# Research on facial emotion recognition model based on alpha-like algorithm and CNN fusion technology

*Hongren Wang**

Dalian University of Technology, Mathematical basic science, 124000 Panjin, China

**Abstract.** This paper studied a facial emotion recognition model based on the fusion technology of Alpha algorithm and Convolutional Neural Network. By combining the spatial feature extraction ability of CNN with the advantages of alpha algorithm in sequence modeling, the performance of emotion recognition model was improved. This paper introduces the theoretical basis of deep learning and reinforcement learning, and proposes a model combining CNN and Alpha-like algorithm. The experimental results show that the accuracy of the fusion model is improved by about 2.1 times in the emotion classification task, especially in the recognition of anger and disgust, which is significantly higher than the traditional algorithm. However, it is also pointed out that the misclassification problem of the model on some complex emotion categories such as surprise and neutral still exists, and the performance of the model needs to be further improved in the future.

## 1 Introduction

The field of face recognition continues to advance with the development of artificial intelligence [1,2]. In the field of face recognition, convolutional neural network (CNN) has become one of the most commonly used technologies in deep learning with its powerful feature extraction capability, and has been widely used in face recognition applications such as identity authentication, security monitoring, and social media [3].

On the other hand, Alpha algorithms based on the Hidden Markov model (HMM) and its variants perform well in sequential data processing [4], but have limited application in face recognition [5]. Many researchers have tried to combine HMM and long short-term memory networks (LSTM) to improve the performance of emotion recognition models [4,6,7]. However, there are still many challenges in the various expressions, occlusion, light changes and subtle emotional expression, as well as the accuracy of the model [8,9]. Therefore, how to combine the deep feature extraction capability of CNN with Alpha algorithm to improve the performance of facial emotion recognition model has become an important direction of current research.

*13796487571@mail.dlut.edu.cn

# 2 Theoretical research

## 2.1 Deep learning

CNN first extracts the features of the input data layer by layer and performs nonlinear transformations to identify complex patterns. Extract and high-level semantic information by using multi-layer convolution and pooling operations to generate feature maps. Finally, the feature mapping is planar as a vector and passed to the fully connected layer for classification (1)[10].

$$\mathrm{Conv}(I, K) = (I * K)(x, y) = \sum_{m} \sum_{n} I(x + m, y + n) \cdot K(m, n) \tag{1}$$

where $I$ represents the input image, $K$ represents the convolution kernel, $x, y$ are the coordinates of the output feature map, and $m, n$ are the coordinates of the convolution kernel [11].

## 2.2 Reinforcement learning

In reinforcement learning, strategy network and value network are used to guide agent's behavior choice and evaluate the potential value of the current state respectively [12]. Monte Carlo tree Search (MCTS) is an important strategy evaluation method, which is combined with decision network and value network, and is widely used in alpha-like algorithms such as AlphaGo and AlphaZero [6]. There are four main stages: selection, extension, simulation, and backpropagation [7]. In this process, the Upper Confidence Bounds applied to Trees (UCT) (2,3) selection criteria were used [13]. MCTS then estimates the potential value of each action by simulating a series of possible future actions through search tree propulsion [14].

$$a_t = \arg \max_{a \in A(s_t)} \left( \frac{W(s_t, a)}{N(s_t, a)} + U(s_t, a) \right) \tag{2}$$

Where， $W(s_t, a)$ is the accumulated value of simulations for action $a$ in state $s_t$,$N(s_t, a)$ is the number of times action $a$ was visited in state $s_t$,$U(s_t, a)$ is an exploration term, typically calculated as:

$$U(s, a) = c_{\text{puct}} P(s, a) \frac{\sqrt{\sum_b N(s, b)}}{1 + N(s, a)} \tag{3}$$

Where， $P(s, a)$ is the prior probability of selecting action $a$ in state $s$ (given by the neural network),$c_{\text{puct}}$ is a constant that controls the balance between exploration and exploitation.

