning for product reserves, specifications, and so on.

Key words: Text sentiment classification; Deep learning; Visual communication; Fusion model

1. Introduction. As 5G era emerges, more and more people choose to communicate on social media and network platforms. Internet technology has been integrated into people's daily life and has had a significant impact on production and lifestyle. Due to the large number of Internet users in China, a large number of comment texts have been produced. Sentiment analysis of these massive comment texts can obtain valuable user sentiment information, which contains great value [1-2]. Emotion classification has its goal to extract emotional information from subjective texts and make accurate judgments [3-5]. The emotional classification of comment text usually includes positive and negative, and it can be classified at aspect level, sentence level and text level according to the processing level. As Internet users and comment texts increase, these texts show a huge and rapid growth trend [6-8]. At the same time, the comment text has the characteristics of unstructured and colloquial, and also contains elements such as network buzzwords and expression packs. Therefore, manually analyzing the emotional information in these massive texts will be time-consuming and limited accuracy. In the process of e-commerce operation, emotional recognition of user comments is crucial. Merchants analyze the sentiment of massive comment text data to understand user preferences and the quality of their products. This is of great significance for merchants to further improve their products and predict the market with targeted measures. To better understand the emotions of user comments and avoid the problem of inaccurate recognition caused by colloquial and image style comments, a new text emotion recognition model has been studied and constructed. The research contribution includes proposing a knowledge enhanced dual loop sentiment classification neural network model, which effectively improves the accuracy of text sentiment classification by adding attention mechanisms. At the same time, combining visual communication technology, emotion recognition is performed on emoticons and emoticons in the text, further enriching the dimension

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of emotion classification. And a global vector word vector model was adopted for text data preprocessing, effectively reducing the dimensionality of text data and improving computational efficiency. This study aims to use deep learning related technologies to classify the emotion of comment text, Knowledge Enhancement Of Double Loop Emotion Classification Neural Network By Adding Attention Mechanism (KEECA) based on Enhanced Representation Through Knowledge Integration (ERNIE) and Bidirectional Recurrent Neural Network (BiGRU) is proposed, And it is tested on different data sets, and finally applied in the actual sales of goods, which provides new ideas and references for text emotion classification.

The study includes four parts. The second part is text emotion classification research summary. The third part proposes a knowledge enhanced double cycle emotion classification neural network model with attention mechanism. The first section preprocesses the text, the second section identifies the emotion of the expression package, and the third section establishes the classification model. The fourth part is a comparative experiment between the two models. The last part is results.

2. Related work. Benefiting from the continuous maturity, more and more natural language processing fields have begun to adopt deep learning models, especially in emotion classification tasks. Guo y et al. proposed a detection method, using the pre-trained Bert model and machine learning algorithm for classification. The evaluation results showed that it had the best classification performance on two data sets [9]. Context free word scoring, proposed by Nimrah et al., served as an effective alternative method for querying. Results revealed that such approximations were highly efficient in attacking black box neural networks [10]. Anuratha et al. proposed a syntactic senti-rule predictive classifier based on the social spider Lex feature set model to improve accuracy. Results showed that the classifier was superior to other emotion classification models, reaching 94.1% performance score [11]. Wang et al. proposed an ATT algorithm and improved converter bidirectional encoder representation (BERT), which was used to solve the redundancy and noise problems in long text sentiment analysis. Compared with typical convolutional neural model, the algorithm significantly improved the relevant evaluation indicators, and exceeded original Bert model [12]. Wang and others compared the performance of traditional machine learning method in financial text classification, using LSTM as deep learning method and xgboost as traditional machine learning method. Research results showed that LSTM model is superior to traditional machine learning methods in all indicators [13]. Arya et al. Analyzed the feature selection technology of heterogeneous text data for emotion classification, compared the bag of words, TF-IDF and word2vector technology, and found that TF-IDF performed best in SVM classifier, which played an important role in developing adaptive system model for heterogeneous sources [14].

