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Emotion Analysis and Opinion Monitoring of Social Network Users Under Deep Convolutional Neural Network

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ABSTRACT

With the development of the internet, the user behavior and emotional characteristics behind social networks have attracted scholars' attention. Meanwhile, identifying user emotion can promote the development of mobile communication technology and network intelligence industrialization. Based on this, this work explores the emotions of social network users and discusses the public comments on the speeches through the speeches of social network users. After 100 times of training, F1 of the BiLSTM algorithm can reach 97.32%, and after 100 times of training, its function loss can be reduced to 1.33%, which can reduce the impact of function loss on emotion recognition. The exploration is of great significance for analyzing the emotional behavior of social network users and provides a reference for the intelligent and systematic development of internet social model as well as the information management.

KEYWORDS

BiLSTM, Convolutional Neural Network, Deep Learning, Emotion Analysis, Internet, Social Network

1. INTRODUCTION

With the development of information technology, the internet becomes a popular platform for information dissemination and interaction. Social network applications, such as microblogs and forums, bring great changes in people's daily life. Artificial intelligence (Naudé, 2020; Thiebes et al., 2021; Vaishya et al., 2020) (AI) is a system built by computing equipment, such as computers or robots, to realize intelligence. The function of AI in early days is reflected in machine translation and machine games. With the development of natural language processing (NLP) and perception technology, AI becomes an indispensable tool to deal with the problems encountered in people's life. With the development of Internet of Things (IoT), AI has made fusion perception, reasoning and emotion achieve intelligence in 2020.

In the environment of big data (Qi, 2020) and the internet (Priatama et al., 2020; Qiu et al., 2020; Sun et al., 2020), the network public opinions are variable and complex, and more attention are given to social events. All kinds of media reports can bring a heated discussion of the public, the social values and personal cognition from the public gradually change. The expression form of

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network public emotions is personalized, and it is an important index to measure and calculate the information on multimedia. The emotional characteristics and states contained in the information can be constructed to form a certain information system. Through the analysis of public opinions, the development trend of society, economy and politics is known about, and the corresponding measures are made to create a stable network information environment (Çömez, 2021; Ocakoğlu et al., 2020; Rueda et al., 2021).

Based on the above, a public emotion network communication model is implemented based on the convolutional neural network (CNN), the deep learning neural network (DCCN) is combined with the emotions of network public opinions, and the emotional interaction of humanoid robots is applied to the emotional state analysis in the public emotion network model, finding the research direction for the exploration of public emotion network communication.

2. RELATED WORKS

2.1 Research on Deep Learning (DL) and Speech Emotion Recognition

With the rapid development of AI, the research on speech emotion recognition based on DL is numerous. At present, speech emotion recognition technology is used and has made some achievements. Mellouk et al. (2020) studied FER (Facial Emotional Recognition) through DL, and developed technologies to explain, encode facial expressions and extract these features for better prediction via computers. The research results prove that DL is an effective algorithm. Masud et al. (2020) studied the intelligent face recognition based on DL in the IoT-cloud environment and compared the performance of the most advanced face recognition model with others. The experimental results show that the accuracy of the proposed model can reach 98.65%. Li et al. (2020) studied the method and performance of medical image fusion based on DL. The results show that the DL can automatically extract the most effective features from the data, which can be used in image fusion to improve the efficiency and accuracy of image processing, and the increase of the training data can improve the training accuracy. Xiong et al. (2021) studied plant phenotypic image recognition based on DL. CNN, deep belief network (DBN)and recurrent neural network (RNN) are used to identify plant species and diagnose plant diseases. The research shows that DL has broad application prospects and great value in the era of smart agriculture and big data. Yang et al. (2021) studied the image recognition of wind turbine blade damage of transfer learning and ensemble learning classifier and proposed a new method for blade damage detection based on DL. The performance of the proposed model is verified by using the image of wind turbine blades. The proposed model has better performance than the support vector machine (SVM), basic DL model and DL combined with ensemble learning method. In summary, deep learning has been applied to speech image recognition, and the results show that DL has great application value in speech image recognition.

