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Psychological Emotion Analysis System for Special Needs Children Based on Neural Network

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Abstract: With the development of modern society and the improvement of living standards, care for special needs children has been increasingly highlighted, and numerous corresponding measures such as welfare homes, special education schools, and youth care centers have emerged. Due to the lack of systematic emotional companionship, the mental health of special needs children are bound to be affected. Nowadays, emotional education, analysis, and evaluation are mostly done by psychologists and emotional analysts, and these measures are unpopular. Therefore, many researchers at home and abroad have focused on the solution of psychological issues and the psychological assessment and emotional analysis of such children in their daily lives. In this paper, a special children's psychological emotional analysis based on neural network is proposed, where the system sends the voice information to a cloud platform through intelligent wearable devices. To ensure that the data collected are valid, a series of pretreatments such as Chinese word segmentation, de-emphasis, and so on are put into the neural network model. The model is based on the further research of transfer learning and Bi-GRU model, which can meet the needs of Chinese text sentiment analysis. The completion rate of the final model test has reached 97%, which means that it is ready for use. Finally, a web page is designed, which can evaluate and detect abnormal psychological state, and at the same time, a personal emotion database can also be established.

Keywords: Deep learning; Special needs children; Psychological emotion; Analysis system

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1. Introduction

1.1. Social background

With the development of modern society and the continuous improvement of living standards, care for special needs children has been increasingly highlighted, and numerous corresponding measures such as welfare homes, special education schools, and youth care centers have emerged. Society's concern for children and adolescents is also increasing. A person's outlook on life and values are usually formed during their childhood all the way to adolescence, and the mental health of this stage is particularly important [1]. The phenomenon of left-behind children exists in some areas, where children are not accompanied by their parents in their daily lives, often resulting in a sense of loneliness and eventually mental health issues. Mental health issues do not only appear in neglected children, but also in special needs children, in which psychological defects are inevitable. Therefore, it is of great significance to evaluate their mental health.

Nowadays, emotional education, analysis, and evaluation are mostly done by psychologists and emotional analysts, and these measures are unpopular. Usually, only those with mental illness and psychological issues will seek help from psychologists. Therefore, in this paper, we designed a smart wearable device, which collects the wearer's daily speech through speech recognition and storage device, converts it into Chinese text, and then performs sentiment analysis to evaluate the psychological state of the wearer.

There are many methods of sentiment analysis. Traditional machine learning methods requires the input of marked target domain data into the network, and the data are classified in other target domains through the classifier obtained by learning. With the large increase of data, labeling the data in the target domain becomes costly, and the efficiency decreases [2]. Even if there is semi-supervised learning, the classification learning of emotional data still cannot be performed well. Transfer learning is a new learning framework that can learn knowledge from the source domain with a large amount of labeled data and transfer it to the target domain with a small amount of labeled data, and transfer learning can realize the learning of the new domain. In addition, transfer learning can achieve cross-domain and cross-language sentiment classification. Therefore, this paper uses the relationship-based emotion knowledge learning and transfer model to evaluate the emotion and emotional tendencies of the wearer based on their words: positive or negative [3]. Reasonable advice can then be given based on the mental health evaluation by this model.

1.2. Research status at home and abroad

Research on sentiment analysis began many years ago. In 2002, Turney *et al.* first proposed the task of sentiment classification, which mainly analyzes the emotional tendencies of data: neutral, positive, and negative [4].

The main research methods of affective learning are either dictionary-based or machine learning-based. The dictionary-based only requires the construction of a thesaurus with a large number of labeled data, which contains a large number of symbolic words that can represent the emotional tendency of the text. The data in the thesaurus can then be used to predict the emotional tendency of the input sample data. When a sentence is input into the emotion dictionary as a sample, it will be split into symbolic words one by one, and then matched in the lexicon with positive, negative, and neutral words, and finally the overall emotion coefficient is calculated, so that the emotion tendency of the whole sentence can be predicted. However, the dictionary-based sentiment analysis method only relies on the dictionary database, but in reality, the application scenarios of text data are diverse and flexible, so this method is not practical. Therefore, Pang *et al.* proposed the use of machine learning methods for sentiment classification, among which the deep learning method is the most popular among researchers.

