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Negative Emotion Recognition Algorithm of Network Catchwords Based on Language Feature Dimension

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The traditional negative emotion recognition algorithm has a limited language feature dimension, which leads to the inaccuracy of negative emotion recognition. In order to improve the identification and analysis of emotion in network buzzwords, the back propagation of error (BP) and the restricted Boltzmann machine (RBM) algorithms are adopted to effectively solve the problem of insufficient data for emotion analysis in different contexts. First, a method is proposed to identify negative emotions, and a deep neural network (DNN) model is constructed. Then, experiments were carried out, which used manually labeled data sets and divided them into different emotion categories, and which compared the BP algorithm, Gaussian Mixture Model (GMM) and Hidden Markov Model (HMM) for negative emotion recognition of online buzzwords. The experimental results show that the DNN model performs well in the recognition of anger, sadness, fear and disgust, with the accuracy reaching 93.56%, 93.58%, 89.84% and 88.53% respectively, which is obviously superior to the other three methods. The designed DNN model has a potential application prospect in the negative emotion recognition of online buzzwords, which can be further popularized in the future.

ACM CCS (2012) Classification: Computing methodologies → Artificial intelligence → Natural language processing

Keywords: emotion recognition, deep neural network, network buzzwords, negative emotion, language feature dimension

1. Introduction

Emotion is a mental activity mediated by personal needs and is a cognitive process when people face the external world. Emotion is a subjective experience, and different people may express different emotions in the same situation. As a result, previous emotion recognition techniques may have some misjudgements and fail to accurately capture the complex emotional state of an individual. Emotion recognition is a very useful technique. The deep neural network word frequency computation model for establishing emotion recognition and analysis of Internet buzzwords has the advantages of high-dimensional feature representation, automatic feature extraction, contextual information modelling, robustness and generalization ability, and scalability, which can improve the accuracy and effectiveness of emotion recognition. For example, teachers can use emotion recognition technology to improve the quality of classroom teaching, and they can also respond accordingly to students' emotional reactions.

With the continuous development of society, the research on emotion recognition has gradually increased, and it is especially necessary to effectively recognise emotions and to intervene and resolve negative emotions in a timely manner. At the current stage, the research on emotion recognition mainly focuses on the recognition of non-physiological signals and physiological signals. Because using a single physiological signal to improve the accuracy of emotion classification has encountered a bottleneck. Therefore, Yang *et al.* starts from the aspects of emotion recognition, information fusion, and classification based on physiological signals, and combs through the development process and current research status of multi-physiological signals in the field of emotion recognition in recent years, as well as summarises and concludes the main problems and challenges that exist at present [1]. In order to help researchers make necessary progress in recognizing human emotions, Zepf *et al.* provided a comprehensive literature review on human emotion recognition in the automotive environment [2]. Yan *et al.* proposed a rhythmic time Electro-encephalogram (EEG) emotion recognition model based on long and short memory networks. By applying this model, the classification results of different rhythms and time scales were different [3]. Vikrant and Pirouz involved the analysis of epoch data from EEG sensor channels and the comparative analysis of multiple machine learning technologies for dimensionality reduction. The results showed that different classification models must be used to identify different emotional states [4]. According to the characteristics of EEG, Zhang *et al.* identified emotions in time domain, frequency domain, time-frequency domain and spatial domain [5]. Although these studies promoted emotion recognition to some extent, they were not combined with the actual situation.

At the same time, DNN has gradually attracted widespread attention from the academic community. Zhao *et al.* proposed to recognize video emotion in an end-to-end way based on a convolutional neural network. Emotion recognition in user-generated video played an important role in human-centered computing. The existing methods mainly used the traditional two-level shallow pipeline, namely, extracting visual and/or audio features and training classifiers, which provided ideas for the improvement of DNN [6]. Tehmina *et al.* proposed a method based on mixed feature descriptors to recognize human emotions from facial expressions. Through the spatial information involving features, an improved feature package was used for facial emotion recognition, which had a certain reference value for the use of DNN [7]. Vaishali and Ghongade proposed proposed an improved differential entropy feature extractor to detect the nonlinearity and non-Gaussian of EEG signals. The experiment proved that the average accuracy of emotion detection using improved differential entropy and two-way long-term and short-term memory network was better than the established method, which would promote the depth of DNN application in new research [8]. Traditional emotion recognition methods may not be able to capture the nuances of negative emotions. Deep neural networks, on the other hand, are able to automatically extract abstract and more discriminative features through the learning of multiple layers of neurons, thus improving the recognition accuracy of negative emotions. Therefore, it is feasible to use deep neural networks for the negative sentiment recognition algorithm of Internet buzzwords based on the dimensions of linguistic features.

The understanding of others' emotions is the premise for people to conduct learning, social cognition and social activities. Therefore, how to make computers feel people's emotions and make correct decisions is also a major direction of artificial intelligence research, which is also called emotional computing. In this paper, the negative emotion recognition methods are described in detail, including the introduction of emotion recognition and the negative emotion recognition based on the feature of word fusion. On this basis, the DNN model was analyzed, including the DNN structure, BP structure, Deep Belief Network (DBN) and RBM realization of deep learning. In addition, this paper also made a comparative analysis of the negative emotion recognition algorithms of network catchwords based on the language feature dimension of DNN model. Through experimental analysis with various methods in terms of recognition time and recognition rate, it was concluded that the DNN model in this paper had better recognition rate than other methods.

2. Recognition Method of Negative Emotions

2.1. Emotional Recognition

Speech is the main carrier of human communication. It contains both semantics and emotion. It is an important part of human emotional computing. In recent years, people are more and more interested in speech emotion recognition by analyzing input speech [9–10]. Emotion recognition includes feature extraction, feature selection and classification. Speech emotion recognition can be considered as a simple pattern recognition task, including feature extraction, classifier and speech emotion database. EEG based emotion recognition is a challenging and active research field in emotion computing [11].