2.2 Social Image Visualization and Users' Emotion Recognition

The studies on image visualization and emotion recognition are plentiful. Murugesan et al. (2019) conducted a comparative study on the visualization and interaction of DL with others. Two case studies are conducted to give a preliminary evaluation on the effectiveness of different types of models. Cashman et al. (2019) studied the visual analysis of discovering neural architecture, introduced the rapid exploration of model architecture and parameters, and allowed the model builder to quickly discover DL through the exploration and rapid experiment of the architecture of neural networks. And the advantages and disadvantages of the model is evaluated in detail. Wang et al. (2020) studied the deep volume synthesis network for segmentation and visualization of sparse and noisy image data and proposed a multi-stream framework based on CNN to effectively learn 3D volume and 2D feature vector, respectively. Then, they explored their interdependence by back-projection of 2D feature vector into the joint volume synthesis embedding space. Patel et al. (2020) analyzed and studied DL in computer vision applications. The results show that DL-based AI is widely used in network security, automobile, health and banking, retail, and financial fields. Wu et al. (2021) discussed the application of DL in visualization. The great success of DL in computer vision, NLP and speech recognition provides new opportunities for data visualization and analysis. Studies show that these technologies can be used to identify visual representations and perform analytical tasks, and DL should be introduced to perform new visualization tasks. Lv et al. (2021) studied fine-grained visual computing based on DL. Combined with CNN and Network 16 model, a multi-level fine-grained image feature classification model is constructed, and the TensorFlow platform is used for experimental simulation. The results show that the accuracy of the multi-level classification fine-grained image classification algorithm is 85.3%, and the shortest training time is 108s. This shows that the algorithm has higher accuracy and shorter training time and provides experimental reference for users' emotion recognition.

3. USERS' EMOTION TRANSMISSION MODEL BASED ON NEURAL NETWORKS

3.1 Public Opinions on Networks

Network public opinions (Hemmatian & Sohrabi, 2019) are generally aimed at the social phenomenon that the public pays more attention to, and the current social problems that the public are interested in. The phenomenon or problem that develops into a public opinion should go through three stages: (1) it appears on the network; (2) it attracts a large number of internet users to express their views; (3) it is spread by some media or authorities. The core components of network public opinions are subject, object and carrier. The subject is the public in the network environment, the object is the event, and the carrier is the internet communication platform. And network public opinions are affected by many influencing factors. And they include the internal factor, namely the influence of the event itself, and the external factor, namely the driving force of internet users and various media. Due to the non-publicity and virtuality of networks, network public opinions are mixed with a large number of unreal information. The authenticity of information cannot be effectively guaranteed, which will cause many malicious users to disseminate false information and have a bad impact on social stability. The schematic diagram of the formation of network public opinions is shown in Figure 1.

Network public opinions can truly reflect the public's inner thoughts even if they may bring negative effects. They can play a positive role in the government propaganda after a deep analysis is done.

3.2 Users' Emotion Analysis Based on CNN

Bi-direction Long Short-Term Memory (BiLSTM) is proposed on the basis of RNN (Lin et al., 2021) and CNN (Wan et al., 2020). This model uses the bidirectional cyclic neural network to obtain the context of the imported text, and then uses CNN to extract the representative features, so that the BiLSTM model can learn the vector representation of the text more accurately, thereby improving the accuracy of the BiLSTM model. BiLSTM combines the advantages of BiRNN and Long Short-Term Memory (LSTM) and has good learning effect for users' emotions. Its structure is shown in Figure 2.

Human emotions are complex and diverse, and there is not a unified emotional expression model. A relatively mature emotion model, PAD three-dimensional emotion model, is proposed from the perspective of psychology. The model projects human specific emotions into a three-dimensional space composed of P (Pleasure-displeasure), A (Arousal-non-arousal) and D (Dominance-submissiveness). And the result shows that PAD can explain human complex emotions. The three dimensions can show users' emotions and their subjective experience and form a good mapping effect with the external manifestation. And the emotional PAD value can be obtained through psychological experiments.