# 3 Methods and models

### 3.1 Mathematical preprocessing process

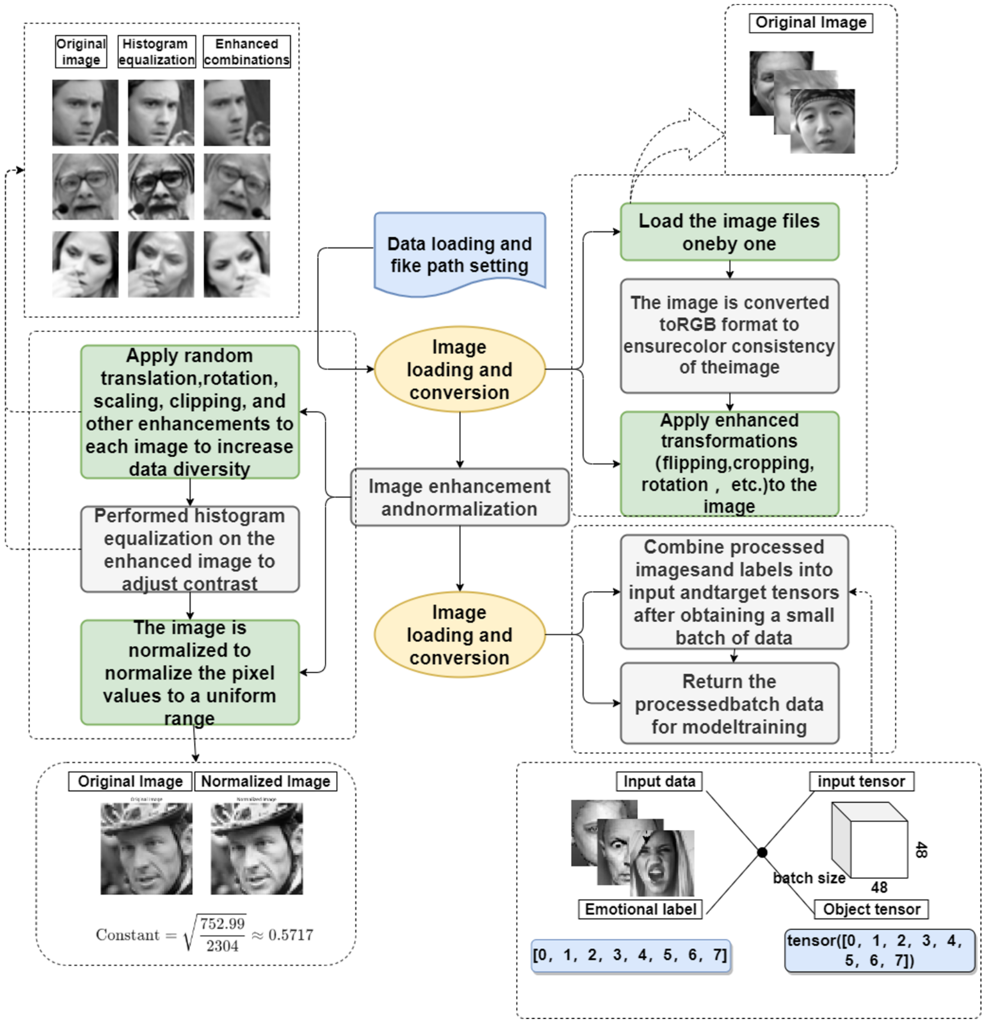


**Fig. 1.** Mathematical preprocessing process

When processing FER+ dataset (Fig. 1.), the training set is divided into 28207 blocks and the test set is divided into 3134 blocks, the CSV file is loaded to obtain the picture filename and label information, and the full path of the picture is set. Load the image and convert it to RGB format, then apply data augmentation operations on it such as translation, rotation, scaling and cropping to increase the diversity of the data. On this basis, histogram equalization processing is performed on the image to improve the contrast and reduce the influence of illumination changes.

Finally, the image is normalized and the pixel value range is standardized to ensure the stability of the data during the training process. At the same time, according to the majority model, the sentiment category with the most votes in the labeled data is selected as the final label. The above processed images and labels are provided to the model training in the form of batch processing, which ensures the high quality and diversity of the input data, thus effectively improving the generalization ability and training effect of the model.