If the language of identification is consistent with human understanding and their own understanding, their understanding has its own characteristics due to different living environments. Therefore, the thinking, ideological, cultural and intellectual nature of all languages have their own characteristics, thus forming their own characteristics. For example, from the west to the east, the vast central plains constitute the Chinese people's mind, thinking, culture and cognitive system, which makes Chinese unique. This means that mastering multiple foreign languages is not only good for communication, but also for better understanding of the world.

In the four levels of learning, a perception of language rules is formed, namely grammar. Vocabulary is a cognitive concept formed in the process of four-dimensional acquisition. In addition, speech recognition and the thinking system are the basic forms of language. Vocabulary, especially English vocabulary, is a marker technology for human memory and thinking. Therefore, language learning from the beginning of writing is an act of putting the cart before the horse.

The concept of language education is to improve cognitive ability and learn real language through comparison, analysis, synthesis, judgment, creation and other ways of thinking from the perspective of cognition, thinking and culture.

As a typical type of emotion, the impact of negative emotions such as anger, sadness and depression on the daily production and life of humans cannot be ignored. The impact of negative emotions is shown in Figure 1.

It can be seen from Figure 1 that negative emotions are very harmful and would have a certain impact on human health, thus causing various physiological discomfort. In addition, negative emotions can also hinder social activities, thus affecting daily life.

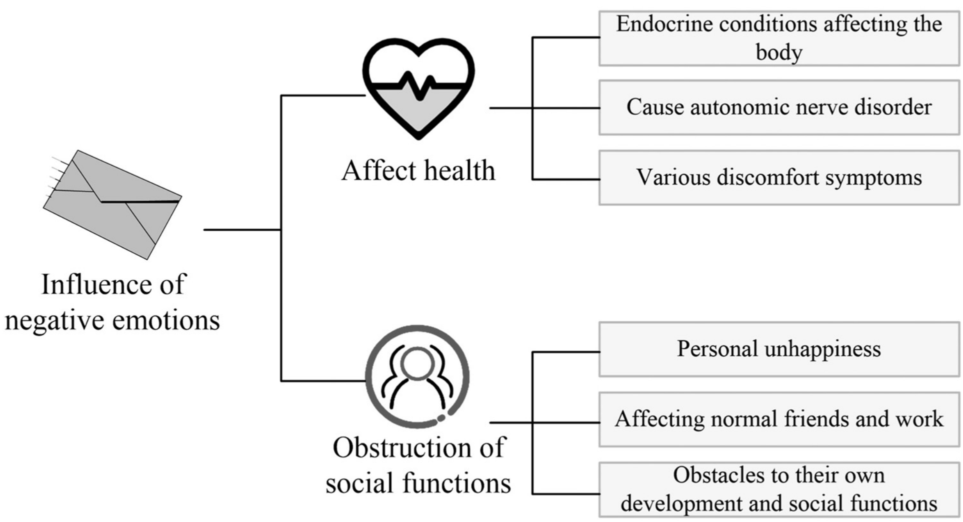


Figure 1. Impact of negative emotions.

Influence on physical health: Long-term adverse emotions would affect the endocrine status of the human body and the disorder of vegetative nerves, thus causing various physical discomfort. If the mood is bad, the endocrine would be affected, thus resulting in delayed menstruation. If the mood is bad, the disorder of vegetative nerve would be caused, and the disorder of gastrointestinal function would also be caused, thus leading to indigestion, constipation and other symptoms. In addition, bad mood can also cause blood pressure in the body to rise. In the long run, it would cause angina pectoris, myocardial infarction and other diseases.

Obstruction of social function: Long-term negative emotions would not only make people unhappy, but also affect friends and work, so as to hinder their own development and social activities.

Emotion recognition is mainly carried out through four main methods, namely facial expression recognition, physiological signal recognition, voice signal variation and text semantics [12]. There is a large number of negative emotions in the tourism industry, and there is also a large number of positive and negative emotional network buzzwords among the massive network buzzwords [13–14]. The research object of this paper was the negative emotion of network catchwords, so it was very important to distinguish positive and negative emotions in a large number of network catchwords. Emotion recognition can effectively reduce the objects of emotion analysis and improve the effect of emotion classification.

2.2. Negative Emotion Recognition Based on Word Fusion Feature

Negative emotion recognition method based on word fusion feature: At present, negative emotion recognition method based on machine learning usually adopts word package model, and selects words as text features for text representation. This text representation method depends largely on the performance of the word segmentation algorithm. For non-standard spoken or written popular online languages, most word segmentation algorithms have difficulties to obtain correct word segmentation results. Therefore, this paper attempted to improve the performance of negative emotion recognition by combining word features and text word features with neural networks.

The negative emotion recognition technology based on character fusion proposed in this paper integrated character features and word features to some extent, so that the characteristics of words and the characteristics of words complemented each other, so as to better reflect the network buzzwords in the dimension of language characteristics. Figure 2 shows the structure of the model.

Specifically, as shown in Figure 2, the characteristics of popular words on the Internet are described by using the characteristics of words and characters; the DNN model is used to extract deeper hidden features from the characters represented by word features and character features; finally, through the fusion of the two hidden layer features, the fusion features of the word feature and the word feature are extracted, and then they are forwarded into the fully conneced layer and the Sigmoid layer, so as to identify the negative emotions of the network catchwords.

In order to give full play to the characteristics of word features and word features, this paper proposed a network model based on DNN. This model combines word feature and word feature information, so that it can express the text in a deeper level.

First, the text is divided into word feature representation T_u and word feature representation T_v, and then two different feature representation methods are used to learn the higher-dimensional hidden layer features.

$$h_u = LSTM_u(T_u) \tag{1}$$

$$h_v = LSTM_v(T_v) \tag{2}$$

Among them, h_u and h_v represent the word hidden layer features and word hidden layer features learned from the model.

