A fusion convolution neural network-local binary pattern histogram algorithm for emotion recognition in human

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Article Info

Article history:

Received Jun 9, 2024
Revised Jun 14, 2025
Accepted Jul 10, 2025

Keywords:

Convolutional neural network
Emotion recognition
Human
Image analysis
Linear binary pattern histogram

ABSTRACT

This paper proposes a fusion of algorithms namely convolution neural networks (CNN) and local binary pattern histogram (LBPH) techniques to comprehend the emotions in humans for greyscale images. In this work, the combined advantages of CNN for its ability to extract features, suitability for image processing and LBPH algorithm to identify the emotions of the human images are included. Though there are enhanced fused algorithms with CNN for image processing, the combination of LBPH with CNN is precise and simple in design. In this work, the secondary data sample is used to recognize the human emotions. The secondary data set consists of 160 samples with emotions of happy, anger, sad, and surprise is considered for making decisions. In comparison, the accuracy of the proposed method is high compared to the other algorithms.

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1. INTRODUCTION

Human emotion identification is a key area of research after the era of smart generation. Most AI-based smart applications use the human face identification system to authenticate, interact, or validate its purpose. Though machine learning and deep learning algorithms are utilized for image recognition, the linear binary pattern histogram (LBPH) is preferred for the feature extraction of the human face as it involves binary number manipulation with its histogram.

The human face image is transformed to wayang orang image using the unsupervised generative attentional network with adaptive layer-instance normalization image translation. This method considers the background along with the human face for its translation [1]. Automatic face recognition is attained using the modify bidirectional associative memory algorithm that extracts the human face features for the sake of identification [2]. The emotion of humans and the velocity of the obstacles are manipulated in case of any emergency evacuation is needed using the emotional reciprocal velocity obstacles method [3]. The camera-based face recognition for the resident is developed using the Haar transform and LBPH method to make contact less automated door opening [4].

The LBPH seems to be a powerful algorithm in comparison to the other algorithms used for image classification [5]. The uniform LBPH is prone to noise sensitivity and is used for the emotions in the human face [6]. The facial emotions are recognized under different weather conditions and are implemented using the LBPH algorithm [7]. The LBPH human face recognition under varying conditions can be used for identifying criminal persons [8].

In recent times, the LBPH algorithm has been utilized in different environments for its high accuracy compared to the other algorithms. The LBPH algorithm is utilized to find the six emotions of humans by considering the different regions of the face and several age groups [9]. The human emotion understanding can be enhanced by focusing on the lip and facial images that could enhance the accuracy [10]. The identification of the human is based on the ear images using the LBPH [11].

The histogram analysis plays a pivotal role in face recognition using the LBPH technique. The scores are assigned to the histograms and oriented to classify the color texture [12]. The equalization of the histogram of the LBPH method exhibits high accuracy when the face is detected at low light intensity [13]. These merits of the LBPH can be incorporated with the other algorithms to attain multiple objectives of the image analysis. The fusion of moments and the LBPH algorithm evaluates the center of the object to detect the shapes of the environment [14]. The low-resolution images are checked for face identification using the combination of LBPH and Haar cascade classifier [15].

The application of LBPH varies from several authentications to the validation of individuals in the banking sector, schools, universities, and corporate offices. The automatic attendance is marked in real-time by using LBPH-based face recognition [16]. The convolution neural networks (CNN) algorithm can be used to find the improvisation of multi-label classification on the X-rays images of the chests [17]. The seismic happenings can be recognized automatically using the transfer-based CNN algorithm [18]. The image with low resolution can be recognized for the facial features using the CNN [19].

The multi-task CNN algorithm can be utilized to identify the public for the purpose of health safety in hospital and in public domains [20]. The CNN is combined with the auto-encoder to recover the medical images that are transferred through the cloud and IoT [21]. The combination of the CNN and recurrent neural network (RNN) proves to be meritorious in identifying the speaker based in their characteristic of voice [22].

The use of AI in the wild-life video capturing can save the time and collect accurate data when it occurs [23]. In Ayurveda medicine, the human faces are checked for dosha variations to detect the diseases that could emerge due to instability in Doshas. The image outliers are extinguished using the binary classifier by matching the Euclidian distance manipulation between two images under test [24]. The cloud-based image recognition namely Imagga and Google are assessed for enhancement with or without text and black-and-white or color images [25]. In this paper, the fusion of CNN and LBPH is used to recognize the facial emotions in human faces.