### 3.2 Algorithm combination: model design method

In the CNN model (Fig.2.), the decision network and the value network share three convolutional layers. The first convolutional layer (Conv1) has 64 output channels, the convolution kernel size is 3x3, and is accompanied by BatchNorm1 and MaxPool1. The second convolution layer (Conv2) has 128 output channels, also accompanied by batch normalization layer (BatchNorm2) and maximum pooling layer (MaxPool2). The third convolutional layer (Conv3) with 256 output channels is also accompanied by batch normalization layer (BatchNorm3) and maximum pooling layer (MaxPool3). The fully connected layer of the decision network and the value network linearly transforms each element of the input with the weight matrix respectively (4), and then adds a bias term. Then the ReLU activation function (5) is used in the middle layer (hidden layer) to enable the model to learn the features of more complex emotional changes.

$$y = \mathbf{W}x + \mathrm{b} \tag{4}$$

$$Re\,LU(x) = \begin{cases} 0, \mathrm{if}^{x} < 0 \\ x, \mathrm{if}\,x \geq 0 \end{cases} \tag{5}$$

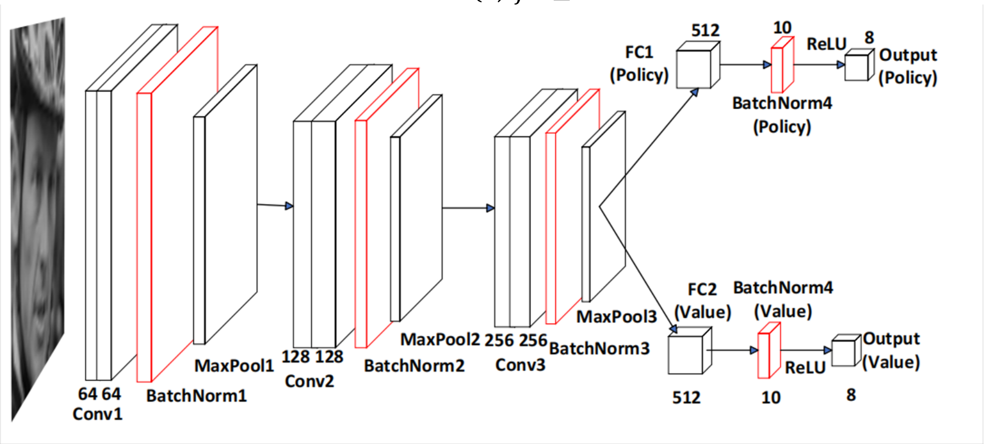


**Fig. 2.** EmotionModel (CNN model)

In the policy network, a 512-dimensional vector is mapped to an 8-dimensional output vector, where the value of each dimension represents the score or propensity of the corresponding sentiment category. The input data are linearly transformed and then these scores are normalized to a probability distribution through the Softmax activation function (6) to ensure that the scores of all categories sum to 1, making it suitable for multi-category classification tasks. In the value network, the feature vector of 512 dimensions is input to the output layer, which is mapped to a scalar value through another linear layer, and the Tanh activation function (7) is used to limit the value between $[-1,1]$, and finally the confidence degree of the emotion classification result representing the output is obtained.

$$y_i = \frac{\mathrm{e}^{zi}}{\sum_{j=1}^{n} \mathrm{e}^{z} j} \quad for\ i = 1,2,\ldots,n \tag{6}$$

$$\mathrm{Tanh(x)} = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{7}$$

As shown in Fig. 3., after the trained EmotionModel outputs data, MCTS uses the output of EmotionModel to initialize the root node of the search tree, and then computes the UCT value. The child node $S_2$ with the highest potential is selected for expansion, and the UCT value combines the number of visits and value evaluation of the node as well as the output probability of the decision network. The probability distribution of the output of the decision network makes the emotion classification path with higher probability more likely to be

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selected. The decision network runs on the selected node $S_2$ and outputs a probability distribution, which is used to guide MCTS how to select the next child node to be expanded. The distribution will be further expanded to generate new child nodes $S_{3,1}$and$S_{3,2}$. Each child node represents possible emotion classification. The value network is used to simulate and evaluate each new node $S_{3,1}$ and$S_{3,2}$, in order to predict the expected emotion classification that can be obtained by continuing the search along a specific path from the current node. The value network outputs a value for each extension node to represent classification confidence. The simulated value will be transmitted layer by layer from leaf nodes$S_{3,1}$ and $S_{3,2}$. At each passed node, MCTS will update the number of visits and total value of the node, helping MCTS adjust and optimize the future selection path, and effectively improve the accuracy and robustness of face emotion recognition.