In this paper, h_u and h_v were spliced and fused as the input of the Merge layer.

$$h_{uv} = h_u \oplus h_v \tag{3}$$

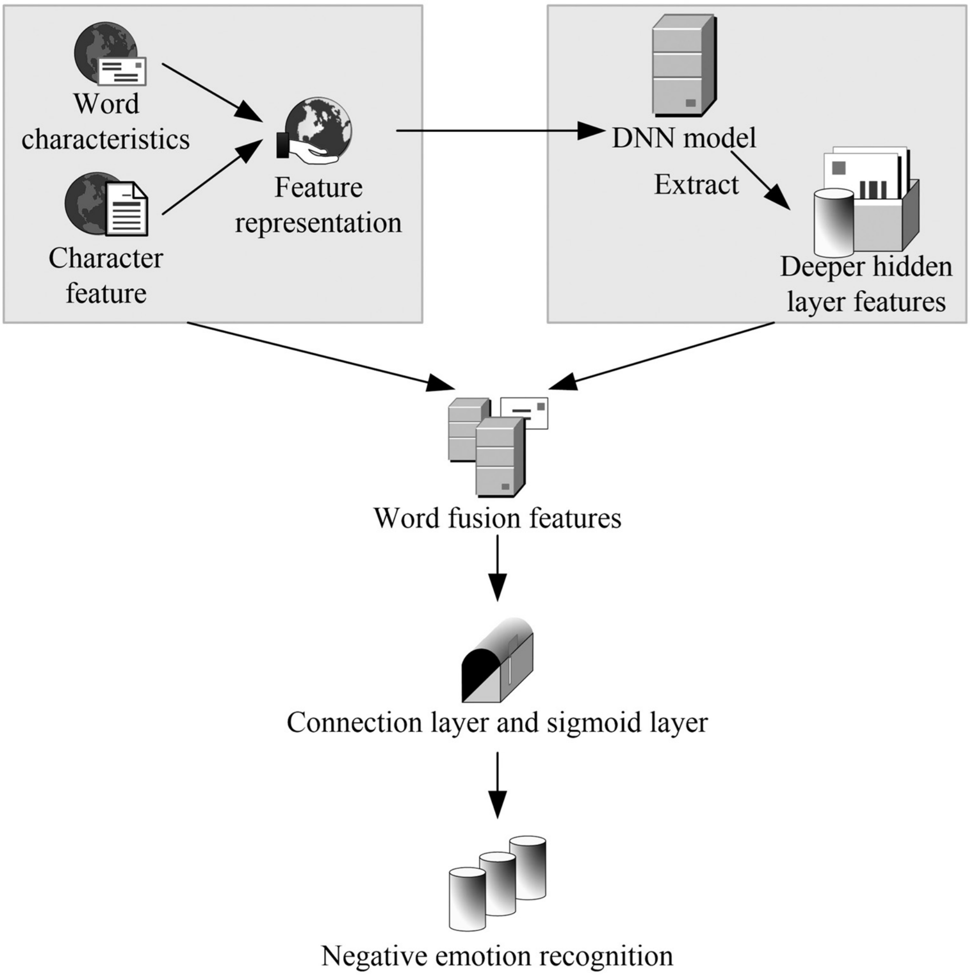


Figure 2. Negative emotion recognition model based on word fusion feature.

Among them, h_{uv} is the word fusion feature of the text, and $\oplus$ represents the vector splicing.

There is a complete connectivity layer, which can understand the fusion characteristics of words and words at a deeper level. The Dropout layer is added above the whole connection layer to reduce the complexity of the model and avoid the problem of network over-fitting. When the model is trained, the Dropout layer would make some hidden layer nodes in the network not work properly.

$$h^* = \beta\,(U^T h_{uv} + q) \tag{4}$$

$$h^d = h^* \cdot D(a) \tag{5}$$

Among them, h^* is the output of word fusion feature h_{uv} after passing through the full connection layer; U^T and q are the corresponding weight matrix and bias vector; β is an activation function.

Finally, the Sigmoid layer is used for emotional recognition of network buzzwords. The Sigmoid function is used to map the vector value to 0–1 and use it as a probability a to predict whether the network buzzwords contain negative emotions. The method is as follows:

$$a = sigmoid(U^d\, h^d + q^d) \tag{6}$$

Among them, a is the prediction probability, while U^d and h^d represent the weight matrix and offset vector of this layer respectively.

In the training process, the weight u is updated using the BP algorithm:

$$u \leftarrow u - \mu \frac{\partial V}{\partial u} \tag{7}$$

Among them, μ is the learning rate.

2.3. DNN Model

DNN is an important key technology launched by Canadian neural network experts in 2006. It is an important improvement model of traditional neural network [15–16]. In recent years, a large number of voice control and semantic understanding have emerged in many fields such as voice control and semantic understanding. Among them, emotion recognition is an important part of such systems, and its application directly affects the quality of its use. Therefore, how to improve the correctness of emotion recognition is particularly important. The previous emotion recognition is based on HMM-GMM technology, but its accuracy is not high. With the continuous development of DNN technology, the application of HMM-DNN is also increasing. This method replaces the feature transmission probability with the mixed Gaussian model based on DNN, which greatly improves the correctness of the emotion recognition system.

In recent years, many countries have listed DNN as an important topic, and conducted in-depth research on DNN, which have also applied it to emotion recognition, text conversion, image processing and other aspects [17]. For example, Baidu, Microsoft, IFLYTEK and other famous enterprises have applied this technology in their emotion recognition field, and the effect is remarkable.

(1) DNN structure

The characteristic of DNN is that there are many layers in the network, and each layer has independent training. The classification of the last layer is also independent. The independent training of each layer adopts the back-propagation BP algorithm. This method uses basic features to express high-level features, and then finds the feature representation of distribution. Its essence is feature learning. In particular, the graphic calculator has fast and efficient computing ability, which effectively overcomes the problems of the traditional multi-level network, such as slow computing speed and long time, and effectively improves the speed of speech recognition.