When deep learning is applied to sentiment analysis, in order to improve the accuracy of sentiment data classification, it is generally required that the training data of the input network and the test data of the test model conform to independent co-distribution. In order to adapt to the test data samples in many cases, the training data should be sufficient with a wide range, so that a model with good emotion classification function can be trained. Neurons in neural networks can learn from input samples and capture the characteristics of input samples well. The core of deep learning is feature learning. Feature learning automatically extracts the basic features that can represent the sample [5], transfers these features layer by layer, and then updates the model parameters through backpropagation algorithm, and finally obtains effective fitting result. Both convolutional neural network (CNN) and recurrent neural network (RNN) can be used for emotion classification of text. Kim *et al.* proved that CNN is better than RNN in classification performance alone. However, CNN and RNN both have some disadvantages. When the depth of the neural network increases, the classification effect is often better. However, as the depth of the network increases, problems such as gradient explosion and exploding gradients are prone to occur. Besides, it cannot process text-related data effectively. Therefore, Zhu *et al.* used long-short-term memory network (LSTM) to classify long text emotions, and its performance was better than CNN.

However, in the case of large amount of training data, the cost of neural network is also high. Transfer learning has better performance where it can learn knowledge from a large number of labeled data and transfer it to a small number of labeled data domain. In this research, transfer learning was applied in sentiment classification. In addition, relation-based emotional knowledge learning was also used to learn the source domain data and the target domain data, which improves the classification ability of the network.

2. Scenario analysis

2.1. Scheme I

RNN will process the data based on the input order of the text. The RNN also has a three-layer network structure: an input layer, a hidden layer, and an output layer. The previous output data will be used as input data of the RNN input layer. The reason why RNN can combine the context of the text to train the network is that it has a cycle kernel. The cycle kernel in the network can realize parameter sharing at different times and the sequential time extraction of the input speech text. In the process of forward propagation, the information at time t is stored in the memory, and the data in the parameter matrix is unchanged. In the process of backward propagation, the data in the parameter matrix will be updated according to the gradient descent method.

2.1.1. Analysis

Although RNN network is useful for emotional analysis of this kind of language text, but it also has a major disadvantage. For the emotional analysis of long texts, each keyword is significant, and when we read it as human beings, we will take it into account. However, for RNN network, if two keywords are passed, then the first keyword will have no effect on the update of the network parameters, which means that RNN may have the problem of gradient disappearance.

2.2. Scheme II

To overcome the shortcomings of RNN, a long short-term memory network (LSTM) can be used. There are many gate control units in LSTM. These gate control units transmit information over a long distance, that is, the previous data can be effectively applied to the subsequent network parameter updates. Compared to RNN, the basic unit in the hidden layer of LSTM is different, in which LSTM uses the LSTM unit. The LSTM unit can solve the problem of gradient disappearance in RNN.

2.2.1. Analysis

The Bi-GRU model used in this paper uses the transfer learning method to get the cross-domain invariant emotional knowledge from the source domain. The relationship between the target domain and the source domain will then be analyzed to learn the private emotional knowledge of non-shared knowledge. The combination of the cross-domain invariant sentiment knowledge and private sentiment knowledge in classifying the target domain will improve the accuracy of the target domain sentiment classification, and this model is simpler and more efficient compared to LSTM.

3. Model structure

The structure of the overall model is shown in **Figure 1**.

