Efficient facial emotion recognition model using deep convolutional neural network and modified joint trilateral filter

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Abstract

Facial emotion recognition extracts the human emotions from the images and videos. As such, it requires an algorithm to understand and model the relationships between faces and facial expressions, and to recognize human emotions. Recently, deep learning models are extensively utilized enhance the facial emotion recognition rate. However, the deep learning models suffer from the overfitting issue. Moreover, deep learning models perform poorly for images which have poor visibility and noise. Therefore, in this paper, a novel deep learning based facial emotion recognition tool is proposed. Initially, a joint trilateral filter is applied to the obtained dataset to remove the noise. Thereafter, contrast-limited adaptive histogram equalization (CLAHE) is applied to the filtered images to improve the visibility of images. Finally, a deep convolutional neural network is trained. Nadam optimizer is also utilized to optimize the cost function of deep convolutional neural networks. Experiments are achieved by using the benchmark dataset and competitive human emotion recognition models. Comparative analysis demonstrates that the proposed facial emotion recognition model performs considerably better compared to the competitive models.

Keywords: Image, Emotions, Neural networks, Labeling, Deep learning

1. Introduction

Extracting visual information from images is one of the fundamental skills of human intelligence [1]. With the advancement in artificial intelligence, it is assumed that robots can understand the feelings of human beings. However, recognizing emotions in an efficient manner is defined as ill-posed problem [2]. Human emotions can be recognized by considering various methods such as face recognition, speech recognition, physiological signals, etc. Speech and facial expressions are the natural methods to recognize emotions [3]. Many emotion recognition techniques are designed and implemented in the literature to recognize human emotions [4]. In this paper, our main concentration is to recognize the facial emotions.

The objective is to recreate a similar level of intellectual ability in artificial intelligence, which has motivated researchers from computer vision and natural language communities to design automatic emotion

recognition systems [5]. Facial emotion recognition represents the content of an input image in the form of human emotions by using various machines and deep learning models [6]. Thus, it initially extracts the face information and thereafter, it provides a descriptive emotion [7]. Recently, many Convolutional Neural Networks (CNN) and Recurrent Neural Network (RNN) based emotion recognition models have been designed and implemented [8].

Li and Deng [9] proposed Artificial neural network (ANN) model to recognize facial emotions. Zhang et al. [10] designed spatial-temporal recurrent neural network to recognize facial emotions. Kim et al. [11] used hierarchical deep learning (HDL) to extract adaptive facial features to obtain better results.

From the existing literature, it has been found that the Decision tree (DT) [12, 13], Support Vector Machine (SVM) [14, 15], Random Forest (RF) [16, 17], and Artificial Neural Network (ANN) [9] are commonly utilized to recognize the human emotions. Jain et al. (2019) [18] designed deep neural networks (DNNs) using deep residual blocks. Wang et al. (2020) [19] combined CNN and RNN (CCNNRNN) to classify the human emotions. Arpita et al. (2020) [20] implemented a ResNet and attention block (CRAB) based human emotion recognition model. Lakshmi et al. (2021) [21] implemented a modified histogram of oriented gradients (HOG) and local binary pattern (LBP), i.e., HOGLBP to extract the features. Although these methods achieve good performance, but suffer from the overfitting issue. Moreover, these models perform poorly for images which have poor visibility and noise.

The main contributions of this paper are as follows:

1. A novel deep learning based facial emotion recognition tool is proposed.
2. The joint trilateral filter is applied on the obtained dataset to remove the noise.
3. Contrast limited adaptive histogram equalization (CLAHE) is applied to the filtered images to improve the visibility of images.
4. Nadam optimizer is also utilized to optimize the cost function of deep convolutional neural networks.
5. Experiments are considered by using the benchmark dataset and competitive human emotion recognition models.

The remainder of the paper is structured as follows: Section 2 discusses the related work. Section 3 mathematically defines the proposed model. Comparative results are discussed in Section 4. Concluding remarks are presented in Section 5.

2. Related work

Hung et al. [22] used multilevel transfer learning based on a fine-tune approach to recognize facial emotion. Lakshmi et al. [23] recognized facial emotion by utilizing Whale optimization algorithm (WOA) and teaching-learning-based optimization (TLBO). In this, Multi-Support Vector Neural Network (MultiSVNN)

was used to build the model based on WOA and TLBO. Liu et al. [24] captured human facial emotions using multi-channel electroencephalography (EEG) signals and textual feature fusion method. Using both
45 frequency and spatial domains, features were extracted. The model was trained using the SVM to recognize the facial emotions. Ngai et al. [25] enhanced facial recognition using 2-channel EEG and eye modality. CNN model was used to recognize and classify facial emotions.