2. THE PROPOSED FUSION FACIAL RECOGNITION METHOD

The proposed fusion CNN- LBPH-based emotion recognition algorithm consists of taking the secondary image data samples. These secondary data samples consist of 4 different emotions namely happy, sad, surprise, and angry. The number of samples considered for this work is 160 with 40 samples each per emotion. The block diagram for the proposed method is depicted in Figure 1.

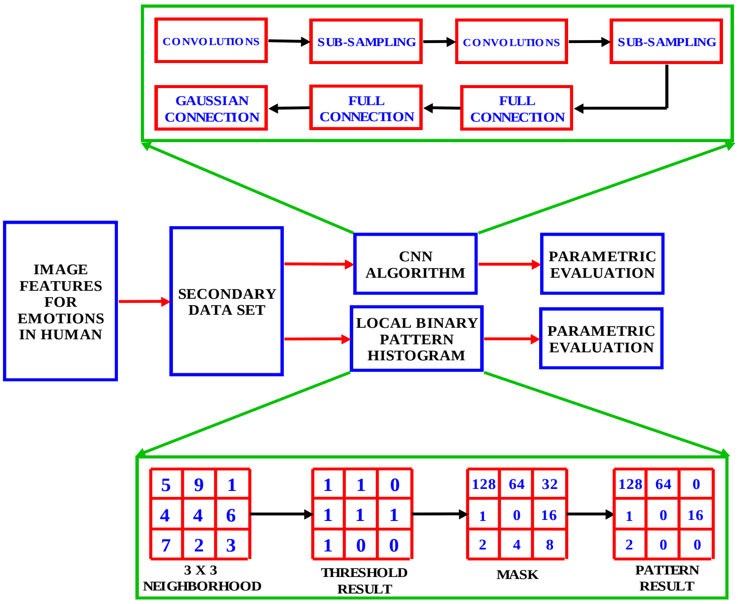

Figure 1. Block diagram for the proposed fusion CNN-LBPH algorithm

The image data samples are collected based on the emotions of humans and are considered as the secondary data sample. These secondary data samples are given with the option of selecting either the CNN or the LBPH algorithm. The CNN algorithm is the common algorithm utilized for image-based manipulation. The image features are extracted for the emotions in the images. The CNN algorithm goes through two stages of convolutions and sub-sampling. The sub-sampled images from the second stage, are fed to the fully connected layers to recover the image signals. The Gaussian connection is the activation layer to have non-linearity in the image from the input to the output of the CNN algorithm.

The LBPH algorithm works with the numbers as the image is classified into its binary pattern by considering the images as 3×3 matrices. Each of the 3×3 matrices are subjected to a thresholding process. In thresholding, the value of the center pixel is compared with the neighboring pixels and if the center pixel is greater than or equal to the neighbor pixel, the binary high value of "1" is assigned in its corresponding pixels; else if the center pixel is less than the neighbor pixel, the binary low value of "0" is assigned to the corresponding pixels. The mask matric for the LBPH is selected based on the required feature to extract for emotion recognition in human face images. The resultant pattern is evaluated to be the updated 3×3 matrix. This process is repeated for all the pixels with their neighbor in the image under test. Now based on these evaluated matrices of all the pixels, the histogram is plotted for the LBPH value.

3. ALGORITHMIC FLOW FOR LOCAL BINARY PATTERN HISTOGRAM

The LBHP algorithm is activated for parameters namely radius, neighbors, grid ‘x’ and ‘y’. Where “radius” refers to the circular LB pattern and default value is ‘1’. “Grid x” is used to move through the horizontal direction of the pixels, whereas the “Grid y” is to move through the vertical direction of the pixels. “neighbor” refers to the pixel surrounded by the center pixel under LBPH operation. The initialization to pass the parameter structures, the init function is utilized. The slices of images and labels are passed by using the parameters to train the LBPH algorithm. Note that all images are equal size and IDs are defined as labels to avoid redundancy of images.