If a DNN system D is composed of Z-layer network, it can be written as D_1, D_2, ..., D_z; the input is O; the output is P. If the output of the system is the same as the original input, input O would not be lost in the system. P = 0 is output. That is to say, D_z is the repeated expression of O without change. Deep learning can be divided into three types: The first is the deep generative structure; the second is the recognition of deep structure; the third is the mixed deep structure. This type of structure is evaluated for probability $A(Z|P)$.

On this basis, through the introduction of the BP algorithm, the connection weights between learning neurons are continuously adjusted to obtain the best model. However, the BP algorithm is a typical multi-layer neural network training method. For the depth network with multiple hidden layers, its training effect is not ideal.

(2) BP network structure

BP network is a feedforward network composed of nonlinear transformation units, and its transfer function is generally an S-type function:

$$f(x) = \frac{1}{1+e^{-x}}. \tag{8}$$

BP network has good nonlinear mapping ability, good generalization ability, good classification ability, simple structure and other advantages, which is widely used in speech and emotion recognition. The BP network generally has one or more hidden layers, and generally adopts the S-type transformation method, while the pure linear transformation method is used in the output layer. Its conversion function can be differentiated and can be accurately learned.

The BP network has some disadvantages, as shown in Figure 3.

In view of the problems of BP network, a trust-based network structure is proposed and elaborated in detail.

2.4. Deep Belief Network (DBN)

DBN is an artificial neural network model consisting of a stacked architecture of multiple Restricted Boltzmann Machines (RBM). It is an unsupervised learning model for feature extraction and representation learning of data. There is a link between the visibility and the hiding degree of RBM, which is a DBN com-

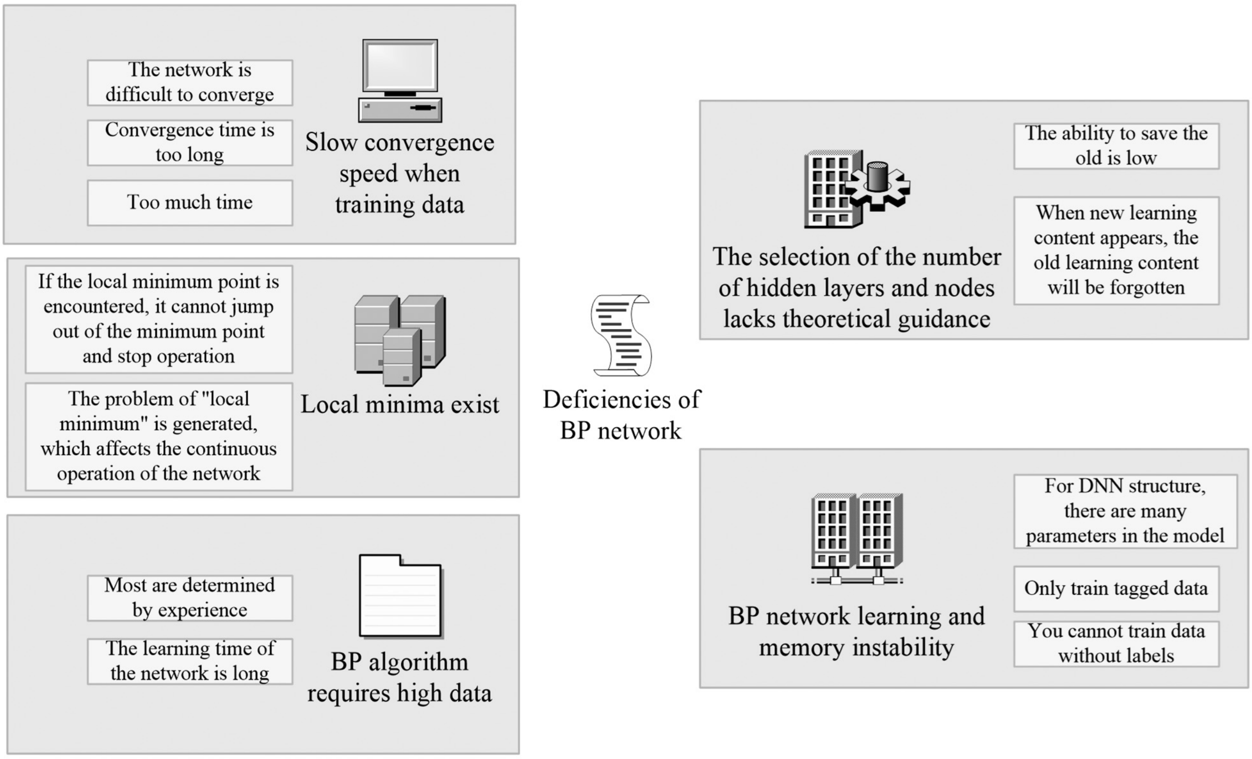


Figure 3. Shortcomings of BP network.

posed of multiple RBMs from bottom to top. This method can solve the problems of the above BP algorithm in multi-level network training.

What this paper needed to do was to identify the negative emotions of the network catchwords, as shown in figure 4 below. With text as the input, the text is first input into the system and trained by the low-level RBM, and then output it in the form of the two-level RBM. After many exercises, multi-layer hidden layers are added as required. Multi-layer RBMs overlap with each other, and top-down connection is used near the visible layer. The top layer is the undirected layer.

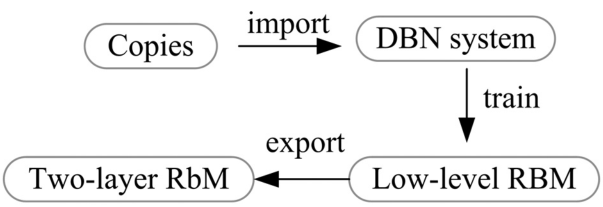


Figure 4. Flowchart of the DBN model for recognising emotions.