In terms of emotional analysis, Singh S K and others developed a good emotional analysis (SA) system, which was suitable for data sets in many fields. The system was tested on four different data sets, and it showed that it had better accuracy than the existing technology on social media data sets, which increased by 3%, 1.5%, 1.35% and 4.56% [15]. Bie et al. proposed an end-to-end model that comprehensively used for emotion analysis. The experimental results showed that the model had advantages in using text information and can utilize syntactic and semantic information for emotion analysis [16]. Sahu et al. proposed a framework that combines emotional analysis and hybrid recommendation system to recommend upcoming films. This study combined emotional analysis and recommendation system to provide personalized film recommendation by using the public data of film database [17]. Capecchi et al. Used the data of TripAdvisor platform to study the success factors of Tuscany wine tourism by combining the methods of text mining and emotion analysis. The results of the study identified six success factors, including guide, logistics, wine quality, food quality, complementary tourism activities and landscape historical villages [18]. Han et al. proposed a dual-mode fusion network to overcome the limitations of dynamic utilization of independence and pattern correlation in multimodal emotion analysis. Results verified the significant advantages on selected data sets [19]. Kota et al. introduced a method combining CNN, bi-LSTM and attention method for emotion analysis. This method used CNN to reduce complexity. Results showed that it was effective and provided a new emotion analysis method [20].

In summary, sentiment recognition in existing literature can be divided into aspect level sentiment classification and document level sentiment classification. Although aspect level sentiment classification can pay attention to sentiment tendencies in text at a fine-grained level, it is prone to ignoring the interaction between aspect words and context. Therefore, research adopts a dual loop approach to further enhance the connection

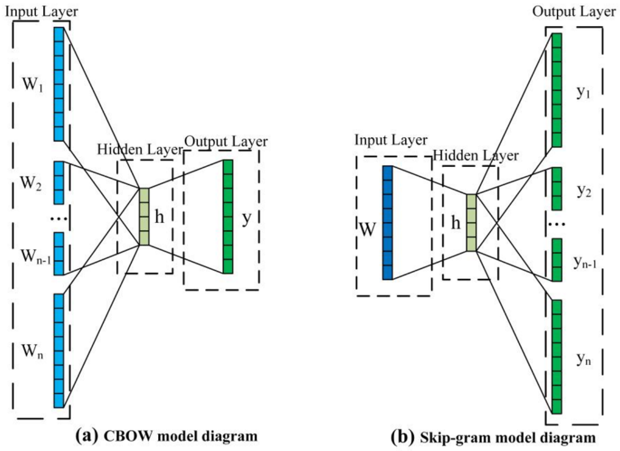


Fig. 3.1: CBOW and skip gram model diagram

between global features and local features. Document level sentiment classification mainly uses static word vectors for modeling, which will lead to words with similar context but different sentiment polarities being mapped to adjacent positions, further affecting classification performance. It introduces attention mechanism into text feature extraction, which can further improve classification performance. In this study, attention mechanism will be considered for application. Based on this, this study combines the advantages of the ERNIE and BiGRU models, and introduces attention mechanisms to propose a more effective KEECA model.

3. Text classification emotion model construction based on visual communication and deep learning algorithm. In the text classification, the initial text needs to be preprocessed, and the convolutional neural network (CNN) is used to classify text expression package emotion. Then, the processed text data set is trained according to the deep learning algorithm, and finally the text emotion classification results are output by the trained model.

3.1. Preprocessing and vectorization of text sentiment classification. The early text quantification method is one hot coding, but with the increase of text complexity, the number of words to be labeled becomes more and more, and One-Hot method is difficult to meet the requirements. Word2vec is a distributed representation method, which maps words to vector space and distinguishes word semantics by word vector distance and vector space region, making up for the deficiency of One-Hot coding. Word2vec has Continuous bag-of-words model (CBOW) and Skip-gram model[21-22]. Their structure is shown in Figure 3.1.

The CBOW uses context to predict words. The CBOW model is shown in Figure 1 (a). The input layer is vector obtained by one hot encoding, which is multiplied by weight matrix w in hidden layer to obtain corresponding vectorized representation. Finally, hidden layer output vector is obtained by summing and averaging it, as shown in formula (3.1).

$$h = \frac{1}{n} W^T (W_1 + W_2 + ... + W_n) \tag{3.1}$$

In formula (3.1),h is hidden layer output vector, $W^T$is weight,n is number of hot coded vectors,$W_1 ... W_n$ is the hot coded vector. The output vector is calculated in the output layer, as shown in formula (3.2).

$$y = soft\max(W^T h) \tag{3.2}$$

In formula (3.2), y is the output vector after normalizing the product of $h$andW^T. The structure of Skip-gram is opposite to that of CBOW. It predicts the context in the window according to the head word. Its