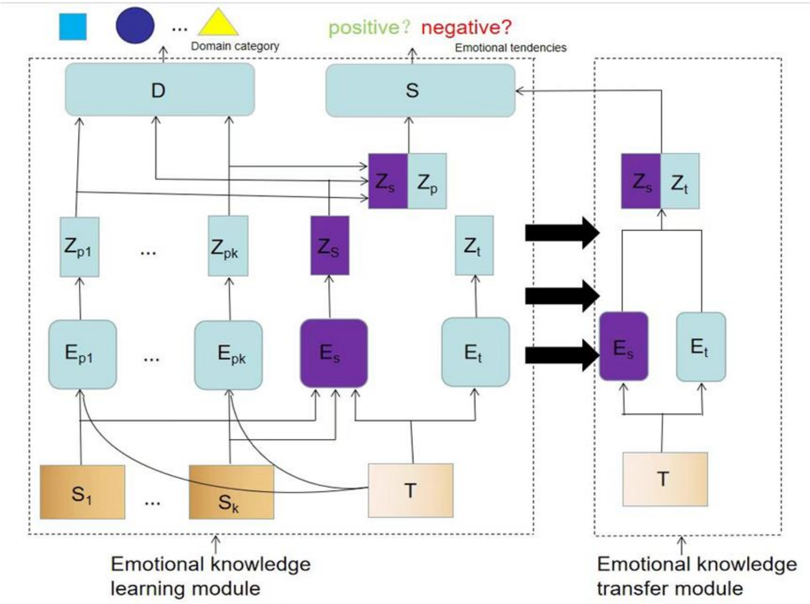

Figure 1. Model structure

This model is divided into two parts, one is emotional knowledge learning, the other is emotional knowledge transfer.

The model is set up with S_1,S_1..S_n, with a total of *n* source domain and 1 target domain, *T*. The input of the model is the preprocessed data of these *n* data with a large number of labels. In **Figure 1**, E_{pn} shows the private feature extractor unique to the *n*th source domain, and the private features extracted by the extractor are stored in Z_{pn}. E_t is the feature extractor of the target domain, while Z_t is the result extracted by the feature extractor. There is also a shared feature extractor in the model, where E_s is the result is saved in Z_s, which is a cross-domain shared feature of *n* source and target domains. The D network is the discriminator network referenced from the GAN network, and it can be seen in **Figure 1** that the input of the D network is the sum of the private feature and the shared feature. C is the classification network, which is used to classify the emotional tendency of keywords.

3.1. Knowledge learning module

This model mainly trains the E_s and E_t.E_s. The training is the same as the antagonistic learning idea of GAN network. After E_{pn} and E_s were input into the D network, the D network was trained. The output of the discriminator could determine which domain the feature belongs to. The discriminator was then subjected to antagonistic training until the discriminator cannot determine which domain the feature E_s in the input network belongs to. Through such a process of confrontation, the network could not distinguish which field the E_s it belongs to, because the E_s had the common characteristics of all fields. In this way, cross-domain invariance with features can be achieved.

E_s draws on the antagonistic ideas of GAN networks, while E_t draws on the ideas of knowledge distillation. As mentioned earlier, the relation vector between the target domain and the source domain is needed, so the relation vector was obtained by the D network. The specific process was as follows: data of the target domain was input into *n* private feature extractors of the source domain, then the obtained *n* private features was input into the D network, and the output of the D network was normalized to obtain a relation vector, W. The learning target of the private feature extractor was obtained by weighting and averaging the *n* private features with W, and then the parameters of the network were updated according to the loss E_t.

If each target domain data is regarded as a sample of *n* source domains, the classifier will output different results. Therefore, when the data in the target domain is input to $n + 1$ (1 represents the E_t private feature extractor) private feature extractors, $n + 1$ features will be obtained, and then they will be sent to the classification network, and there will be $n + 1$ classification results. In this paper, the relation vector W was used to weight each private feature, and the classification result of the target domain was obtained according to the weighted data, and then the classification result was used as the pseudo-label of the target domain, the pseudo-label was considered applicable when the confidence level of the pseudo-label is in a certain range. The pseudo-label and the data in the target domain were included in the training set$T^{\sim}$.

3.2. Migration module

The other part of the model is the transfer module (emotional knowledge transfer module), which can be used to train a network model that can classify the samples in the target domain accurately. The input of this part was the pseudo-label training set$T^{\sim}$mentioned above, and the $E_t + E_s$ was the network trained by the previous emotional knowledge learning module. After the training set$T^{\sim}$was sent to the two trained networks, two features were obtained, which were sent to the classifier C, and the parameters of the classifier C and the feature extraction network E_t were updated according to the classification loss. During the whole training process of the model until the end, the loss of the model gradually converged, and the classification ability in the target domain was also enhanced.