2.5. RBM's Implementation of Deep Learning

Firstly, RBM is defined. For variables B, h, $B = [B^1, B^2, ..., B^m]^T$, $h = [h^1, h^2, ..., h^n]^T$ and $B^0, h^k \in \{0, 1\}$, $o = 1, 2, ..., m$; $k = 1, 2, ..., n$, the distribution functions can be expressed in the following way:

$$A(B,h) = \frac{1}{C} e^{-E(B,h)} \tag{9}$$

$$C = \sum_{B,h} e^{-E(B,h)} \tag{10}$$

Where C refers to the normalisation factor and $E(B, h)$ refers to the energy function.

The energy function of RBM can be expressed in the following way:

$$E(B,h,\phi) = -\sum_{o=1}^{m}\sum_{k=1}^{n} w_{ok} V_o h_k - \sum_{o=1}^{m} s_o V_o - \sum_{o=1}^{m} q_k V_k. \tag{11}$$

Where V_o denotes the number of nodes in the visible layer, $S_o\, w_{ok}\, V_k$ denotes the weights connecting node o in the visible layer to node k in the hidden layer, q_k denotes the bias term of node k in the visible layer, and q_k denotes the bias term of node k in the hidden layer.

A series of random variables satisfying the above conditions are the RBM. In the RBM system, the maximum likelihood estimation method is used to solve the system parameters $\phi(w_{ok}, s_o, q_k; o = 1, 2, ..., m, k = 1, 2, ..., n)$, so as to minimize the sum of the system's free energy.

It can be seen that the probability of hidden nodes $A(B, h)$ is related to the energy function. In this paper, a concept called free energy is introduced, which can calculate the maximum likelihood value. The free energy function is as follows:

$$FreeEnergy(B) = -\ln \sum_h e^{-E(B,h)}. \qquad (12)$$

Formula (13) is as follows:

$$A(B) = \frac{e^{-FreeEnergy}}{C}. \qquad (13)$$

Formula (14) is as follows:

$$\sum_B \ln A(B) = \ln\left[\prod_B A(B)\right] \qquad (14)$$

Among them, $\ln\left[\prod_B A(B)\right]$ is the likelihood function, and the maximum likelihood estimation is to maximize $\ln\left[\prod_B A(B)\right]$. In order to obtain the maximum likelihood, its corresponding parameter $\phi(w_{ok}, s_o, q_k; o = 1, 2, ..., m, k = 1, 2, ..., n)$ must be calculated. The likelihood function of RBM system is $\prod_B A(B)$, which can be expressed in the following format:

$$Z(\phi \mid B) = \prod_B A(B). \qquad (15)$$

The two sides of Formula (15) are taken as logarithms, and the training set probability is taken as a logarithm. The partial derivative of weight $w_{ok}(o = 1, 2, ..., m, k = 1, 2, ..., n)$ is calculated and simplified as follows:

$$\Delta w_{ok} = \alpha\left(\langle B_o h_k\rangle_{data} - \langle B_o h_k\rangle_{model}\right). \qquad (16)$$

In Formula (16), the first item on the right of the equal sign represents the expected free energy of an input sample. Its function is only to traverse the possible corresponding hidden nodes in the system training samples; the second item on the right side of the equals sign is the expected value of free energy of the samples generated by the model. It is necessary to traverse all possible training samples.

In order to maximize the likelihood function of the system, this paper could find a parameter that minimized the total free energy of the system from the problems discussed above. Therefore, the hierarchical RBM training is adopted to better train the multi-hidden layer DNN model, so as to obtain better recognition rate of negative emotions.

3. Experiment and Evaluation of Negative Emotion Recognition Algorithm

3.1. Experiment Preparation

In this paper, the OPTIPLEX9020 of Dell, the core i7 processor and 8 GB memory were used in the experiment. The development platform of the system was based on Python's in-depth learning framework Theano.

The experiment in this paper mainly discussed the identification of negative emotions and non-negative emotions. Negative emotions included anger, sadness, fear and disgust, and non-negative emotions included happiness, surprise and neutrality. IEMOCAP is a commonly used emotional speech dataset, the full name is Interactive Emotional Dyadic Motion Capture Database. Therefore, this paper uses the samples in the IEMOCAP dataset for the experiments. The IEMOCAP dataset contains recordings of voice interaction dialogues between two people, which in total includes 718 dialogue scenes from 10 actors (5 males and 5 females), amounting to about 12.5 hours of recording data. Each dialogue scene contains two actors engaging in a free-flowing voice exchange in virtual meetings and scenarios. In total, there are 120 negative and 90 positive emotions. The number of each emotion is 30. According to the DNN model designed in this paper, the negative emotion recognition rate was finally calculated. This paper selected BP algorithm, GMM model and HMM to carry out comparative experiments.

The parameters of the different algorithms were set prior to the experiment and selected to test the recognition rates at different batch sizes as shown in Table 1.

According to Table 1 it is found that these algorithms have the highest recognition rate when the batch size is 210.

3.2. Identification of Non-negative Emotions and Negative Emotions

Table 2 shows the average recognition rate of non-negative emotions and negative emotions. The recognition rate, also called recognition accuracy, is a ratio between 0 and 1. The closer it is to 1 means that the model has a higher classification accuracy.

Table 1. Recognition rates of different algorithms for different batch sizes.

Algorithm	**Batch size**	**Non-negative emotion**	**Negative emotions**	**Algorithm**	**Batch size**	**Non-negative emotion**	**Negative emotions**
BP	190	71.57%	72.49%	HMM	190	75.65%	79.52%
	200	72.45%	75.64%		200	77.43%	80.32%
	210	75.81%	77.45%		210	79.64%	81.56%
	220	73.41%	74.45%		220	77.42%	80.54%
GMM	190	77.45%	79.89%	DNN	190	87.45%	89.65%
	200	79.43%	81.23%		200	88.9%	90.42%
	210	80.38%	82.71%		210	89.86%	92.48%
	220	78.98Z%	82.12%		220	88.79%	91.42%

Table 2. Average recognition rate of non-negative emotions and negative emotions.