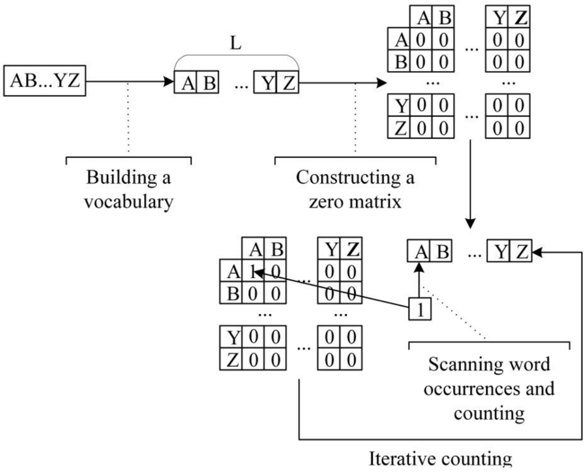


Fig. 3.2: Flowchart of the glove word model

structure is shown in Figure 3.1 (b) and formula (3.3).

$$P(c|w)\frac{e^{u_c \cdot u_w}}{\sum e^{u}c'^{u_w}} \tag{3.3}$$

In formula (3.3), P is conditional probability, c is central word, w is the context word, $u_w$and u_c is the vectorized representation of w and c, U is the collection of all context words, and c' represents a word in the collection U. In the skip gram model, each word acts as a central word and a context word. Greater$P$ shows higher similarity between $c$and$w$, which means that they have similar meanings. The global vectors for word representation (GloVe) word vector model for word representation incorporates statistical information based on word2vee, which can reflect the co-occurrence of words in the context before and after, and more accurately express the global meaning[23]. The process of GloVe word model is shown in Figure 3.2.

As can be seen from Figure 3.2, column J in row I represents the co-occurrence times of words w_i within the window with words w_j as the center word, and x_i represents the total number of occurrences of any word within the window with words as the center word, then the co-occurrence probability is shown in formula (3.4).

$$P_{i,j}{=}P(w_i|w_j) = \frac{x_{i,j}}{x_i} \tag{3.4}$$

When there is a given wordw_k, formula (3.5) is used to judge its correlation with w_i and w_j.

$$F(w_i, w_j, w_k) = \frac{P_{\text{ik}}}{P_{\text{ik}}} \tag{3.5}$$

If the value F is large, the correlation between the expression w_k and w_i is high; If the value is small, the correlation between the expression w_k and w_j is high; If the value is close to 1, the indicator$w_k$may be associated with both w_i and w_j, or not associated with them.

3.2. Visual communication emotion recognition based on CNN. Visual communication is a behavior of using visual means to actively disseminate information. It transforms a single text into an attractive image, thus providing a variety of information access for the audience. As a new way of communication, expression pack has been widely popular on the Internet. Emoticon is a kind of non-verbal language expression in modern network communication, which is used to convey the image symbol of emotion. CNN is used as a tool to combine feature extraction of expression package and emotion classification for an end-to-end network. The specific network structure includes convolution layer, relu activation function, pooling layer, local response normalization (LRN), full connection layer and softmax layer[24-25]. When extracting features of expression packs, CNN performs convolution operations by using convolution kernels to extract features, as shown in formula (3.6).

$$x_j^k = f\left(\sum_{i \in R_j} x_i^{k-1} * w_{ij}^k + b_j^k\right) \tag{3.6}$$

In formula (3.6), x_j^k is j convolution neuron value in layer$k$, w_{ij}^k is convolution kernel weight, b_j^k is j offset value in k, R_j is characteristic graphs, and f is activation function. After completing the convolution operation, after simplifying the extracted features in pooling layer, features with the most effective information are input into the classifier for result. The LRN calculation formula is shown in formula (3.7).

$$b_{x,y}^i = a_{x,y}^i/(k + \alpha \sum_{j=\max(0,i-n/2)}^{\min(N-1,i+n/2)} (a_{x,y}^j)^2)^\beta \tag{3.7}$$

In formula (3.7), i represents subscript, that is, subscript that calculates the pixel value from 0; j is the square cumulative index, indicating the sum of the squares of pixel values from $j$to$i$; x, y is the coordinate position of the pixel; a is specific value of pixel$i$; N is number of columns of inner vector. k, α, $n/2$, and $\beta$are super parameters specified by the prototype. Softmax improves the calculation speed and accuracy through normalization. Suppose there are 100 different types of pictures, and a 100-dimensional vector is output through the Softmax layer. In the vector, each element denotes the probability of the current image belonging to a specific category, where the summation of all elements equals 1. Its calculation is presented in equation (3.8).