Zhang et al. [26] proposed a model to recognize facial emotions using the correlation emotion label distribution learning. The six basic facial expressions were learned using a constructed convolutional neural
50 network. Chen et al. [27] recognized the facial emotions by applying a softmax regression model. In this, facial expressions were learned through a deep sparse autoencoder network. It overcomes the issues such as gradient diffusion and local extrema in training of a model. Tan et al. [28] recognized facial expression using EEG and multimodal emotion recognition method. The issue of small dataset was resolved using Monte Carlo strategy that further improved the results. In this, recognition rate was achieved near to 83.33%.

Wang et al. [19] fused speech features and facial expressions using bimodal fusion method to recognize
55 human emotion. The facial emotions were recognized by combining RNN and CNN. The speech emotions were captured using CNN and LSTM. After that, facial and speech emotions were fused using a weighted decision fusion method. Li et al. [29] applied ResNet-50 to capture the facial emotions of humans. This helped to improve the robustness and generalization ability of the recognition models. Lakshmi et al. [21]
60 proposed hybrid model to recognize facial emotions. In this, face regions were selected through Viola-Jones method. Then, the required features are extracted from selected regions using local binary pattern and histogram of oriented gradients. Deep stack auto encoder was utilized to reduce the dimensionality of extracted features. Lastly, Multi-class SVM was applied to recognize and classify the emotions.

Deng et al. [30] recognized the facial emotions using Conditional generative adversarial network-based
65 approach (cGAN). Zhang 9187342 used a multimodal face recognition model with EEG and deep automatic encoder. The objective features were selected using a decision tree. Du et al. [31] detected the emotions of players using facial expression and heart beat signals. Heart rate signals were learned through Bidirectional long and short term memory (Bi-LSTM) networks. Facial features were learned via CNN. Li et al. [32] recognized the continuous emotions by combining the facial expression and EEG. Choi et al. [33] used
70 metric learning to recognize the continuous emotions. Hua et al. [34] used ensemble deep learning model to recognize facial expressions. Choi et al. [35] utilized 2-D landmark feature map to recognize facial micro-expression.

From the related work, it has been observed that the majority of the existing methods achieve good performance, but suffer from the overfitting issue. Additionally, the existing models perform poorly for
75 images which have poor visibility and noise.

3. Proposed methodology

In this paper, a novel deep convolutional neural network model is proposed to recognize the human emotions from facial images. The proposed model can dynamically focus on the salient features in the images during the training process. Initially, the joint trilateral filter is applied to the obtained dataset to remove the noise. Thereafter, CLAHE is applied to the filtered images to improve the visibility of images. Finally, a deep convolutional neural network is used for training the emotion recognition model. Nadam optimizer is also utilized to optimize the cost function of deep convolutional neural networks.

3.1. Modified joint trilateral filter

To remove the noise from images, a modified joint trilateral filter is proposed. It is an edge preserving filter which does not introduce various types of artifacts on the filtered images. Initially, a guided image G_d i.e., the actual image I_κ itself is considered. Assume that I_{val} and G_{val} are the illumination values at pixel q and the guided image. W_r is a kernel window at k dependent on the bilateral filter [36, 37]. The modified joint trilateral filter can be defined as:

$$J_{tf}(I_\kappa) = \frac{1}{\sum_{q \in K_r} M_\theta^{pq}(G_d)} \left(\sum_{q \in K_r} M_\theta^{pq}(G_d) \times I_q \times \sigma^2(I_q, G_d) \right) \quad (1)$$

Here, the kernel weight function ($M_\theta^{pq}(G_d)$) can be evaluated as:

$$M_\theta^{pq}(G_d) = \frac{1}{|n|^2} \sum_{n:(p,q) \in k_r} \left(1 + \frac{(G_{dp} - \mu_n)(G_{dq} - \mu_n)}{\sigma_n^2 + \epsilon} \right) \quad (2)$$

Here, μ_n and σ_n^2 show the mean and variance of G_d in the local window k_r . $|n|$ defines the total number of pixels in window. When G_{dp} and G_{dq} are on the identical sides of an edge, the weight assigned to pixel q is maximum. When G_{dp} and G_{dq} are on diverse sides, a minimum weight can be assigned to the pixel q .