Algorithm	**Non-negative emotions**	**Negative emotions**
BP	75.81%	77.45%
GMM	80.38%	82.71%
HMM	79.64%	81.56%
DNN	89.86%	92.48%

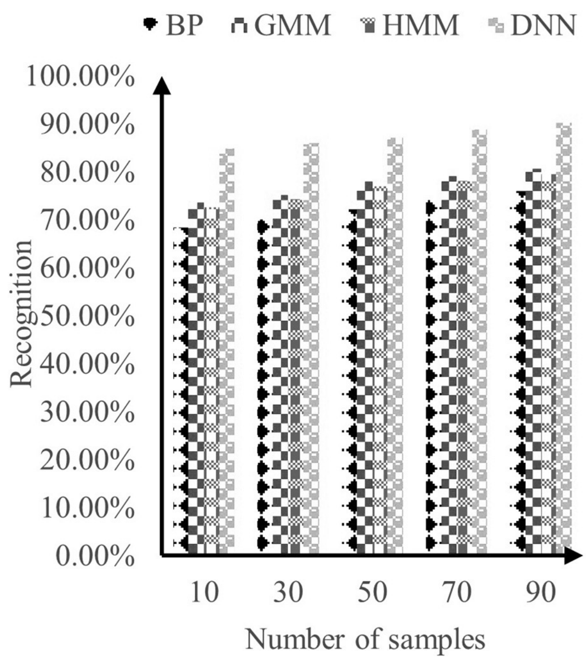
Table 2 shows that the average recognition rate of BP algorithm in non-negative emotion and negative emotion recognition was 75.81% and 77.45% respectively; the average recognition rate of GMM algorithm in non-negative emotion and negative emotion recognition was 80.38% and 82.71% respectively; the average recognition rate of HMM in non-negative emotion and negative emotion recognition was 79.64% and 81.56% respectively; the average recognition rate of DNN in non-negative emotion and negative emotion recognition was 89.86% and 92.48% respectively. It can be seen that the average recognition rate of different algorithms in non-negative emotions and negative emotions was not different, but the average recognition rate of negative emotions was slightly higher than that of non-negative emotions. This paper speculates that it was affected by the number of samples, so the number of samples was tested.

Figure 5 outlines the relevant experimental data of different algorithms for identifying different sample numbers.

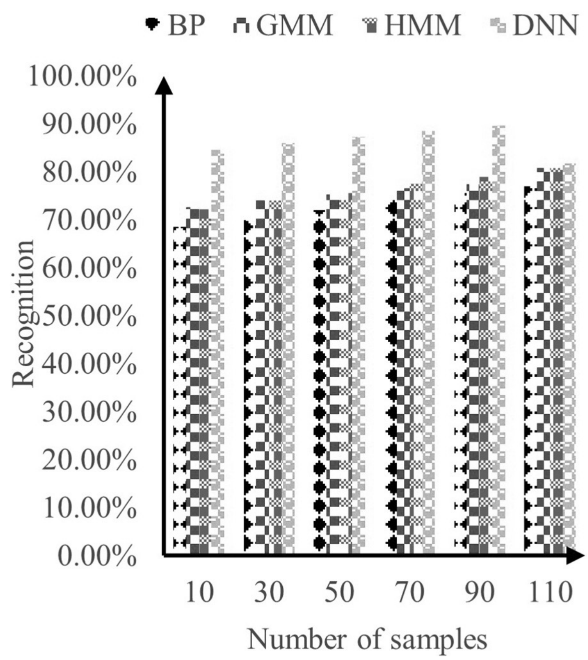
It can be seen from Figure 5 (a) that in non-negative emotions, when the number of samples was 10, 30, 50, 70 and 90, the recognition rate of BP was 68.42%, 70.08%, 72.22%, 74.13% and 75.98% respectively; the recognition rate of GMM was 73.57%, 75.21%, 77.98%, 79.16% and 80.64% respectively; the recognition rate of HMM was 72.60%, 74.34%, 76.97%, 78.05% and 79.59% respectively; the recognition rate of DNN was 84.84%, 85.98%, 87.13%, 88.88% and 90.18% respectively.

It could be seen from Figure 5 (b) that in negative emotions, when the number of samples was 10, 30, 50, 70, 90 and 110, the recognition rate of BP was 68.56%, 69.94%, 72.08%, 74.12%, 75.64% and 77.01% respectively; the recognition rate of GMM was 72.65%, 74.05%, 75.28%, 76.56%, 77.34% and 80.74% respectively; the recognition rate of HMM was 72.25%, 73.99%, 75.63%, 77.52%, 78.92% and 80.78% respectively; the recognition rate of DNN was 84.64%, 86.02%, 87.21%, 88.54%, 89.60% and 81.77% respectively.

It can be seen from the data that under the same sample number, the recognition rates of different algorithms for non-negative emotions or negative emotions were not different. However, with the increase of the number of samples, the recognition rate of the algorithm was increasing as a whole.



(a) Non-negative emotions.



(b) Negative emotions.

Figure 5. Recognition rate of different sample numbers.

However, during the study, it was found that the training process of BP algorithm is more time-consuming and easy to fall into the local optimal point. In high dimensional data, the GMM model has higher computational complexity. The HMM model is based on state transfer and is relatively ineffective in modelling long time dependencies. DNN is better than the other three algorithms and is able to extract the features automatically but requires a larger amount of data and computational power for training.

3.3. Experimental Evaluation of Negative Emotion Recognition

This paper was mainly focused about the identification of negative emotions in network catchwords, so the following only studies the identification of negative emotions. It could also be seen from the above experiment that the number of samples had an impact on the accuracy of emotion recognition, so the number of negative emotion samples was expanded. Among them, the number of negative emotion words in online catchwords increased to 200, and the number of anger, sadness, fear and disgust was 50 respectively.

Table 3 represents a comparison of the average recognition time of different negative emotions when the number of samples was 50.