Figure 1. Formation of network public opinions

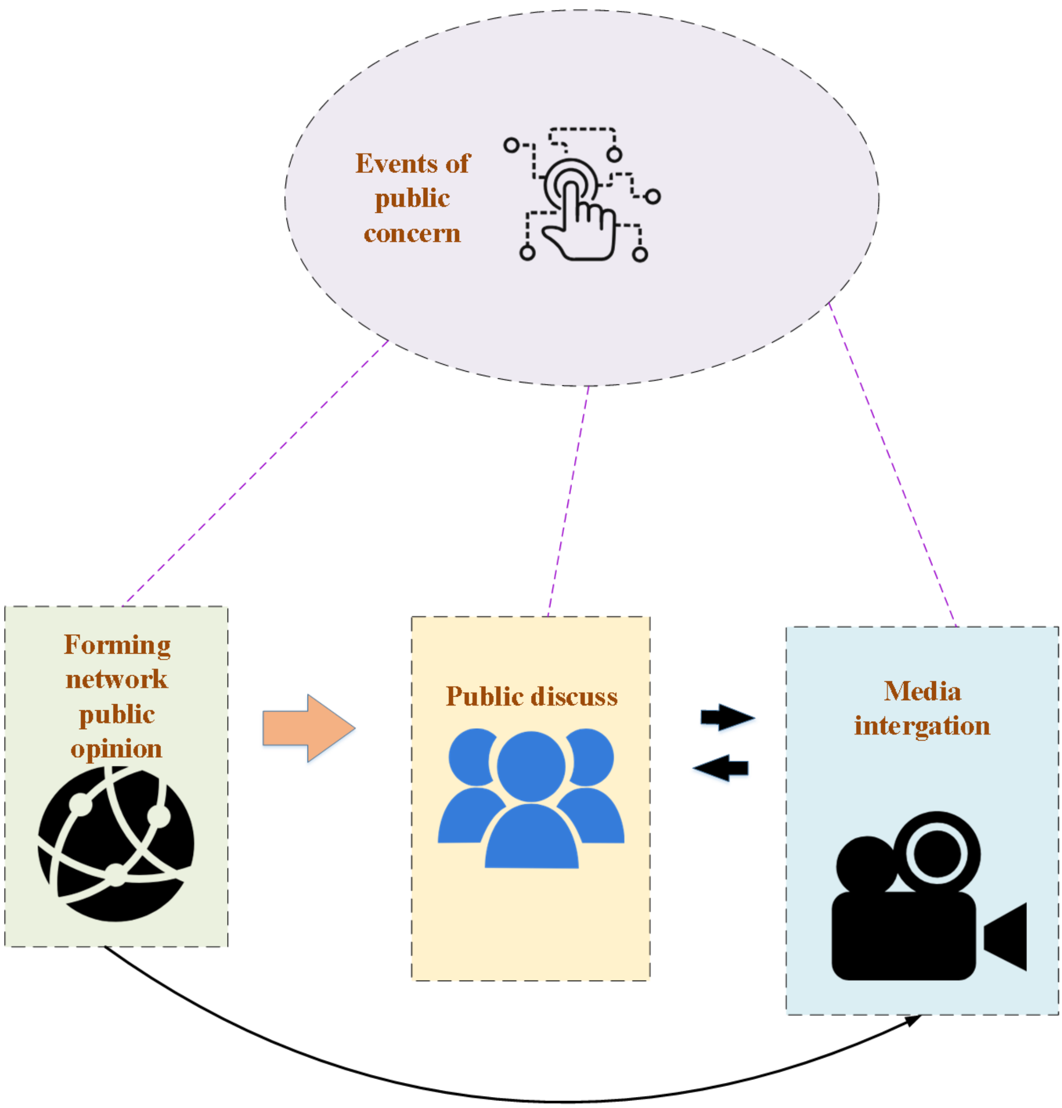
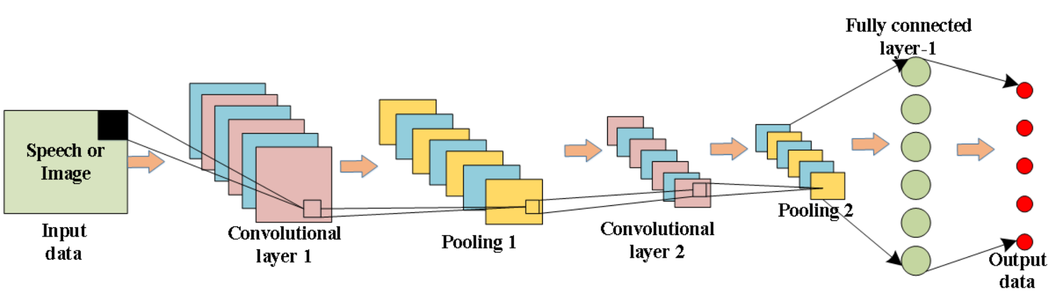