3.2. Contrast limited adaptive histogram equalization

Reducing the effect of numerous lighting circumstances is a nontrivial issue in the field of image processing. The precision of emotion recognition is generally low if the visibility of the face changes. However, the standard histogram equalization based approaches are not effective for uneven lightening conditions as they may result in overenhanced images [38]. CLAHE has the ability to overcome the excessive amplification of noise by limiting the contrast. It can be implemented as follows:

$$f(D) = (1 - \omega y)((1 - \omega x)f_{ul}(D) + \omega x f_{bl}(D)) + \omega y((1 - \omega x)f_{ur}(D) + \omega x f_{br}(D)) \quad (2)$$

For every pixel, the mapping of four adjacent values of the histogram cumulative distribution function (CDF) to the pixel are desirable. ωx and ωy show the distance between pixels and the center of the left upper mask.

3.3. Deep convolutional neural network

Recently, CNN models have been extensively utilized to classify the computer vision problems [39, 40]. Various filters are utilized to compute potential features. Therefore, it achieves better performances than the handcrafted features. Figure 1 represents an CNN model. Remaining section discusses the CNN model layers.

Figure 1: Diagrammatic flow of CNN model

3.3.1. Convolutional layers

These layers are responsible for extracting the visual features automatically by utilizing various kinds of filters at each layer. Nodes of every layers transmit extracted features to proceeding layers to obtain better features [39, 40].

Every layer evaluates a new feature map. The value of feature $y_{ij} \in k^{th}$ feature map can be computed as:

$$Z_{ab,L} = \sum (\omega_L \odot u_{ab}) + d_L \quad (3)$$

Here, d_L and ω_L show the bias and average values of L^{th} mask. Input mask located at (a, b) is represented using u_{ab} . Hadamard product between matrices are represented using $\odot$. Computed coefficients are transmitted to proceeding nodes to reduce the complexity of CNN.

Figure 2: Convolutional layer process.

3.3.2. Nonlinear layer

This layer utilizes an activation function to handle all the nonlinear dependencies of the feature maps. An improved average biased ReLU (for details please see [41]) activation function is utilized in this paper.

3.3.3. Pooling layer

This layer has no direct weight, it attempts to achieve shift invariance by reducing the size of feature maps by using the activation properties of the local range of CNN. Maximum and average operations are utilized to implement the pooling layer. It considers $k \times L$ mask and computes a distinct value. For $M \times M$ layer, the output is a $\frac{M}{L} \times \frac{M}{L}$ layer.

3.3.4. Fullyconnected layers

Fullyconnected layers use high-level reasoning. Every input-output pair has connections with all the activations in the succeeding layer. Their activations can be evaluated with a matrix multiplication followed by a bias offset.

3.3.5. Loss layer

This layer is utilized to compute the trained emotion recognition model. For emotion recognition, a softmax activation function is used. Mathematically, loss can be computed as:

$$k = \frac{1}{M} \sum_{m=1}^M \ell(\theta; \mathbf{z}^{(m)}, \mathbf{Q}^{(m)}) \quad (4)$$

125 Here, θ shows parameters of CNN model like kernel and bias operators. To compute M sets, $\mathbf{z}^{(a)}$ is a target class composing a^{th} input and $\mathbf{Q}^{(a)}$ represents the output of CNN.

3.4. Nadam optimizer

Nadam optimizer is utilized to optimize the cost function $k(\theta)$ in Algo. 1. β_1 — is utilized for decaying the mean of gradient. β_2 — is utilized for decaying the mean of the square of gradient. α is a step size. ϵ — is utilized to avoid division from 0 error. $f(\theta)$ is a stochastic objective function with θ parameter. θ_0 is an initial attribute vector. m_0 and v_0 represent 1^{st} and 2^{nd} vector, respectively. t defines the timestamp. g_i computes the gradients by considering the stochastic objective at t . m_i and v_i store the computed biased 1^{st} and 2^{nd} moment values, respectively. $\widehat{m}_i$ and $\widehat{v}_i$ store the evaluated bias-corrected 1^{st} and 2^{nd} moment estimates, respectively.

Algorithm 1: Nadam optimizer

Input: $\alpha, \beta_1, \beta_2 \in (1, 0]$, $f(\theta)$, and θ_0
 $m_0 \leftarrow 0$
 $v_0 \leftarrow 0$
 $t \leftarrow 0$
while θ_i not converged **do**
 $t \leftarrow t + 1$
 $g_i \leftarrow \delta_\theta f_i(\theta_{t-1})$
 $m_i \leftarrow \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_i$
 $v_i \leftarrow \beta_2 \cdot v_{t-1} + (1 - \beta_2) \cdot g_i^2$
 $\widehat{m}_i \leftarrow m_i / (1 - \beta_1^t)$
 $\widehat{v}_i \leftarrow v_i / (1 - \beta_2^t)$
 $\theta_i \leftarrow \theta_{t-1} - \alpha \cdot \widehat{m}_i / (\sqrt{\widehat{v}_i} + \epsilon)$
 return θ_i
end