Table 3 shows that the average recognition time of BP in anger, sadness, fear and disgust was 0.73s, 0.72s, 0.75s and 0.81s respectively; the average recognition time of GMM in anger, sadness, fear and disgust was 0.64s, 0.63s, 0.66s and 0.72s respectively; the average recognition time of HMM in anger, sadness, fear and disgust was 0.70s, 0.71s, 0.74s and 0.80s respectively; the average recognition time of DNN in anger, sadness, fear and disgust was 0.60s, 0.59s, 0.62s and 0.68s respectively.

Figure 6 provides a comparison of the time consuming of different algorithms for negative emotion recognition.

According to Figure 6 (a), when the number of anger samples was 10, 20, 30, 40 and 50, the average time consumption of BP was 0.18s, 0.26s, 0.36s, 0.49s and 0.74s respectively; the average time of GMM was 0.13s, 0.20s, 0.29s, 0.41s and 0.63s respectively; the average time consumption of HMM was 0.15s, 0.24s, 0.35s, 0.47s and 0.71s respectively; the average time of DNN was 0.08s, 0.17s, 0.25s, 0.37s and 0.59s respectively.

According to Figure 6 (b), when the number of sadness samples was 10, 20, 30, 40 and 50, the average time of BP was 0.17s, 0.24s, 0.35s, 0.48s and 0.73s respectively; the average time of GMM was 0.13s, 0.19s, 0.28s, 0.40s and 0.63s respectively; the average time consumption of HMM was 0.14s, 0.25s, 0.36s, 0.46s and 0.72s respectively; the average time of DNN was 0.08s, 0.16s, 0.24s, 0.36s and 0.58s respectively.

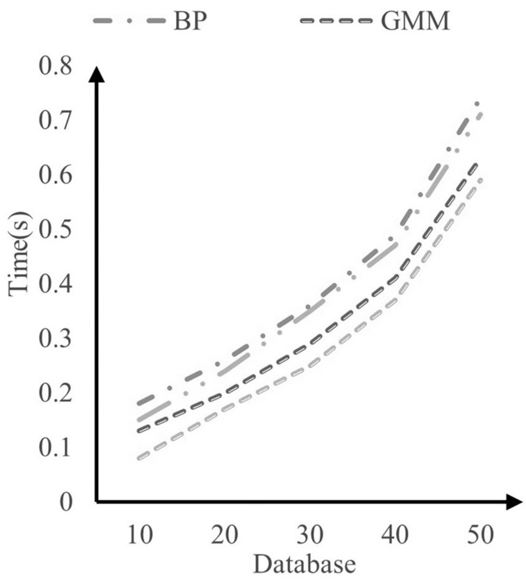
It could be seen from Figure 6 (c) that when the number of fear samples was 10, 20, 30, 40 and 50, the average time of BP was 0.20s, 0.25s, 0.37s, 0.51s and 0.76s respectively; the average time of GMM was 0.15s, 0.21s, 0.31s, 0.43s and 0.65s respectively; the average time consumption of HMM was 0.17s, 0.25s, 0.36s, 0.49s and 0.73s respectively; the average time of DNN was 0.10s, 0.18s, 0.27s, 0.39s and 0.62s respectively.

Table 3. Average recognition time of different negative emotions (s).

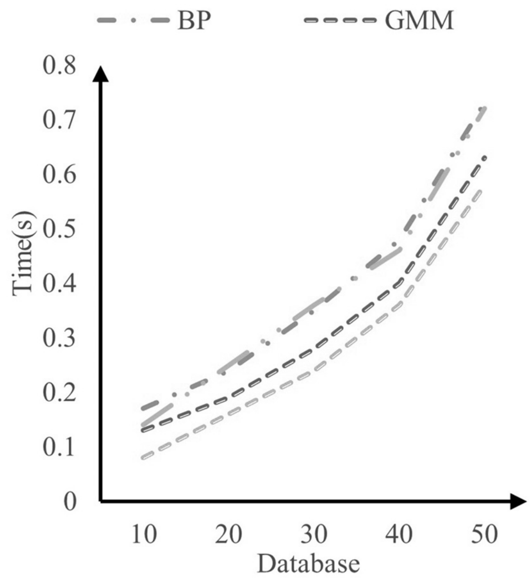
Algorithm	Anger	Sadness	Fear	Hate
BP	0.73	0.72	0.75	0.81
GMM	0.64	0.63	0.66	0.72
HMM	0.70	0.71	0.74	0.80
DNN	0.60	0.59	0.62	0.68

It could be seen from Figure 6 (d) that when the number of disgust samples was 10, 20, 30, 40 and 50, the average time of BP was 0.24s, 0.31s, 0.42s, 0.58s and 0.81s respectively; the average time of GMM was 0.19s, 0.26s, 0.35s, 0.47s and 0.72s respectively; the average time consumption of HMM was 0.20s, 0.30s, 0.41s, 0.56s and 0.79s respectively; the average time of DNN was 0.14s, 0.23s, 0.32s, 0.44s and 0.68s respectively.

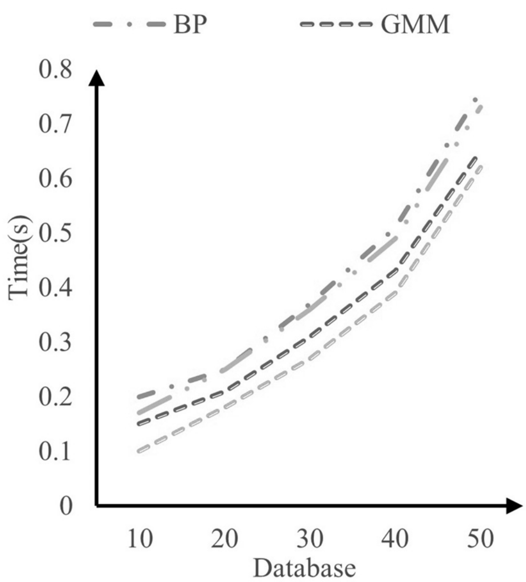
It could be seen from the data that among the negative emotion recognition time of online catchwords, anger and sadness took less time, and the difference between the two was not significant. Disgust took the most time on average. It could be seen that disgust was the most difficult to recognize among the four emotions.