$$f(z_j) = \frac{e^{z_j}}{\sum_{i=1}^n e^{z_j}} \tag{3.8}$$

In formula (3.8), z is the neuron emotion parameter. Because this study identifies seven expressions, and the softmax layer has seven output neurons. The program returns seven probability values, indicating the possibility of neutral, surprise, sadness, happiness, fear, disgust and anger. The maximum probability corresponds to the most likely emotion.

3.3. ERNIE and BiGRU fusion text sentiment classification system with attention mechanism. This study proposed KEECA model by improving ERNIE and BiGRU and adding attention mechanism layer and pooling layer to improve classification by combining advantages of different layers. KEECA structure is shown in Figure 3.3.

In Figure 3.3, $\{E_1, E_2...E_n\}$ represents the original text statement after vector expression in ERNIE layer, and then complete the feature extraction in BiGRU layer, and then input it into the attention layer to express the feature vector according to different weights, that is$\{A_{1,}A_2...A_n\}$. After the feature extraction is completed in the pooling layer, it goes to softmax layer. When recognizing text emotion, the premise of classification is that each feature of the text sample is independent of each other, and its probability distribution is shown in formula (3.9).

$$P(c|x) = \frac{P(c)P(x|c)}{P(x)} = \frac{P(c)}{P(x)} \prod_{i=1}^d P(x_i|c) \tag{3.9}$$

In formula (3.9), $x$is the text to be classified$X = (x_1, x_2, x_3...x_d)$, $c$is the text category$C = \{c_1, c_2, c_3...c_k\}$, $d$is attributes number of the text sample, $x_i$is attribute value of text sample$i$. The probability value of the text sample$x$ contained in the category$c$ is shown in formula (3.10).

$$c_{nb} = \arg\max_{c \in C} P(c) \prod_{i=1}^d P(x_i|c) \tag{3.10}$$

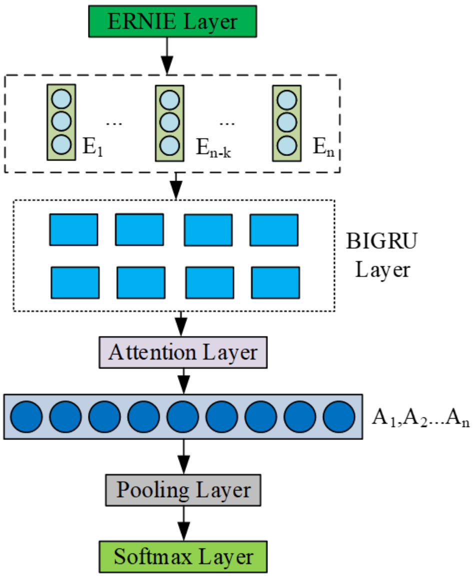


Fig. 3.3: KEECA model structure

In formula (3.10), $P(c)$ is probability that text sample$x$ is included in the category$c$. During training, the class prior probability$P(c)$ and attribute prior probability$P(x_i|c)$ are estimated during training. $P(c)$ is shown in formula (3.11).

$$P(c) = \frac{N_c}{D} \tag{3.11}$$

In formula (3.11), N represents samples number included in category$c$; $D$is samples sum. The calculation method$P(x_i|c)$ is as follows.

$$P(x_i|c) = \frac{N_{cx_i}}{N_c} \tag{3.12}$$

In formula (3.12), N_{cx_i} represents the number of sample $x_i$attribute values contained in the category c and N_c is samples number of c. Tree structure is used in the classification decision. Its structure is shown in Figure 3.4.