135 4. Comparative analysis

We first evaluate the proposed model on the CK+ [42] facial emotions dataset [43], which is the most commonly used test bed for emotion recognition. Some examples of the CK+ dataset are shown in Figure 3. Here, we can see that we have multiple numbers of emotions, but we have considered only seven features to train and test the proposed model. The selected features are as Happiness Surprise, Anger Disgust, Happiness Surprise, Fear Anger, Neutral Sadness, Fear Happiness, Anger Sadness and all other classes. These classes are labeled from 0 to 6, respectively.

The experiments are done in MATLAB 2013a on Intel core i7 processor with 16-GB RAM. Some well-known competitive models such as DNNs [18], CCNNRNN [19], CRAB [20], HOGLBP [21], DLP-CNN [9], and HDL [11] are considered for experimental purpose.

Figure 3: Human facial emotions

145 4.1. Performance metrics

In this section, various confusion matrix-based quality metrics are discussed.

4.1.1. Accuracy analysis

It evaluates the ratio of the total number of correctly recognized emotions over the actual number of emotions. The accuracy (A_c) can be defined as:

$$A_c = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \times 100 \quad (5)$$

Here, T_p , T_n , F_p , and F_n define true positive, true negative, false positive, and false negative values, respectively. $A_c \in [0, 100]$. A_c is desirable to be 100.

150 4.1.2. F-measure analysis

Accuracy is not an effective measure for an imbalanced dataset. Thus, f-measure is utilized to compute the weighted mean among precision (p) and recall (r). Therefore, it utilizes the values of both false positives and negatives. Mathematically, F-measure can be computed as:

$$F - measure = 2 * \frac{r * p}{r + p} \quad (6)$$

where p can be evaluated as:

$$p = \frac{T_p}{T_p + F_p} \quad (7)$$

r can be computed as:

$$r = \frac{T_p}{T_p + F_n} \quad (8)$$

F1 Score needs to be maximized.

4.1.3. Kappa statistic

Cohen's kappa statistic (κ) is a performance metric which computes the inter-rater precision (i.e., reliability) between True (T) and Negative (N) classes. Inter-rater precision is considered if your data raters provide a similar score to the same data item such as emotions in this research work. κ is a more efficient measure than the simple percent agreement computation. $\kappa \in [0, 1]$ and should be maximum.

4.2. Quantitative analysis

Figure 4 demonstrates the comparative analysis of accuracy and loss curve. The best accuracy and lesser loss is obtained during the 8th epoch and 47th iteration. Thus, the proposed facial emotion recognition model convergence at good speed.

Figure 4: Comparative analysis of the proposed model

Figures 6 and 6 represent the confusion matrix of all classes of human emotions by using the proposed model with and without using CLAHE and joint trilateral filter. Since it is found that the there are majority

of true positive and negative classes. Thus, the proposed model is least affected from the over-fitting issue.

165 In Figure 6, diagonal values represent the true and negative classes. Assume that class 0 is our true class, that means all other classes from 1 to 6 come under negative classes. Here, the value 27 in Figure 6 at coordinate (0,0) indicates the True positive (T_p) class, whereas the sum of all other diagonal classes shows the true negative (T_n) class. Similarly, all vertical values represent the corresponding false values. Therefore, in this figure, when we assume the target class as anger, then we have false positives (F_p)= 0 and false negatives
170 (F_n)= 0. Overall, analysis indicates that the proposed model with without joint trilateral filter and CLAHE obtains better performance as compared to without the use of joint trilateral filter and CLAHE.

Output Class	anger	26 13.3%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
	contempt	0 0.0%	11 5.6%	0 0.0%	0 0.0%	0 0.0%	1 0.5%	1 0.5%	84.6% 15.4%
	disgust	0 0.0%	0 0.0%	35 17.9%	0 0.0%	0 0.0%	1 0.5%	0 0.0%	97.2% 2.8%
	fear	0 0.0%	0 0.0%	0 0.0%	9 4.6%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
	happy	0 0.0%	0 0.0%	0 0.0%	3 1.5%	41 20.9%	0 0.0%	0 0.0%	93.2% 6.8%
	sadness	1 0.5%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	15 7.7%	0 0.0%	93.8% 6.2%
	surprise	0 0.0%	0 0.0%	0 0.0%	3 1.5%	0 0.0%	0 0.0%	49 25.0%	94.2% 5.8%
		96.3% 3.7%	100% 0.0%	100% 0.0%	60.0% 40.0%	100% 0.0%	88.2% 11.8%	98.0% 2.0%	94.9% 5.1%
		anger	contempt	disgust	fear	happy	sadness	surprise	
		Target Class							

Figure 5: Confusion matrix of the proposed model without joint trilateral filter and CLAHE on emotion recognition's dataset

Figures 7 to 11 demonstrate the notched boxplots analysis of the proposed model in terms of various performance metrics. The median of the evaluated parameters is demonstrated using red color. The confidence interval approaching towards median is represented using the notch of boxplot.