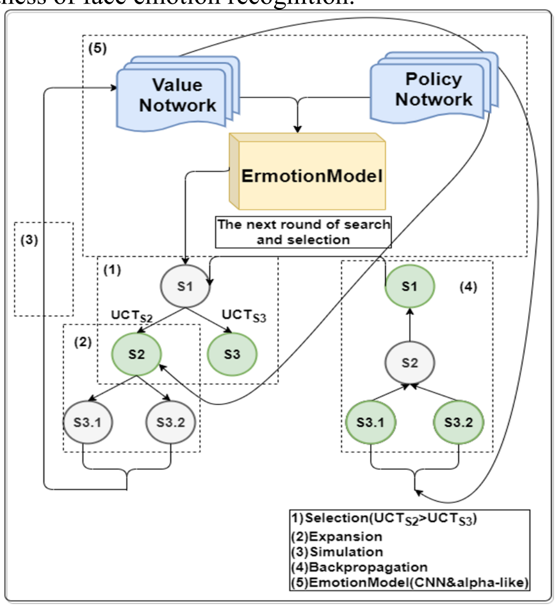



**Fig. 3.** Alpha-like algorithm and CNN combined model

## 4 Results

### 4.1 Comparison of accuracy between training and validation sets

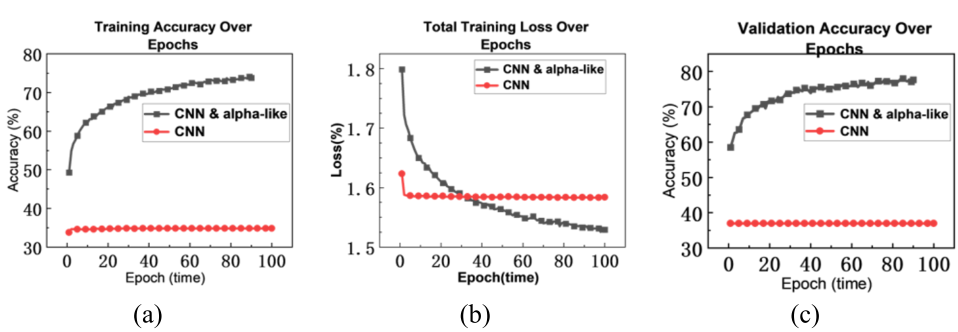
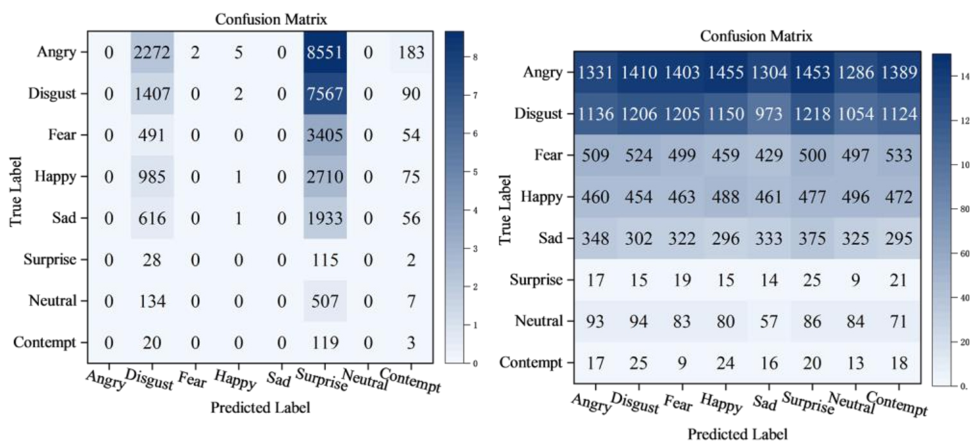



