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Deep Convolutional Neural Networks for Facial Expression Recognition

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Abstract: Facial expression recognition technology has been widely used in traffic, medical and criminal investigation and other fields. At present, facial expression recognition technology refers to feature extraction, classification and recognition through facial expression. In order to solve the shortcomings of the existing recognition technology research, this paper discusses the Softmax classifier function equation, facial expression and (DCNN), and briefly discusses the sample data and parameter configuration of the proposed facial expression recognition technology. Finally, the recognition process structure designed in this paper is applied to the five collected facial expressions (angry, sad, happy, afraid and calm) and the other two recognition models (GAN) and (LSTM) to compare the recognition rate. The experimental data show that the recognition rate of the proposed algorithm (CNN) is 95.2% and 94.9%, respectively, which is significantly better than that of the recognition model (GAN) and (LSTM). In the recognition of happiness, fear and calm, the average recognition rate of the proposed (CNN) reaches about 96.3%, while the highest recognition rate of the recognition model (GAN) and (LSTM) is only 92.7%. Therefore, it is verified that facial expression recognition based on depth (CNN) has a good performance effect.

1. Introduction

The machine will be intelligent for human language, action and expression recognition and judgment. However, facial expression brings different influences in all aspects of daily life, and the research of facial expression recognition in the two fields of machine learning and deep neural network is becoming more and more abundant.

Nowadays, more and more scholars pay attention to the research of various computer technologies and system tools in facial expression recognition, and through practical research, some research results has been achieved. Yolcu G presented the design of a facial expression recognition (FER) model based on RNN. The model uses facial components to discuss a facial expression recognition scheme, which combines expression detection, feature extraction and classification algorithms. The two-channel convolutional neural network is used, in which the expression (RP) is used as the input of the first hidden layer, and the image expression of the two layers is collected in the output layer to obtain the overall expression information from the image features. Experiments were conducted on a dataset of female facial expressions. Experiments show that this model has higher classification accuracy [1]. Taee E developed machine learning algorithms to recognize expressions of facial emotions. Facial expressions play a role in non-verbal communication in reflecting inner emotions, which are reflected in facial expressions. This work has used machine learning algorithms to extract the features of eyes and lips from the face, and DNN models and algorithms are used in face recognition. It can be used to detect people′ s anger, disgust, fear, despair and other emotions [2]. The main purpose of Chavan U B is to use intelligent technology RTA model. The proposed model includes facial expression information collection, expression classification, extraction and recognition. Firstly, the facial emotion dataset is classified. Feature extraction (IFT) is used to identify the main information of facial expression recognition by hybrid meta-heuristic algorithm. The RTA model was further optimized by the beetle swarm optimization (GET) algorithm [3]. Although the existing research on facial expression recognition is very rich, the research on facial expression recognition based on deep convolutional neural networks still has some limitations.

This article first to the softmax classifier function equation and facial expressions, augmented the real-time data, data normalization, face alignment and (DCNN) concluded that the concept of the second based on the investigation and analysis of sample data and parameters configuration created based on RNN recognition process of the structure, finally through a concrete analysis of experimental data, The validity of recognition model based on RNN is obtained

2. Facial Expression Recognition in Deep Convolutional Neural Networks

2.1. Facial Expressions

Facial expression preprocessing in facial expression recognition mainly includes real-time data augmentation, data normalization and face alignment [4].

(1) Real-time data augmentation

Real-time data augmentation is mainly achieved by randomly cutting out the four corners and the central area of the input image in the training process, and then mirror inversion. The output image obtained will be ten times the size of the original training dataset [5].

(2) Data normalization

For non-standard face images, they are often accompanied by changes in illumination intensity and head posture [6]. The change of illumination and head pose will bring great changes to the image, which will affect the performance of expression recognition. Illumination normalization and pose positivity are two typical face normalization methods [7].

(3) Face alignment

Face alignment directly affects the subsequent recognition accuracy [8]. Different from face segmentation to determine the face contour, face alignment is mainly used to generate a rectangular box to locate the face image [9].

2.2. Deep Convolutional Neural Network

(1) Convolutional layer

In this layer, the input facial expressions are computed and the features of facial expressions are extracted [10]. The convolutional layers at different levels in the network have different functions, and the shallow convolutional layer mainly extracts the texture and other features of facial expression [11].