175 The accuracy analysis of the designed facial emotion recognition model is represented in Figure 7. The proposed facial emotion recognition model achieve better performance than the existing emotion recognition models. The proposed facial emotion recognition model achieves better accuracy values than the competitive models by 1.7382%.

The precision analysis of the designed facial emotion recognition model is represented in Figure 8. The

Output Class	anger	27 13.8%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
	contempt	0 0.0%	11 5.6%	0 0.0%	0 0.0%	0 0.0%	2 1.0%	1 0.5%	78.6% 21.4%
	disgust	0 0.0%	0 0.0%	35 17.9%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
	fear	0 0.0%	0 0.0%	0 0.0%	9 4.6%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
	happy	0 0.0%	0 0.0%	0 0.0%	3 1.5%	41 20.9%	0 0.0%	0 0.0%	93.2% 6.8%
	sadness	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	15 7.7%	0 0.0%	100% 0.0%
	surprise	0 0.0%	0 0.0%	0 0.0%	3 1.5%	0 0.0%	0 0.0%	49 25.0%	94.2% 5.8%
		100% 0.0%	100% 0.0%	100% 0.0%	60.0% 40.0%	100% 0.0%	88.2% 11.8%	98.0% 2.0%	95.4% 4.6%
		anger	contempt	disgust	fear	happy	sadness	surprise	
		Target Class							

Figure 6: Confusion matrix of the proposed model with joint trilateral filter and CLAHE on emotion recognition dataset

Figure 7: Accuracy analysis of the proposed facial emotion recognition model

Figure 8: Precision analysis of the proposed facial emotion recognition model

180 proposed facial emotion recognition model achieve better precision than the existing emotion recognition models. The proposed facial emotion recognition model achieves better precision values than the competitive models by 1.3749%.

Figure 9: Recall analysis of the proposed facial emotion recognition model

The recall analysis of the designed facial emotion recognition model is represented in Figure 9. The pro-

posed facial emotion recognition model achieve better recall than the existing emotion recognition models. The proposed facial emotion recognition model achieves better recall values than the competitive models by 1.5823%.

Figure 10: F-measure analysis of the proposed facial emotion recognition model

The f-measure analysis of the designed facial emotion recognition model is represented in Figure 10. The proposed facial emotion recognition model achieve better f-measure than the existing emotion recognition models. The proposed facial emotion recognition model achieves better f-measure values than the competitive models by 1.4827%.

The kappa statistics analysis of the designed facial emotion recognition model is represented in Figure 11. The proposed facial emotion recognition model achieve better kappa statistics than the existing emotion recognition models. The proposed facial emotion recognition model achieves better kappa statistics values as compared to the competitive models by 1.7382%.

5. Conclusion

It has been observed that the existing facial emotion recognition models suffer from the overfitting issue. Moreover, these models perform poorly for images which have poor visibility and noise. To handle these problems, a novel deep learning based facial emotion recognition tool was designed. Initially, a joint trilateral filter was implemented on the CK+ facial emotions dataset to remove the noise from images. Thereafter, CLAHE was implemented on the filtered images to improve the visibility of images. Finally, the deep convolutional neural network was trained. Nadam optimizer was also used to optimize the cost function of deep

Figure 11: Kappa statistics analysis of the proposed facial emotion recognition model

convolutional neural networks. Extensive experiments were considered by using the CK+ facial emotions dataset. The performance of the proposed technique was compared with the competitive human emotion recognition model. Comparative analysis has demonstrated that the proposed facial emotion recognition model achieves better results than the competitive models in terms of precision, accuracy, recall, f-measure, and kappa by 1.3749 %, 1.7382 %, 1.5823%, 1.4827 %, and 1.4563 %, respectively.

Availability of data and materials

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Author Contributions

Naveen Kumari: Conceptualization, Formal analysis, Investigation, Methodology, Validation, Visualization, and Original draft preparation.

Rekha Bhatia: Project administration, Resources, Software, Supervision, Review and editing of the manuscript.

Competing Interests

The authors declare that they have no competing interests.

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