**Fig. 4.** data Comparison (a)Training Accuracy (b) Total Training Loss (c)Validation Accuracy

In the Fig. 4., as can be seen from Figure (a), the validation accuracy of the CNN model using the alpha-like algorithm shows higher accuracy and stronger learning ability, which is about 2.1 times higher than that of the traditional model. The accuracy of the CNN model of the alpha-like algorithm quickly improved from 50% to 75%, while the traditional CNN barely improved during the whole training process. In Figure (b), the loss of the CNN model of the alpha-like algorithm decreases significantly in the early stage, while the loss of the traditional CNN decreases slowly and the final loss value is higher, which indicates that the performance of the traditional model in complex emotion recognition tasks is worse than that of the alpha-like algorithm. As can be seen from Figure (c), the combination of alpha-like algorithm and reinforcement learning can effectively improve the generalization ability of the model. The validation accuracy of the CNN model based on Alpha-like algorithm gradually improves with the increase of training times, and finally stabilizes at about 80%. However, the verification accuracy of traditional CNN is almost unchanged in the whole training process, and it cannot effectively learn the classification of complex emotions.

## 4.2 Fuzzy processing




(a) (b)

**Fig. 5.** (a)No MCTS Confusion Matrix (b)Confusion Matrix With MCTS

In the Fig. 5., by comparing the performance of the confusion matrix in (a) and (b), it can be seen that there are obvious differences in the ability of the model to recognize different emotional categories. A model confusion matrix with MCTS predictions has a more balanced performance across most emotional categories (such as "anger" and "disgust"), with a relatively high number of correct categories, while on a few data categories (such as "surprise" and "contempt"), the model is slightly less influenced by a limited number of potentially limited data. However, the model performance of the confusion matrix of the traditional model is extreme, and a large number of samples of the emotion category are misclassified as "surprised", which indicates that the model is too sensitive to this category, and even causes samples of other categories to be misclassified as "surprised". Meanwhile, the "happy" and "disdainful" categories were barely classified correctly, suggesting that the model was very poor at recognizing these categories. This shows that the MCTS prediction model has more balanced performance than the traditional model.

### 4.3 Smoothness analysis of model policy outputs

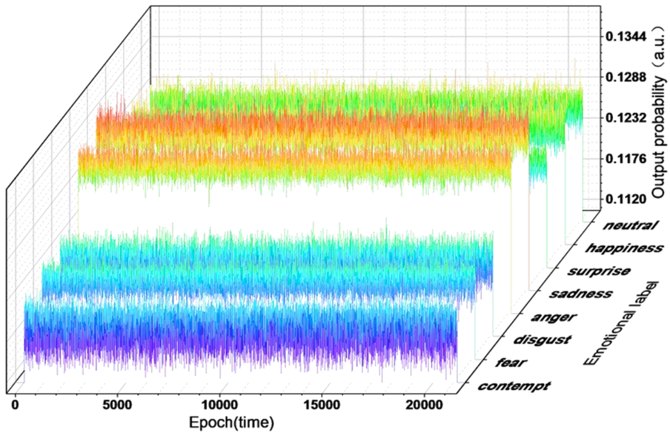



**Fig. 6.** Policy output probability

The results (Fig. 6.) show that the CNN model using the alpha-like algorithm has stable strategy selection on most samples, and some strategies have higher priority than others.

## 5 Conclusion

In summary, we use the CNN model to extract spatial features from image data, and combine with the sequence modeling ability of alpha-like algorithm to finally improve the performance of emotion classification model. In the experimental results, compared with the traditional CNN model, the accuracy of the model based on CNN and alpha-like algorithm is improved by about 2.1 times, the classification error of the model is reduced, the prediction is more balanced and the strategy selection is stable. Although this study has made significant progress in facial expression recognition, the model still has certain classification errors in some complex emotional categories such as surprise and neutral, and future research can increase the amount of data and incorporate multiple modes to further improve the model's performance.

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