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Facial Spots Detection Using Convolution Neural Network

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Authors' contributions

This work was carried out in collaboration between both authors. Author PB designed the study, performed the statistical analysis and wrote the first draft of the manuscript. Author SKB initiated the work, edited all the processes and finalized the manuscript. Both authors read and approved the final manuscript.

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ABSTRACT

Nowadays security became a major global issue. To manage the security issue and its risk, different kinds of biometric authentication are available. Face recognition is one of the most significant processes in this system. Since the face is the most important part of the body so the face recognition system is the most important in the biometric authentication. Sometimes a human face affected due to different kinds of skin problems, such as mole, scars, freckles, etc. Sometimes some parts of the face are missing due to some injuries. In this paper, the main aim is to detect a facial spots present in the face. The total work divided into three parts first, face and facial components are detected. The validation of checking facial parts is detected using the Convolution Neural Network (CNN). The second part is to find out the spot on the face based on Normalized Cross-Correlation and the third part is to check the kind of spot based on CNN. This process can detect a face under different lighting conditions very efficiently. In cosmetology, this work helps to detect the spots on the human face and its type which is very helpful in different surgical processes on the face.

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Keywords: Face detection; Viola-Jones Algorithm; Convolution Neural Network (CNN); Normalized Cross-Correlation (NCC); spot detection.

1. INTRODUCTION

Face identification is one of the most significant processes in biometric authentication. The face is the most important part of the human body. It is observed that due to many reasons different kinds of spots found on the human face. They are categorized by mole, scars, freckles, etc. To identify the facial spots correctly it is needed to identify the different facial parts, left eye, right eye, nose, and mouth correctly.

There are several techniques available to detect and recognize the human face and its facial parts, and different facial spots. In the artificial intelligence field, machine learning with feature exaction is the most common and powerful classification process. But sometimes this process cannot identify related data accurately. Therefore, classification learner process using CNN can be used to detect unknown data very precisely. In this paper, a convolution deep neural network is used to detect spots identification in the faces. Intially After it is required to detect the facial parts. Then validation of facial parts are made. The main aim is to detect the facial spots using deep neural network for identifying the type of disease may present. Normally this process takes measurable time.

This process efficiently detects a human face under different lighting conditions. The process not only applicable to biometric authentication for security purposes but also applicable to facial surgery as well as in cosmetology.

2. RELATED WORK

Face detection and identification is one of the most significant processes for authentication. There are several works available on face detection.

Rencan Nie et al proposed to extract the facial feature based on Pulse coupled neural network (PCNN). They show a method to transform BMS into the frequency map series (FMS). Then convert the 2D frequency maps to 0D data points. Finally, based on an analysis of characteristics the standard Euclidean distance measure as the distance measure of OTS-FMS features. The experimental results showed that the recognition rate of OTS-FMS is significantly higher than PCA and KPCA and also better than a method based on BMS extracted OTS-BMS features [1].

Lu, Wen-Yao, and Ming Yang used composite features based on the Viola-Jones algorithm. The block features in the Viola-Jones algorithm cannot handle for pure rigid bodies. It cannot identify the face when a rigid spot present in the facial image. The authors proposed overcome this problem [2].

Abuzneid, Mohannad A., and Ausif Mahmood represent an enhanced approach to improve human face recognition using a back-propagation neural network (BPNN). Feature is extracted based on the correlation between the training images. The proposed framework is used on two small data sets, the YALE and AT&T [3]. So the proposed method is not tested for large data set.

Yadav, Kuldeep, et al. proposed a 3-layer CNN architecture for solving the face recognition problem. Here CNN gives a solution that is capable of solving the facial images related problems that contain varying illumination, poses, occlusions, and facial expressions [4].

Hui, Liu, and Song Yu-Jie used a face recognition method based on convolution neural network and fisher criterion is brought up to resolve the difficulty of the poor property of convolution neural networks under small samples. First, they create a discriminant metric function that is added to the cost function of the error and enhance the classification of the network. Then the face features by utilizing the modified convolution neural network are extracted. Finally, the support vector machine used to classify the extracted features. The experimental results show that the face recognition algorithm can achieve good results in the case of fewer samples [5].