This train function will scrutinize all images for similar size and indicates an error if any mismatch in size. Then the basic LBPH manipulate to digitize the neighbor pixels as defined by the radius of ‘1’. The image is shifted by 1 pixel value using the grid functions the histograms for each portion of images are concatenated to create an updated image for further processing of the LBPH algorithm. The predict function will compare the new image parameters with the image, labels, and histograms. Thus, the testing of the LBPH algorithm is initiated. The predict function compares the histograms of the new image with the stored image from the trained data images. The distance metric is used to evaluate the nearest histogram of the new image of the trained image. Though there are other distance metrics such as chi-square, absolute value, and normalized Euclidean metric, this work uses the Euclidean distance metric formula as it is easy to execute. The distance metric used for this LBPH algorithm is Euclidean distance metric as given in (1).

$$D = \sqrt{\sum_{i=1}^{n}(Histogram1 - Histogram2)^2} \tag{1}$$

4. RESULTS AND DISCUSSION

The proposed fusion method of emotion recognition in human faces is been evaluated using the secondary data set. The secondary dataset considered for this work has 160 samples of images of human faces with emotions. The emotions are subdivided into 40 samples each to be considered happy, surprise, sad, and angry. The proposed fusion method is subject to this secondary data to produce evaluation results in terms of percentages. The Python code is developed to evaluate both CNN and LBPH as per the preferences of the user. The CNN uses the NumPy library to access the deep learning algorithm to exhibit the percentage of estimation for all emotions as given in Figures 2 depicting the percentage of accuracy for the 4 different emotions, Figure 2(a) shows happy emotion, Figure 2(b) shows surprise emotion, Figure 2(c) shows sad emotion, and Figure 2(d) shows angry emotion. The emotion of anger is high at the percentage of 89% and the remaining all are under 50%.

In comparison, the proposed CNN-LBPH is more accurate and has high accuracy in all four emotions due to the utilization of LBPH algorithm. The reason behind the accuracy of the LBPH than the CNN is the number of secondary data samples considered for this work is minimal, and the utilization of binary values in the manipulation of the LBPH provides more accuracy than the CNN. The manipulation of the binary number in LBPH is fast compared to the CNN algorithm. The 4 emotions of human faces using the LBPH algorithm are enhanced as shown in Figures 3, Figure 3(a) shows happy emotion, Figure 3(b) shows surprise emotion, Figure 3(c) shows sad emotion, and Figure 3(d) shows angry emotion. With the parameters evaluated for the proposed fusion method, the LBPH method has an overall accuracy of 84% compared to the 65% with the CNN algorithm as given in Figure 4.

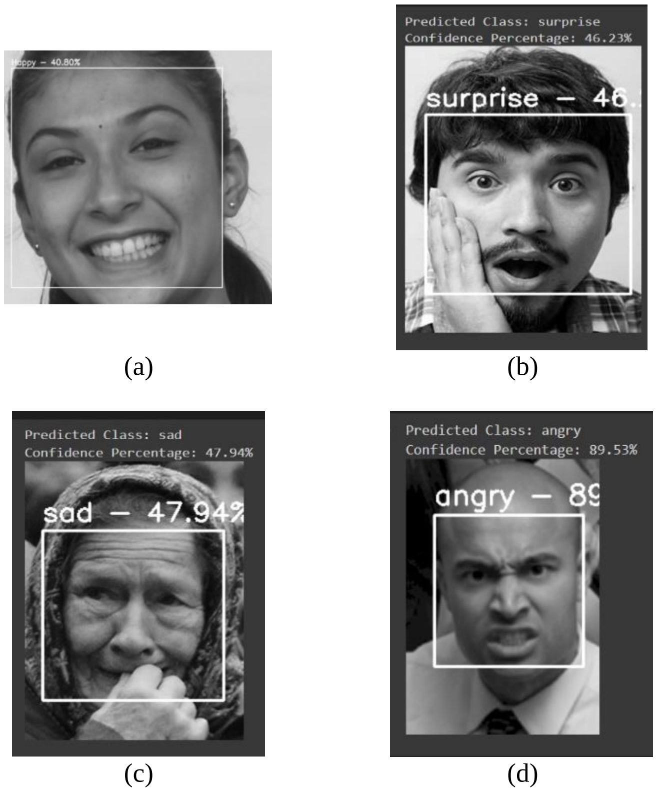

Figure 2. Face recognition of human samples using CNN algorithm for (a) happy emotion, (b) surprise emotion, (c) sad emotion, and (d) angry emotion