Figure 3.4 is the structure diagram of a general decision tree. The first step in the classification process is to build a root node composed of data sets$D$ and divide it into many sub nodes, that is, subsets; The second step is to map the correctly classified subsetD_i at the sub node, and the subset without the correct classification needs to be re divided according to the optimal feature; Finally, the above two operations are recursive until all subsets are correctly classified or have no optional features, and the complete decision tree is established. The calculation process of decision tree establishment is shown in formula (3.13).

$$H(D) = -\sum_{K=1}^{K} \frac{|R_K|}{|D|} \log_2 \frac{|R_K|}{|D|} \tag{3.13}$$

In formula (3.13), $H$is empirical entropy function, $D$is dataset,R is category label, $|D|$is number of samples,$|R_k|$ is number of samples in result categoryR_K. For the feature set$T$, the conditional entropy$H$ calculation formula of the data set$D$ is shown.

$$H(D|A) = \sum_{i=1}^{n} \frac{|D_i|}{|D|} H(D_i) \tag{3.14}$$

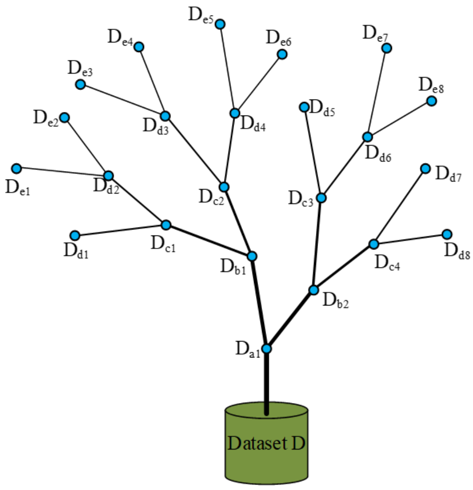


Fig. 3.4: Structure diagram of general decision trees

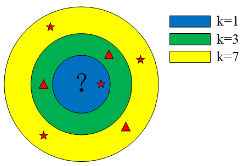


Fig. 3.5: model graph of k-nearest neighbor algorithm

In formula (3.14), A is the feature selection condition andD_i is the subset$i$. According to formulas (3.13) and (3.14), the information gain calculation is obtained in formula (3.15).

$$g(D, A) = H(D) - H(D|A) \tag{3.15}$$

In formula (3.15), g is an information gain function. According to the calculated value$g(D, A)$, a decision tree can be constructed. When finding the sample closest to the given sample in the trained data set, the calculation model is shown in Figure 3.5.

The study utilizes the K-nearest neighbor algorithm in Figure 3.5 to cluster the samples and further classify the text data, laying the foundation for subsequent sentiment recognition classification. The study inputs the training dataset into the K-nearest neighbor algorithm, calculates the distance between each sample and the training sample, and then finds the k nearest neighbors. Next, based on the class labels of these k neighbors, the majority voting principle is adopted to classify the samples. The distance from the processing sample point to each node in the space is calculated by Euclidean distance or cosine similarity, as shown in formula (3.16).

$$\begin{cases} dist(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \\ \cos(x,y) = \frac{x \cdot y}{|x| \times |y|} = \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{n} x^2{}_i \sum_{i=1}^{n} y^2{}_i}} \end{cases} \tag{3.16}$$

In formula (3.16), $x_i, y_i$is point$i$ coordinate in space. After the results are calculated, they are arranged in ascending order by distance. Then, the nearest points$k$ are selected according to the sorting results. The category of most points is the category of pending sample points. When extracting data such as time ordered comment text, it is completed by recurrent neural network (RNN) shown in Figure 3.6.

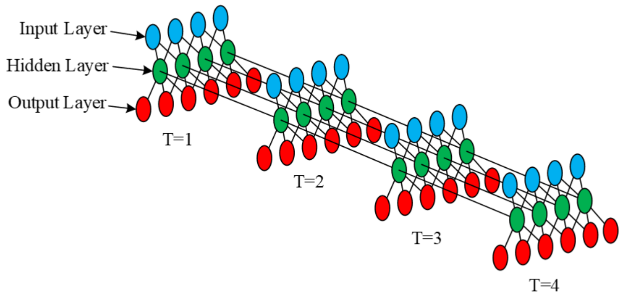


Fig. 3.6: structure diagram of recurrent neural network

Table 4.1: Experimental environment and parameter table for emotional classification of model

Environment		**Hyperparameter list**	
		Parameter	Value
System	CentOS	Epoch_Num	40
		Batch_Size	25
GPU	Titan xp*4	Padding_Size	120
		Hidden_Size	542
Programming language	Python3.6	Filter_Num	425
		Kemel_Size	(3,5,7)
Pre-training model	ERNIE	Dropout	0.2
		LR	1.50E-10