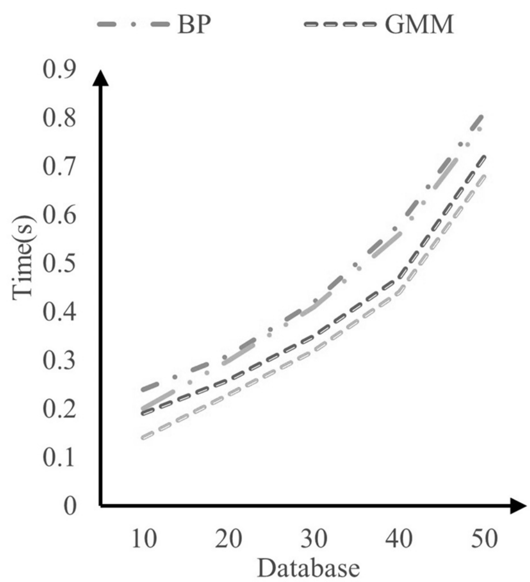
(a) Anger.



(b) Sadness.



(c) Fear.



(d) Disgust.

Figure 6. Time consumption comparison of negative emotion recognition.

Figure 7 provides a comparative analysis of the recognition rate of different negative emotions.

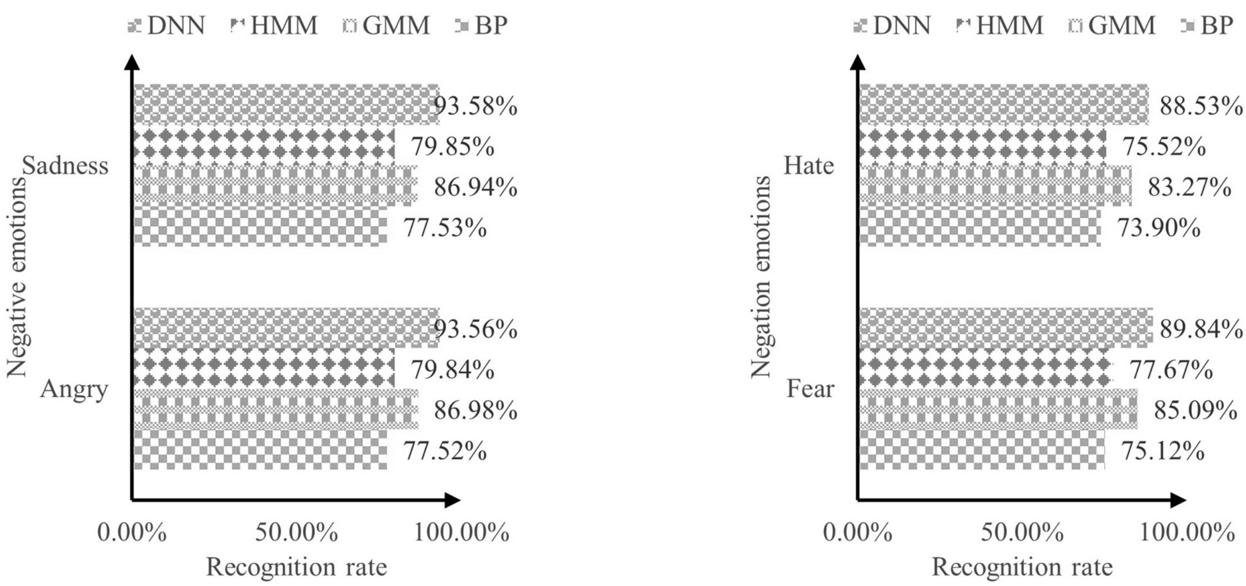
According to Figure 7 (a), BP's recognition rate of anger and sadness was 77.52% and 77.53% respectively; the recognition rate of GMM for anger and sadness was 86.98% and 86.94% respectively; HMM's recognition rate of anger and sadness was 79.84% and 79.85% respectively; DNN's recognition rate of anger and sadness was 93.56% and 93.58% respectively.

It could be seen from Figure 7 (b) that BP's recognition rate of fear and disgust was 75.12% and 73.90% respectively; the recognition rate of GMM for fear and disgust was 85.09% and 83.27% respectively; the recognition rate of HMM for fear and disgust was 77.67% and 75.52% respectively; DNN's recognition rate of fear and disgust was 89.84% and 88.53% respectively.

To sum up, the DNN model designed in this paper played a certain role in the recognition of negative emotions in network catchwords. It had the characteristics of high recognition rate and low time consumption. This model is worthy of further promotion and application.

4. Conclusion

In this paper, we introduce a negative sentiment recognition method based on sentiment recognition, and summarise its features and experimental results by using the novel DNN architecture of RBM for feature extraction of the sentiment of Internet buzzwords. The experimental results clearly show that based on the linguistic feature dimension, the use of deep neural network algorithms for identifying and analysing the sentiment of Internet buzzwords solves the problem of missing and insufficient data for sentiment analysis in different linguistic contexts, and improves the classification effect of negative sentiment. The method can effectively classify and recognise sentiment on a large scale and with high efficiency. However, since the used data represents only some Internet buzzword data, it is still necessary to further expand the scope of the dataset and enrich the linguistic feature dimensions. In the next research, the generalisation ability of the DNN model will be enhanced so that it can accurately identify negative emotions in different contexts. Other features (*e.g.*, discourse, syntax, emotion icons, *etc.*) of the negative emotions of Internet buzzwords can also be combined with textual features and textual features to further improve the recognition ability of the negative emotions of Internet buzzwords.



(a) Sadness and anger. *(b)* Disgust and fear.

Figure 7. Recognition of negative emotions.

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