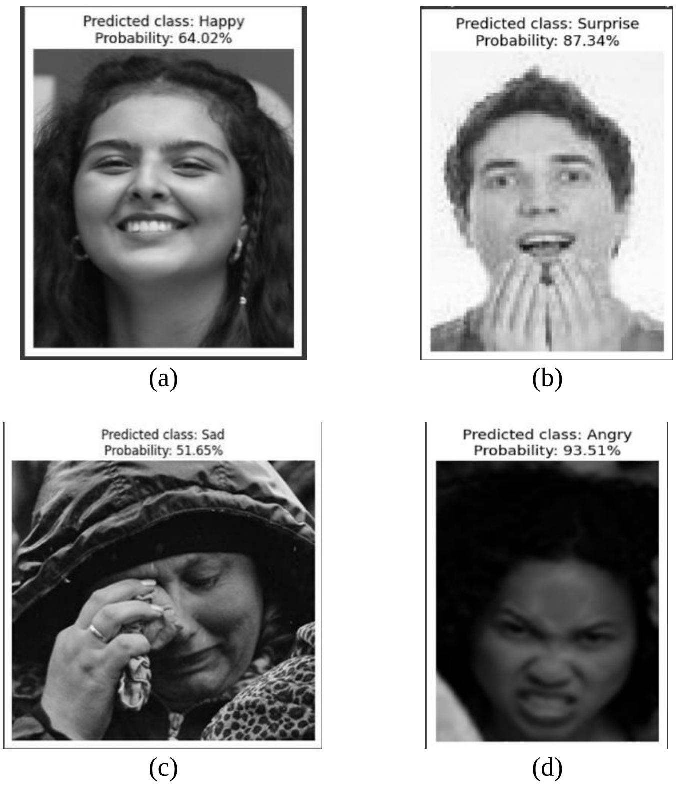

Figure 3. Face recognition of human samples using LBPH algorithm for (a) happy emotion, (b) surprise emotion, (c) sad emotion, and (d) angry emotion

```
correct = 0
total = len(test_images)

for i, img in enumerate(test_images):
    predicted_label, _ = lbph_model.predict(img)
    true_label = test_labels[i]
    if predicted_label == true_label:
        correct += 1

accuracy_percentage = (correct / total) * 100
print("Accuracy:", accuracy_percentage)

Accuracy: 84.375
```

Figure 4. Accuracy calculation for the LBPH algorithm for the given secondary data sample

The proposed fusion algorithm combines the advantage of the LBPH and CNN in the identification of the emotions. The accuracy of the proposed method in identifying human emotion with the given dataset is 84.375%. This accuracy increase is the merit of combining the LBPH and CNN in the proposed algorithm. Table 1 depicts that the comparison of the accuracy parameter to prove that the proposed algorithm is advantageous than the net-based algorithm and the CNN algorithm. Though the accuracy of the proposed algorithm is meritorious, the increase in the data sample has to ensure that there is no drop in accuracy of identifying human emotions by using the proposed algorithm. The extension of this proposed algorithm is to validate the accuracy for considering larger dataset with different emotions of human.

Table 1. Comparison of accuracy in percentage using the proposed method

Reference	Method	Year	Accuracy (%)
[26]	Match-Net, 6-Channel-Net, Siamese-Net	2019	73.6
[27]	Feature extraction convolutional neural network (FECNN) and super resolution and FECNN (SRFECNN)	2020	81
Proposed method	Fusion CNN and LBPH algorithm	2024	84.375

5. CONCLUSION

The proposed fusion CNN-LBPH-based emotion recognition in human faces is implemented successfully using Python code. The accuracy of the proposed algorithm is well comparatively high at 84.375% than the other fusing algorithms. This work has considered only 160 data samples for its manipulation. Further, the accuracy could be improved when large data samples are tested with the developed code. Future work can be concentrated on the real-time digital implementation of the proposed fusion CNN-LBPH algorithm in identifying the emotion of the human face.

ACKNOWLEDGEMENTS

The authors would like to thank the Sri Siddhartha Academy of Higher Education, Karnataka, India for the sustained encouragement to complete this work.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Arpana Giridhar Katti	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			✓	
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C	: **C**onceptualization	I	: **I**nvestigation	Vi	: **Vi**sualization
M	: **M**ethodology	R	: **R**esources	Su	: **Su**pervision
So	: **So**ftware	D	: **D**ata Curation	P	: **P**roject administration
Va	: **Va**lidation	O	: Writing - **O**riginal Draft	Fu	: **Fu**nding acquisition
Fo	: **Fo**rmal analysis	E	: Writing - Review & **E**diting		

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

No animals or human were involved in this research work.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [AGK], upon reasonable request

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