Figure 2. Structure of BiLSTM



3.3 Public Emotion Transmission Model on the Internet

With the wide application of the internet and the birth of media, the public can express their views on the media, and the internet users can receive or publish information at any time on the social platform. When internet users disseminate information, they will express personal emotions in the form of information, so information on the network will cover the emotions of users. When it contains emotions, the information is spread faster, and public opinions are produced and heatedly discussed in this environment. Cognitive psychology suggests that the dissemination and communication of information are affected by emotions, and the carrier of emotional communication is information. People spread information and make emotional communication in the process of interaction. Social groups also express their emotions in the process of interaction, contributing to the production of group emotion. The structure of social networks is very complex, and users' emotions can be transmitted to each other through other users. The transmission mode of information in social networks is the same as that of emotions. Therefore, the dissemination of information and emotion is closely related and complementary. Negative group emotions will weaken people's happiness and affect social stability. Therefore, the study of the interaction between emotional communication and information dissemination is the basic measure to control and manage public opinions.

According to the knowledge of networks, graph theories and network science, social network can be defined as a kind of directed graph W (A, B) based on users. The public users are defined as node A, and the degree of mutual attention of users is defined as B. In the social network topology, the direction of the side can be the direction of information flow. On social platforms such as QQ and WeChat, the side between users is indirect, and the side in microblog is directed. If a node is spreading information, its neighbor nodes 2,4,6,8 will collect the corresponding information at the next time, and only nodes 2,4,6,8 will transmit information, so that more nodes will collect information. After a node collects information, it is only very interested in the information that it can be transmitted in the next step. In the process of transmission, it will attach its own emotion or understanding. On the contrary, the transmission ends. There are some nodes in the network that are not completely in the state and are not interested in the information. Therefore, because of the two-sided characteristics of information transmission, the nodes in the network are divided into five states: the first is the susceptible node S (Susceptible), which contains the characteristics of receiving information instead of the information of users; the second is latent node E (Exposed), which adds itself to the information while receiving it. If the node has received the information and its attitude to the information is positive, the corresponding information will be transmitted to the neighbor node. The fourth is the negative propagation node Ineg (Negative Infected), which passes the information that it receives to the neighbor users, and its attitude to the information is negative. The fifth is the immune node R (Removed), which loses interest in the received information and leaves the propagation path. Both positive and negative propagation nodes are called propagation nodes I (Infected). The nodes that have received information have their own emotions when processing information, and only the communication nodes export the internal emotions outward. In the objective environment, the implicit emotion of nodes is not corresponding to the performance of external output, and the degree of implicit emotion bias of nodes with the same external output to information is different.

The proportion of users with extreme emotions in the network is small, and most users' emotions are normal. If the emotional value is negative, the emotion is negative. If the emotional value is positive, the emotion of information is positive. β (t) is used to represent the absolute value of node emotion at t, and the value is between (Naudé, 2020). If node m interacts with node n at t time, the emotion update rule is:

$$\beta\left(t+1\right)=\beta\left(t\right)+\delta\left(\beta_n\left(t\right)-\beta_m\left(t\right)\right) \tag{1}$$

δ represents the emotion of node m to node n.