Figure 3.6 is the RNN structure diagram, where the hidden layer result at a certain time T is determined by both the input layer and the previous hidden layer. This study inputs the same dataset into RNN for training. RNN captures long-distance information in text by learning dependency relationships in sequence data, and thus obtains classification results. Hidden state at time$T$ is shown in formula (3.17).

$$h_T = f(W_h h_{T-1} + W_x x_T) \tag{3.17}$$

In formula (3.17), $W_h$is the weight matrix of hidden state,h_{T-1} is output at the time$T-1$, $W_x$is input adjustment weight matrix, $x_T$is the input at the time$T$, $f$is a nonlinear function. After preprocessing with K-nearest neighbor algorithm and RNN, the classification results were obtained. The study combines these two results and uses the weighted average method to integrate the results of the two classifiers to obtain the final classification result. Finally, the classification results are integrated with the emotion classification results of the KEECA model to further improve the accuracy of the model's emotion recognition.

4. Performance evaluation of different text sentiment classification models and empirical analysis of KEECA model. In this study, KEECA, ERNIE, BiGRU, RNN and CNN models were tested in different data sets, and then different models were applied to the analysis of mobile phone sales in an online mall. Finally, the rationality analysis was given according to the performance of different models.

4.1. Performance analysis of Chinese comments based on different text classification models. The environment was CentOS, and data set was a public Chinese comment data set. The emotion labels were divided into positive and negative, in which the positive emotion was marked as 1 and the negative emotion was classified as 0.

Table 4.1 shows the environment and parameters of emotion classification experiment, which aims to achieve the best performance by adjusting the parameters. Epoch_Num indicates the number of iterations, Batch_Size

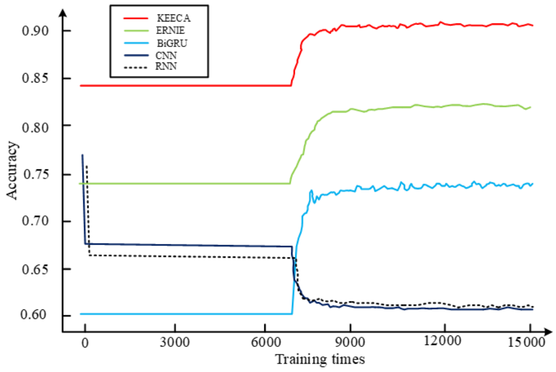
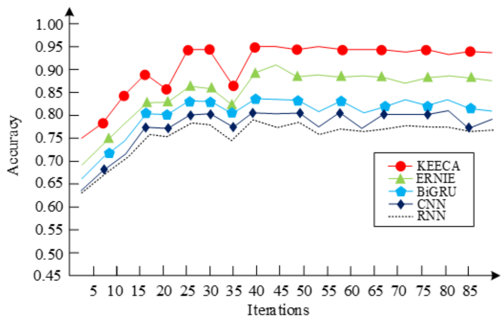
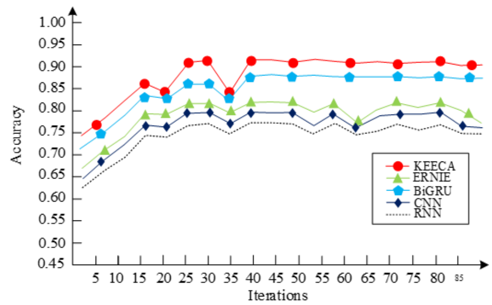


Fig. 4.1: Training performance curves of different models in the training set



(a) Line chart of accuracy rate of each model on M dataset



(b) Line chart of accuracy rate of each model on N dataset

Fig. 4.2: Variation accuracy curve of different model with model training iterations

indicates number of samples input to neural network each time, Padding_Size is the cutting length of the single sentence language in the sample, Hidden_Size is the dimension of the hidden layer, Filter_Num is number of convolution kernels, Kemel_Size is kernel size, Dropout is parameter to prevent over fitting, and LR is the parameter to control the learning rate. The evaluation indexes include accuracy, recall rate and F1 value. The accuracy curve of different models with training times is shown below.

In Figure 4.1, when the training times of all models reached about 7000, the accuracy began to change strongly. The accuracy of KEECA, ERNIE and BiGRU increased as training times increased, while that of CNN and RNN decreased as the increase of training times. When the accuracy was relatively stable, the accuracy of KEECA was 0.947, the accuracy of ERNIE was 0.846, and the accuracy of BiGRU was 0.739. Training performance of fusion model had significant advantages. The accuracies of CNN and RNN were only 0.604 and 0.611 respectively, indicating that the traditional neural network model was not suitable for classifying excessive emotional texts. The change of accuracy of different models in different data sets is shown below.