(2) Pooling layer

Pooling layer refers to the high dimensional character of facial expression map after convolutional layer. In order to reduce the scale of parameters for subsequent recognition, the pooling layer can compress and merge multi-dimensional channels while retaining useful facial expressions to reduce the size of subsequent facial expressions [12].

(3) Fully connected layer

In this layer, all hidden elements on the feature map are expanded into one-dimensional vectors and constructed according to traditional neural networks [13]. The function of this layer is to aggregate all the information of all facial expression feature maps, and map the learned facial expression features in the form of vectors to facial expression sample recognition, as a classifier of facial expression [14].

(4) softmax classifier

Suppose that the output layer is to perform facial expression classification of class r, and there are x facial expressions in the training set [15]. Each face expression is a w-dimensional vector, then all training face expression samples can be expressed in the form of formula (1):

$$G = \{(u^{(1)}, v^{(1)}), \dots, (u^{(x)}, v^{(x)})\} \tag{1}$$

The softmax classifier calculates the rate at which the input facial expression belongs to the r-th recognition:

$$H(v = f | u), (f = 1, \dots, r) \tag{2}$$

After calculation, an r-dimensional recognition rate output vector is obtained [16]. Formula (3) represents the softmax calculation function:

$$k(u^{(t)} | \vartheta) = \begin{bmatrix} h(v^{(t)}) = 1 | u^{(t)}, \vartheta \\ h(v^{(t)}) = 2 | u^{(t)}, \vartheta \\ \dots \\ h(v^{(t)}) = r | u^{(t)}, \vartheta \end{bmatrix} = \frac{1}{\sum_{e=1}^{r} s^{\vartheta_e^G u^{(t)}}} \tag{3}$$

Where $\vartheta - |\vartheta_1^G \vartheta_2^G \dots \vartheta_r^G|$ is the learned parameter in the softmax classifier [17]. The softmax classifier learns the optimal parameter ϑ by learning on all the facial expression samples G, iterating and fitting the facial expression set G continuously.

3. Investigation and Research on Facial Expression Recognition by Deep Convolutional Neural Networks

3.1. Identify the Sample Dataset Settings

Dataset :HTE-AR is a database of 4654 different facial expression images downloaded from the Internet. In this dataset, 4654 images of various expressions were annotated by 20 people with basic expressions and composite expressions, and these annotated images included subsets of 5 basic expression categories and 7 composite expression categories [18]. In the experiment, 5 typical expressions are used to evaluate facial expression recognition. Table 1 describes the distribution of data:

Table 1. Expression data distribution

Expression type	Anger	Sad	Happy	Fear	Calm
Training samples	574	457	236	296	965
Test sample	*369*	*289*	*198*	*207*	*758*

3.2. Identification Parameter Configuration

In this paper, in the process of network training, the random Adam optimizer is used to optimize the network training loss, and the total batch is set as 50 times in the HTE-AR data training. The databases used in this paper have different production standards. Raf-db data set provides cropped 100x100 face pictures. The specific parameter configuration in this experiment is shown in Table 2:

Table 2. Parameter configuration

Parameter item	Parameter value
CPU	Intel(R)UHDGraphics630
Recognition system	WIN10
System environment	PyCharm
System language	Python3.7
Deep learning	FramePytorch1.3
Convolution kernel size	$3\times3\times3\times96=2592$

4. Research on the Application of Deep Convolutional Neural Network to Facial Expression Recognition

4.1. Process Design of Deep Convolutional Neural Network for Facial Expression Recognition

A large number of experimental results show that the recognition framework based on (CNN) can extract facial expression features more effectively. Therefore, using (CNN) for recognition has very important application value. (CNN) The overall process of facial expression recognition is shown in Figure 2:

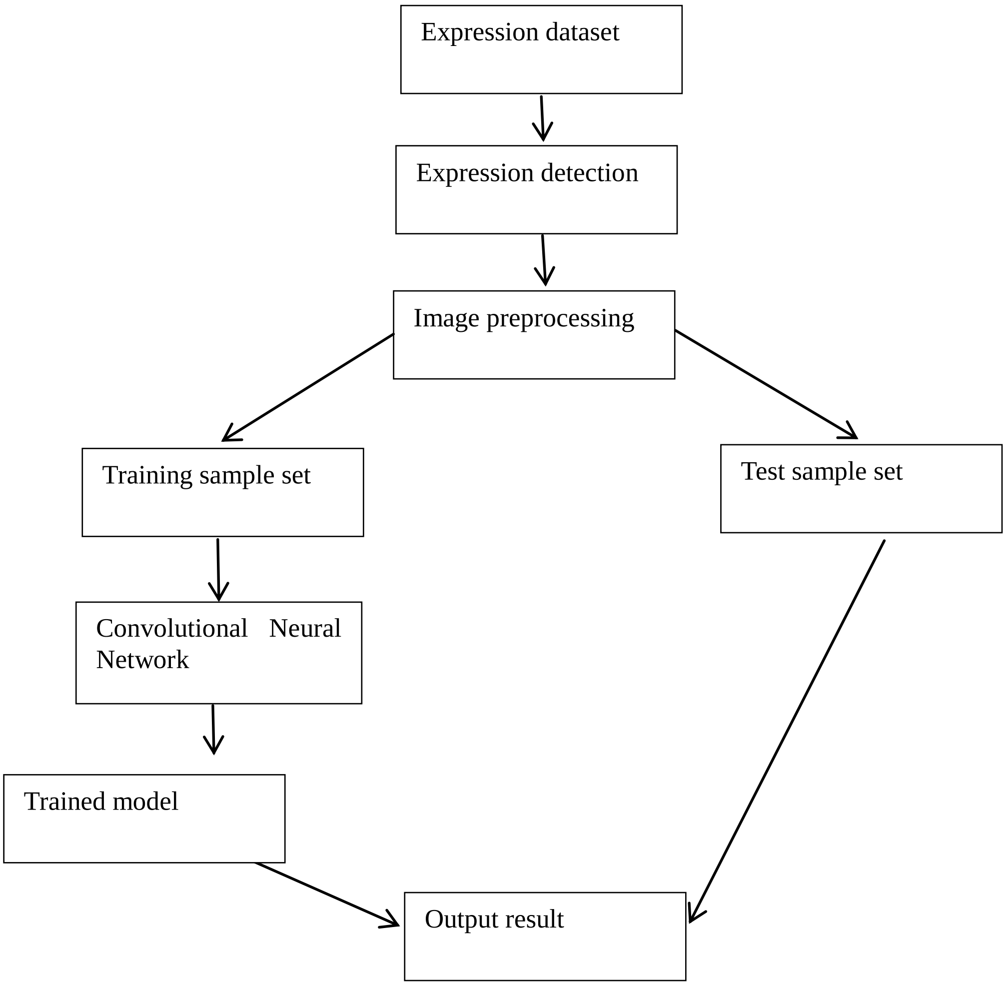

Figure 1. The process of facial expression recognition by deep convolutional neural network

The specific identification process steps are as follows:

(1) Before inputting the convolutional neural network, the original image needs to be trimmed and aligned, thereby reducing the interference caused by the extraction of background information and facial expression features.

(2) Preprocessing the dataset for data enhancement. The methods of data enhancement include: randomly cropping, flipping and rotating the image, which is beneficial to the convolutional neural network to better identify and classify the image.

(3) After the image enters the network, the model parameters will be trained, and the performance of the trained model will be tested in the test module. In the training stage, the image goes through a series of convolutional layers and pooling layers, and the convolutional neural

network generates a feature map with facial expression feature information through convolutional operation. The feature map contains various types of facial expression feature information of each location and units from different feature maps.

(4) The pooling layer will downsample the facial expression feature map to obtain more facial expression features.

(5) The convolutional neural network obtains the final output, and the obtained output features are identified and classified by the classifier, and finally the category probability and label of the image are output.

4.2. Application of Deep Convolutional Neural Network to Facial Expression Recognition

In order to further verify the recognition effectiveness of the proposed algorithm, the technology (CNN) was compared and analyzed experimentally with the other two recognition models of external generative adversarial network (GAN) and long short-term Memory network (LSTM) in the five facial expression sample datasets collected. The specific experimental comparison data are shown in Table 3:

Table 3. Facial expression recognition data

Model	CNN	GAN	LSTM
Anger	95.2%	90.3%	87.9%
Sad	94.9%	89.8%	88.6%
Happy	96.1%	91.7%	90.6%
Afraid	97.2%	92.7%	89.5%
Calm	95.8%	90.5%	88.1%