This rule is positively correlated with the relationship compactness between nodes and the influence degree of nodes. At a certain moment, only the interconnected nodes can produce interactive behavior. The rules of interaction are as follows.

First, when S is connected with I at time t, the emotion of S to the information is negative. S becomes Ineg with the probability of α (t), and the emotion of S to information is positive. Then S becomes Ipos with the probability of α (t) 2, and on the contrary, S is transformed into E. Second, at time t, E becomes R with the probability of (t), and other E interacts with *I*. After connection, E expresses negative emotions to the information, and becomes Ineg with the probability of λ (t). If the emotion is positive, it becomes Ipos with the probability of λ (t) 2. Then, with the increase of time t, *I* will no longer be interested in the information, and the dissemination of information ends. Finally, at time t, *I* is connected with the same emotional bias, and the emotions of the two will change after interaction. If *I* contacts with different emotional bias, the two will not interact.

For the change rules of the states of the above nodes, the parameters in the first rule need to be set according to S's preference for the information, I's popularity, and the popularity of the information itself. The parameters in the second rule are positively correlated with the acceptance of information and the relationship between nodes. The probability in the second and third rules is correlated with the popularity rate of nodes. In the process of establishing information propagation model, the influence factors are considered.

3.4 Establishment of Signal Sampling and Public Opinion Monitoring Database

For continuous analog speech signals, the original signal format is not helpful to data processing and storage. Therefore, format conversion is needed to convert the original signal into discrete data (Hu et al., 2020; Morsali et al., 2020; Tanaka et al., 2020). For the acquisition of sound signals, low sampling rate will lead to low emotion recognition rate of the model, and high sampling rate will increase the running time of the system. In this case, 16KHz or 8KHz is used as the sampling rate. After the sampling is completed, the speech signal is framed and windowed by uniform quantification, and the continuous and stable speech signal is divided into different finite signals.

The feature extraction of speech emotion in the original data are described as follows: (1) the speech signal processed by windowing is subjected to fast Fourier transform, and the obtained signal power spectrum needs to be filtered. The connection between the signals is taken out by discrete cosine transform, and the signal is mapped to the low-dimensional space. The short-term energy characteristics of the speech data are analyzed, and CNN is used for facial emotion image recognition. As the most commonly used DNN to analyze visual images, the parameter sharing mechanism of CNN can reduce the number of parameters in operation, and it is widely used in image and video recognition. In CNN, the input layer is used for data input, and the convolution kernel in the convolution layer is used for convolution operation between the upper input and the data of this layer. Through local connection and global sharing, the number of parameters of CNN is reduced, and the learning efficiency of the neural network is improved. The data extracted from the low-level features are input into the linear rectifier layer and the pooling layer for down-sampling through multi-layer convolution operation. The data after pooling can further reduce the network training parameters, and improve the fitting degree of the model. Finally, the fully connected layer transfers the input data to the neurons and outputs the final results through the output layer.

3.5 Experimental Analysis

The performance of BiLSTM based on attention mechanism is evaluated, and the speech emotion recognition experiment of users is carried out by the German Berlin emotion database. The experimental data are randomly divided into two groups. 80% of the experimental data are used for training datasets, and 20% of the data are used for test datasets. The sampling rate is set to 16 kHz, the moving step is set to 10ms, and the matrix with the feature of 512*34 is extracted for data analysis. The BiLSTM network architecture is constructed by Keras. The optimizer is Adam, the batch number is 32, and the initial learning rate is 10^{-4}. 40 computers are equipped with interface cameras, and the hardware of the computers is Intel (R) i5-7500, 3.40GHZ, 8GB RAM, and Windows 7 operating system. The experiment is implemented per week. During the experiment, the computer program automatically collects user's facial expression images when users use social networks, and the acquisition frequency is set to 2 frames per second. The acquisition time is set randomly and lasts for 5-10 minutes. The performance of the proposed algorithm is compared with that of the traditional CNN algorithm to prove the advantage of the algorithm.