Fig. 4.2 (a) is the curve of the accuracy of different models on the M data set. All model's accuracy rate tended to be stable after 40 training iterations. The accuracy rate of KEECA model was 0.958, which was 5.1 percentage points higher than ERNIE model, the mainstream text emotion classification model, and 9.7 percentage points higher than BiGRU model. After combining the advantages of different models, the accuracy of KEECA model was greatly improved. The highest accuracy of traditional CNN and RNN model were 0.813 and 0.784, respectively, which are inferior to KEECA, ERNIE and BiGRU models. Fig. 4.2 (b) is the curve of

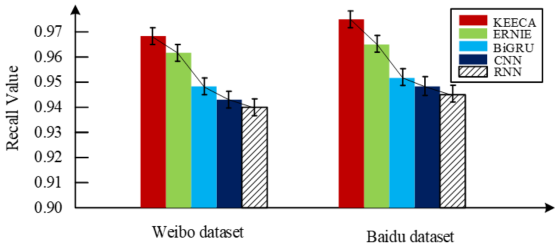


Fig. 4.3: Histograms of recall values for different models

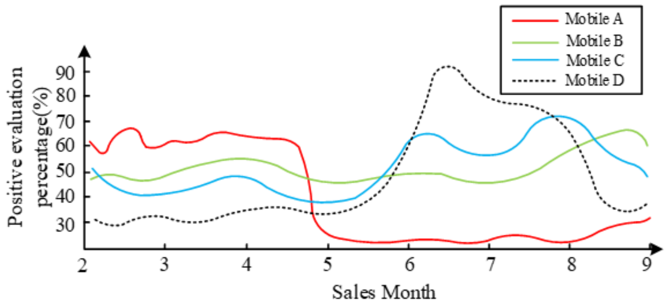
the accuracy of different models on the N data set. The accuracy of KEECA and BiGRU models tended to be stable after 40 training iterations, while the accuracy of ERNIE, CNN and RNN models tended to be relatively stable after 25 training iterations. The highest accuracy of KEECA model was 0.924, the accuracy of BiGRU model was 0.872, and the highest accuracy of ERNIE model was only 0.827. This is because the text of the N dataset was longer than that of the Weibo dataset, and the content was more and more miscellaneous, which made the KEECA model combined with BiGRU and the BiGRU model which had the advantage of long text processing had higher accuracy than other models on the N dataset. The highest accuracy rates of traditional CNN model and RNN model in processing long text were 0.774 and 0.731 respectively, which are also inferior to KEECA, ERNIE and BiGRU models. The recall rates of different models in different data sets are shown in Figure 4.3.

Figure 4.3 shows the recall rates on M dataset and N dataset. KEECA model performed best on the M data set and N data set, with the recall rates of 0.964 and 0.986 respectively, which were 0.007 and 0.013 percentage points higher than ERNIE model, and 0.019 and 0.021 percentage points higher than BiGRU model, indicating that KEECA model had stronger ability to capture emotional information than ERNIE and BiGRU models.

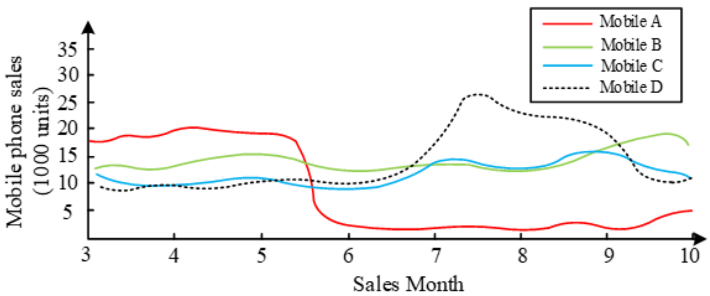
4.2. Empirical analysis of commodity review monitoring based on KEECA model. This study selected the after-sales comment data of four different brands of mobile phones on an e-commerce platform from February to August as the data set, classified the positive and negative comments in the comment text by KEECA model, and then studied the impact of different comments on the daily sales of mobile phones. Figure 4.4 shows the result.