3.3. Loss function

The model comprises a plurality of training networks, including a feature extractor network, a discriminator network, and a sentiment classification network, wherein the feature extractor network comprises $n + 1$ private feature extractor networks and a shared feature extractor network. Bi-GRU model was used for all feature extractor networks, MLP was used for D network, and C network was a fully connected layer network. Adam algorithm was used to optimize the parameters of the network.

The loss of the discriminator network was calculated as follows:

$$\mathrm{Loss}_D = \sum_{i=1}^{k+1} \sum_{j=1}^{N_i} \mathcal{L}_D\big(D\big[E_S\big(x_i^j\big)\big], d_i\big) + \sum_{i=1}^{k} \sum_{j=1}^{N_i} \mathcal{L}_D\big(D\big[E_{pi}\big(x_i^j\big)\big], d_i\big)$$

where I represents the *i*-th source domain, and J represents the *j*-th sample; x_i^j represents the *j*-th sample data in the *i*-th domain.

The loss of the sentiment classification network C was calculated as follows:

$$\mathrm{Loss}_C = \sum_{i=1}^{k} \sum_{j=1}^{N_i} \mathcal{L}_C\left(C\left(E_s\big(x_i^j\big) \oplus E_{pi}\big(x_i^j\big)\right), y_i^j\right)$$

where y_i^j represents the label corresponding to the *j*-th sample data in the *i*-th field.

E_s antagonism was used in the training of the network, so the loss of antagonism loss was calculated as follows:

$$\mathrm{Loss}_{adv} = -\lambda_{adv} \sum_{i=1}^{k+1} \sum_{j=1}^{N_i} \mathcal{L}_D\big(D\big[E_s\big(x_i^j\big)\big], d_i\big)$$

The loss of the network E_t was calculated as follows:

$$\text{Loss}_p = \mathcal{L}_p\left(z_t, \sum_{j=0}^{n} w_j \cdot z_{pj}\right)$$

where$z_t$is the characteristic of the sample in the target domain obtained by the E_t network; $w_j$represents the relationship vector between the target domain and the jth source domain; z_{pj} represents the characteristic of the sample data in the target domain after the jth private feature extractor; and $\mathcal{L}_p$ is the cross entropy loss.

The cross-entropy loss function used in this paper is as follows:

$$\text{Loss}_{SC} = -\sum y_i \log\ h(z_i) + (1 - y_i)\log\left(1 - h(z_i)\right)$$

where z_i represents the feature of the ith sample,$h(z_i)$represents the sentiment label, and y_i represents the true label data of the sample.

3.4. Diagram of training results

The data training accuracy and cross entropy loss of the psychological and emotional analysis system for special needs children based on neural network are shown in **Figures 2** and **3**.