4. RESULT AND DISCUSSION

4.1 Performance Comparison of Emotion Recognition Accuracy of Different Algorithms

Accuracy, Precision, Recall and F1 curves of different algorithms are shown in Figure 3 ~ Figure 6.

Figure 3. Accuracy curves of different algorithms

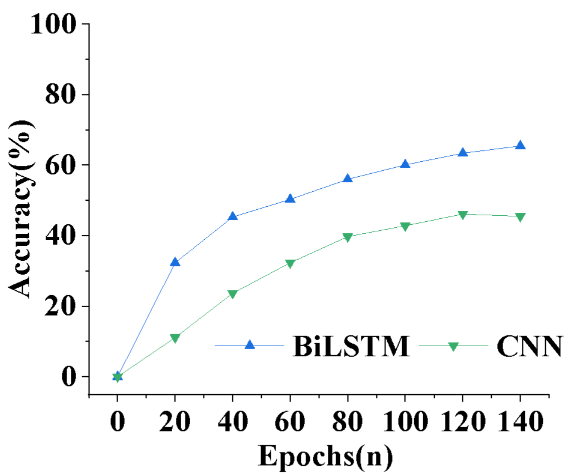


Figure 4. Curves of the precision of different algorithms

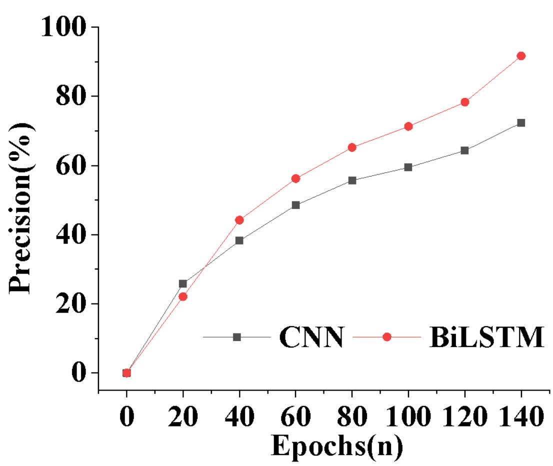


Figure 5. Recall rates of different algorithms

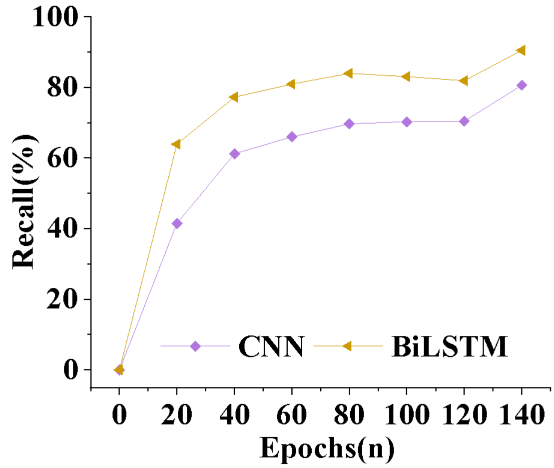
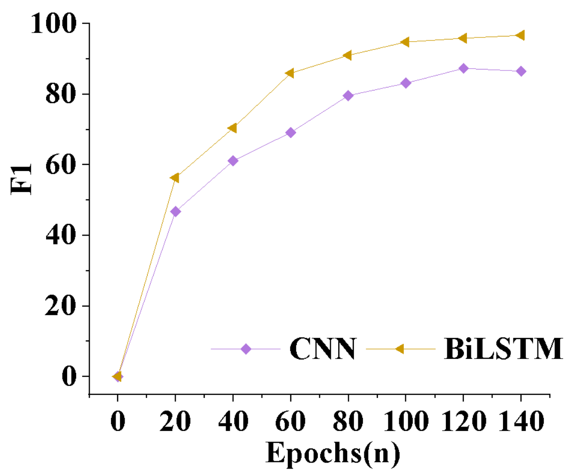


Figure 6. F1 curves of different algorithms



The figure shows that the recognition accuracy of the two algorithms improves as the increase of training periods. However, compared with the traditional algorithm, the recognition accuracy of the proposed BiLSLM improves faster, and the accuracy reaches 98.75% after it is trained 60 times, which is at least 3.15% higher than that of the traditional algorithm.