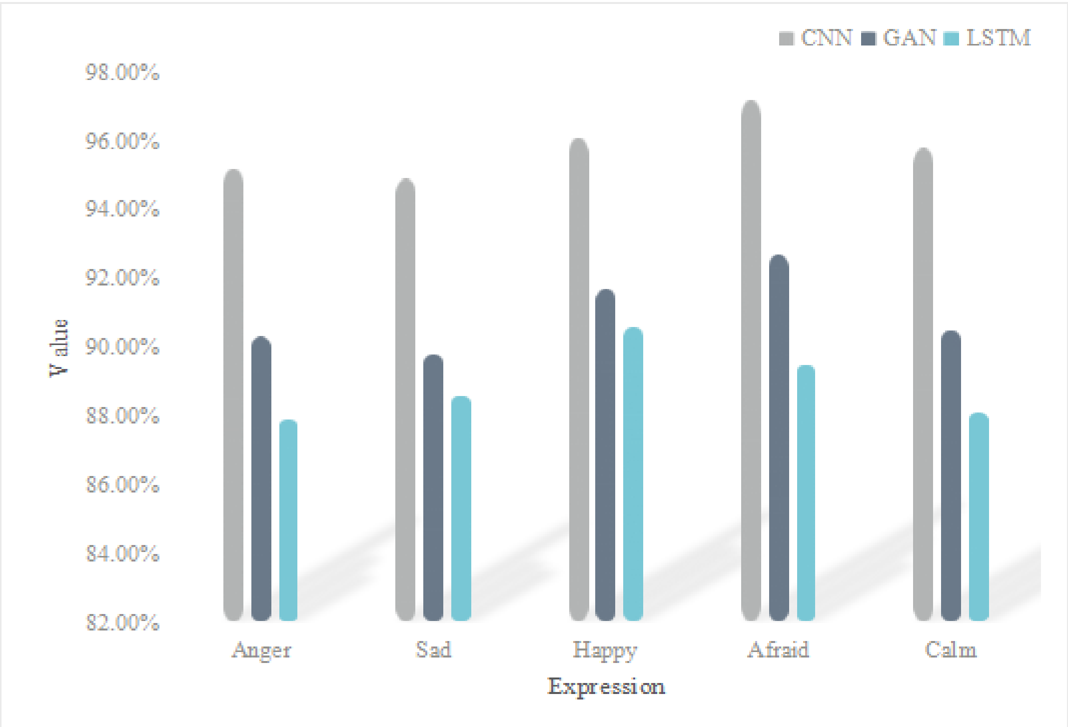

Figure 2. Comparison of facial expression recognition rates

As can be seen from the data in Figure 2, the proposed algorithm (CNN) compares the data results with the other two recognition models of external generative adversarial network (GAN) and long short-term Memory network (LSTM) in the collected five facial expression sample datasets (anger, sadness, happiness, fear and calm). For angry expression recognition, the accuracy of (CNN) reached 95.2%, while the recognition rates of the other two models reached 90.3% and 87.9%, respectively. In the sad expression recognition, the accuracy of (CNN) reached 94.9%, while the accuracy of (GAN) and (LSTM) reached 89.8% and 88.6%, respectively. In the recognition of happy expressions, the recognition rate of the proposed algorithm reaches 96.1%, while the accuracy of (GAN) and (LSTM) respectively reaches 91.7% and 90.6%. In the recognition of fearful expressions, the accuracy of (CNN) reached 97.2%, (GAN) reached 92.7% and (LSTM) reached 89.5%. Finally, in the recognition of calm expression, the accuracy of (CNN) reached 95.8%, and the accuracy of (GAN) and (LSTM) reached 90.5% and 88.1%, respectively. From the above data comparison, it can be seen that the CNN algorithm has the highest accuracy.

5. Conclusion

This paper elaborates on the depth of the convolution neural network technology of facial expression recognition model, contains the softmax classifier function equation and facial expression and the depth of the convolution of the neural network, and the depth (CNN) for facial expression recognition model to build sample data and parameter configuration of the deployment process, at the same time focus on the design depth (CNN) process framework for facial expression recognition. Depth (CNN) was used to compare five facial expressions (anger, sadness, happiness, fear, calm) with (GAN) and (LSTM), which proved the superiority of the information sharing security protection system based on artificial intelligence.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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