Figure 4.4(a) shows the percentage of after-sales reviews of four mobile phones a, B, C and D in the total reviews from February to August. The positive rate of A mobile phone was around 60% from February to April, with a large decline in May. The percentage of positive comments on Model B mobile phones was generally in the range of 40% to 70%, and its change was relatively gentle. The positive rate curve of model C mobile phones changed mildly before June, increased by about 20% in June, and did not fall until August. The positive rate of model d mobile phone was relatively low before May, and then it continued to rise, reaching a maximum of 90% in mid-June, and then gradually declined. Figure 4.4(b) shows the sales curve of four mobile phones A, B, C and D from March to September. On the whole, sales curve change of mobile phones was consistent with that of the favorable comments in Figure 4.2 (a). The difference is that the change of the sales curve lagged behind that of the favorable comment's percentage curve by one month, which showed that the favorable comments percentage of the mobile phone after-sales in the current month was positively correlated with the sales volume in the following month. The classification experimental data of different models on the mobile phone after-sales comment data set are shown below.

Table 4.2 shows percentage comparison of favorable comments, the accuracy of the classification of favorable comments, and the correlation between sales and the percentage of favorable comments in the data set of mobile phone after-sales reviews by different models. KEECA model had the highest accuracy rate for classification of high praise, and the accuracy rates for a, B, C and D mobile phones were 96%, 97%, 94% and 97%, respectively. The accuracy of BiGRU model and ERNIE model was similar, and the overall accuracy was 90%. However, the accuracy of RNN and CNN models' praise classification was relatively low, and the accuracy of D brand praise classification was very low, only 34% and 37% respectively. From the perspective of the correlation rate between



(a) Percentage of positive reviews from different brands of mobile phones after sales



(b) curve of sales changes for different brands of mobile phones

Fig. 4.4: Percentage of after sales positive reviews and daily sales curve for different brands of mobile phones

Table 4.2: Empirical classification results of mobile phone after sales review datasets using different models

Model name	Positive feedback percentage (%)				Positive classification accuracy (%)				Positive reviews and sales relevance			
Mobile	A	B	C	D	A	B	C	D	A	B	C	D
Keeca	44	53	57	49	96	97	94	97	0.94	0.98	0.97	0.94
RNN	61	52	40	74	70	96	81	34	0.71	0.91	0.76	0.12
Bigru	41	44	54	53	92	84	91	86	0.91	0.74	0.89	0.84
CNN	64	66	71	22	73	76	71	37	0.53	0.61	0.51	0.27
ERNIE	43	56	55	52	92	88	91	87	0.91	0.84	0.93	0.83

sales and positive reviews, KEECA also had obvious advantages over other models, and the correlation rates were above 0.9, indicating that KEECA had a more realistic response to commodity sales than other models.

5. Conclusion. The development of information technology provides technical support for network social media, which provides a platform for free expression for the majority of Internet users. To solve low classification efficiency and poor accuracy in existing emotion classification research and different application fields of emotion classification, KEECA model is proposed. Experiments showed that KEECA had the best performance in the training set, and its accuracy was 0.947. On N data set, KEECA model accuracy was 0.958, which was 5.1% and 9.7% higher than ERNIE model and BiGRU model, respectively. The recall rate of KEECA model was 0.964, which was 0.7% and 1.9% higher than ERNIE and BiGRU models, respectively. On M, KEECA model accuracy was the highest 0.924, which was 9.7% and 5.2% higher than ERNIE model and BiGRU model, respectively. The recall rate of KEECA model was 0.986, which was 1.3% and 2.1% higher than ERNIE and BiGRU models, respectively. In the empirical analysis, KEECA model had the best response to the actual situation of sales. The classification accuracy rates of a, B, C and D mobile phones were 96%, 97%, 94% and 97%, respectively, which were 4%, 9%, 3%, 10% and 4%, 13%, 3% and 11% higher than ERNIE and BiGRU respectively. In terms of correlation rate, KEECA model was 0.03, 0.14, 0.04, 0.11 and 0.03, 0.24, 0.08, 0.1 higher than ERNIE and BiGRU respectively, which means that the description of data set by KEECA model is the closest to the actual situation. In a word, KEECA model can better meet the needs of text sentiment classification and provide important reference value for other application scenarios. However, the model proposed in this study can only classify positive and negative emotions, so we need to improve the richness of emotions.

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