Figure 4 shows that the accuracy rate of BiLSLM is always the best. When the precision of the traditional algorithm slows down, the precision of BiLSLM still grows rapidly.

Figure 5 shows that the recall rate of BiLSLM is at least 7.13%, higher than the traditional algorithm, and the recall rate of the algorithm can reach 86% after the iterations times are 80, which is higher than the traditional algorithm.

Figure 6 shows that F1 of BiLSLM rises with the increase of training times. After it is trained 100 times, F1 of the algorithm can reach 97.32%. The performance of the algorithm is superior and its recognition accuracy for social network users' emotions is high.

4.2 Data Transmission Performance Comparison of Different Algorithms

The data transmission performance of different algorithms is compared and analyzed. The variation curves of verification accuracy and function loss value of different algorithms are shown in Figures 7-8.

Figure 7 shows the verification accuracy curves of different algorithms. The verification accuracy of the model changes little with the change of the learning rate. As the initial learning rate increases exponentially, the verification accuracy decreases linearly.

Figure 8 shows that the function loss value decreases rapidly with the increase of training period. After it is trained 100 times, the function loss value of BiLSLM drops to 1.33%, which reduces the influence of function loss on emotion recognition accuracy.

5. CONCLUSION

With the development of the internet, the characteristics of users' behavior and emotions behind social networks attract the attention of scholars. Recognition of users' emotions can promote the development

Figure 7. Curve of validation accuracy of the algorithm with the increase of the initial learning rate

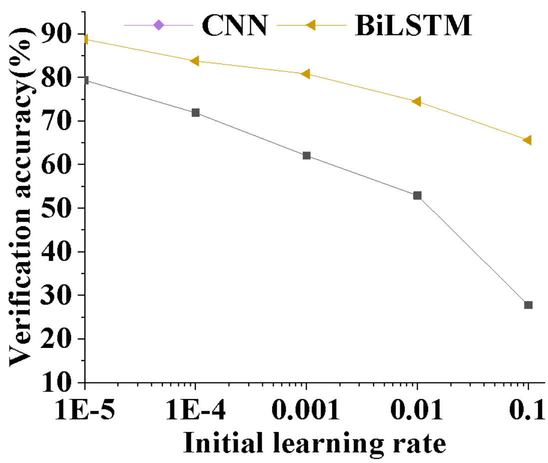
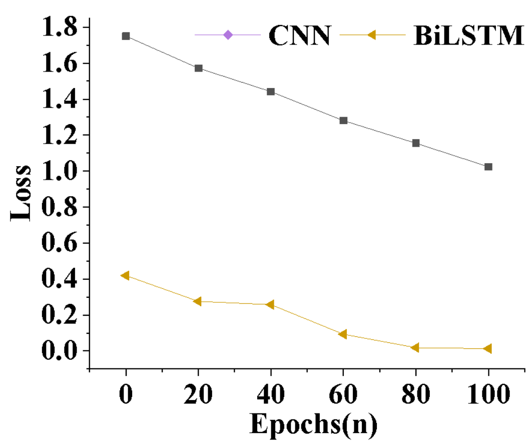


Figure 8. The curve of the function loss value with the increase of the training times



of intelligent industrialization of mobile communication technology and networks. Based on DCNN, public opinions of social network users are analyzed, and the network public opinions are monitored. The accuracy of the proposed algorithm reaches 98.75% after it is trained 60 times, which is at least 3.15% higher than that of the traditional algorithm. The function loss value of the algorithm drops to 1.33% after it is trained 100 times, which greatly reduces the influence of function loss on emotion recognition. The research has great significance for the analysis of emotions of social network users. However, there are still some shortcomings. In the process of analyzing the user's emotions, the expressions of emotions are multiple emotions because it is difficult to conduct in-depth research on the deeper emotions of users. In the follow-up research, the user's emotions should be described at multiple levels, and the accuracy of user's emotion analysis should be further improved.

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