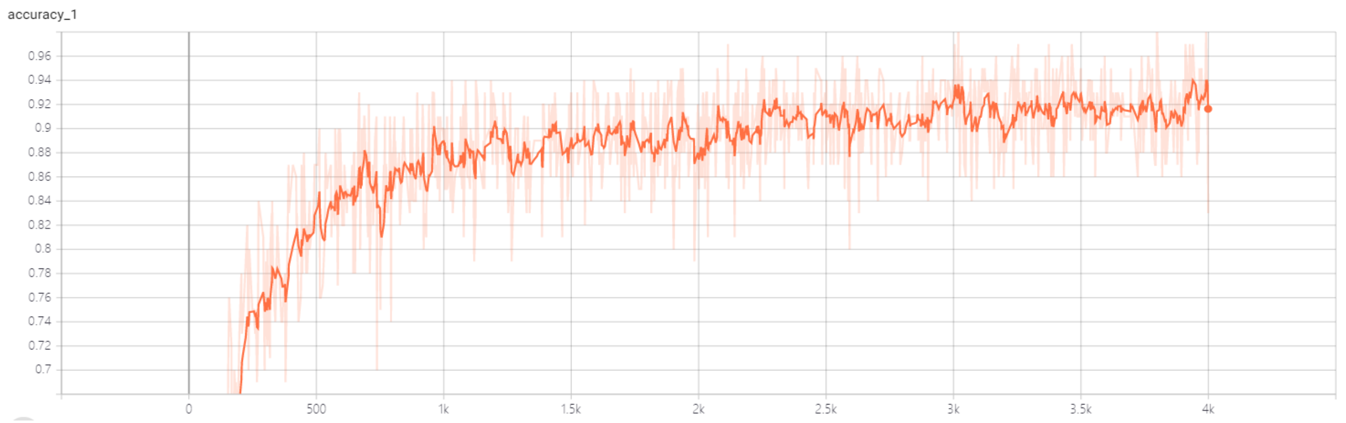

Figure 2. Training accuracy chart

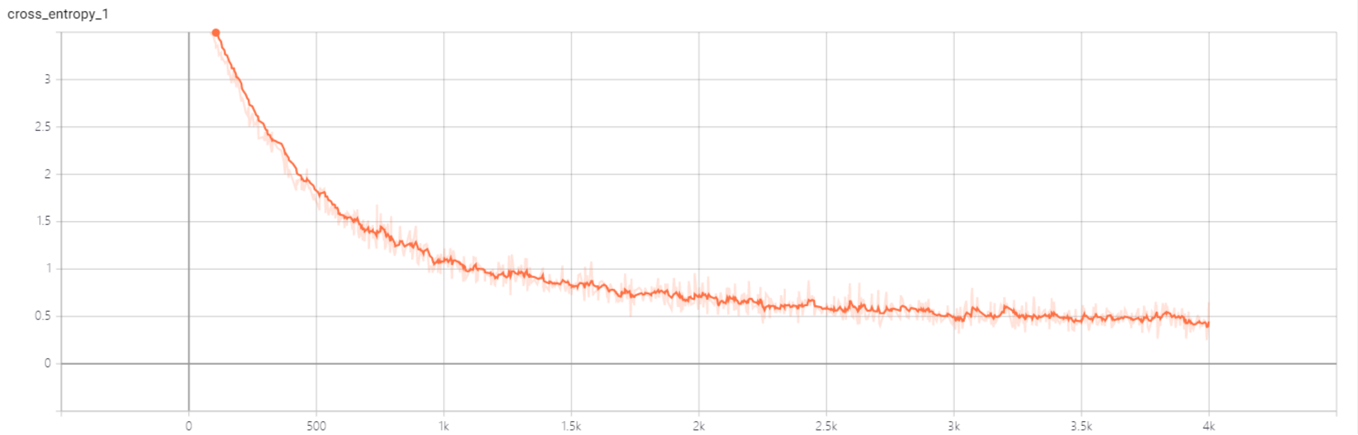

Figure 3. Cross entropy loss diagram

4. Test and analysis

4.1. Functional test

Table 1. Functional test

Category	Comments	Emotional tendencies
Children's toys	So cool, I love it!	Positive
	The quality of the toy car is very good.	Positive
	Cool and cute.	Positive
	The workmanship and quality are good	Positive
	Kids don't like it.	Negative
	It's a little expensive.	Negative
	The material is not good.	Negative
	It's similar to the toys at the dollar store.	Negative
	Too bad	Negative
	Simple and fun to use, very suitable for children.	Positive
	It's good. Kids like it.	Positive
	Good value for money and had a great time.	Positive
	Received, my kids like it very much, and the quality of the items are good.	Positive

4.2. Webpage display

The web page designed by HTML can display the psychological emotional scores based on emotional analysis and realize the visualization of data. (**Figure 4**)

Figure 4. Display of psychological and emotional scores

5. Summary and prospect

The living standards of people are developing along with the development of modern society, and children's mental health are increasingly highlighted. An emotional knowledge learning and transfer model is used in this research to classify the emotional state through text. In this model, words from daily conversations can be collected and converted into texts, and the text are input into the model to classify the emotions. The accuracy of emotion classification is very high, and the results can be used for psychological assessment to monitor the mental health of children.

Due to the limited collection of sample data, daily conversations cannot be covered completely in this study, and more sample data should be collected in the future. We can also consider introducing the RERT model in future works.

Disclosure statement

The authors declare no conflict of interest.

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