Gogoi, Usha Rani, et al. used an automatic prominent mole detection and validation method that can help to reduce the adverse effect of illumination in face recognition [6].

Hsieh, Chen-Chiung and Jun-An Lai Proposed image processing technique to detect and verify the face mole. In the first part, they used the

Voronoi diagram for partition the given sample mole-face into regions. In the second part, they used Laplacian of Gaussian to get the prominent features on the face. Aspect ratio and area are two features for mole verification. Lastly, they develop an algorithm to warp the detected user moles to the sample mole-face by Thin-plate Spline Analysis for mole recognition [7].

The accurate identification of specific facial features and landmarks is a foundational process by which a number of more complicated image analysis problems are solved. Tasks such as facial identification, expression analysis, age estimation, and gender classification are often built upon a facial landmarking component in their methods [8-9].

While the process of identifying features such as the corner of an eye on a face is a natural and instinctive task for human vision; it has proven somewhat more challenging for computer vision, which has not benefited from millenia of evolution. Despite the overall similarity in the general content of facial images, common differences such as variation in pose, lighting, facial expression, and variations in the facial features themselves can be problematic for many computer vision systems leading to significant errors in land marking accuracy [10-11].

Fuji et al. distinguished several types of skin lesions such as comedo, reddish papule, pustule, and scar by using a multispectral image (MSI). The proposed process still requires manual inspection which is highly unreliable [12].

Alamdari et al. [13] proposed two-level k-means clustering with the HSV model for skin lesion segmentation after processing the close-up pictures taken by a mobile phone which achieved an average accuracy of 70%. Here fuzzy-c-means and Support Vector Machine (SVM) were used to separate acne scarring from active inflammatory lesions having 80% and 66.6% accuracy respectively.

Phillips et al. [14] used the principle of polarized light photography to observe and count the comedo and acne. Polarized light coming from electric and magnetic fields further vibrated in a single plane. Skin features along with color, lighting, and framing are boosted in the polarized photo in order to find the acne certainly.

3. SYSTEM ARCHITECTURE

The Fig. 1 depicted the whole proposed system architecture.

The proposed system architecture, as shown in Fig. 1, divided into three parts. The first part is to detect the human face and identify the different facial parts, left eye, right eye, nose, and mouth. Based on their position, the second part is to detect whether any spot presents on the face and after detection, the third part is to identify the spot type.

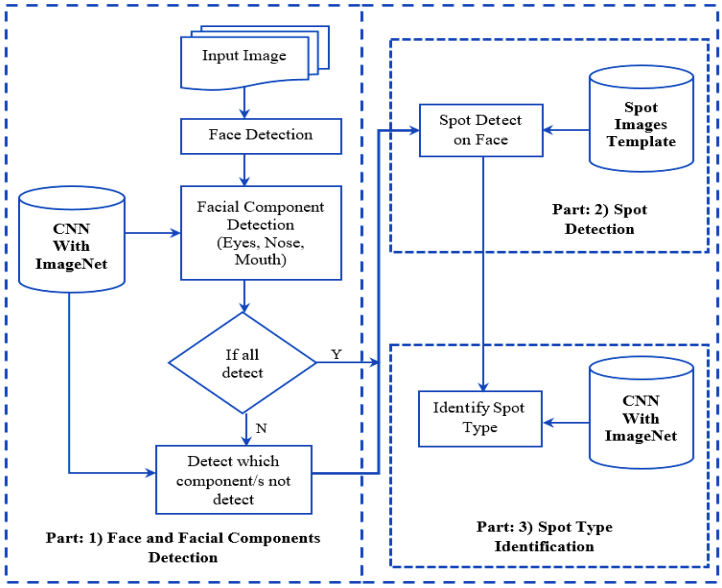


Fig. 1. System architecture

4. FACE AND FACIAL COMPONENTS DETECTION

For detecting the human face, here the most effective method Viola-Jones Algorithm [15-17] is used. Based on this algorithm the detection process depends on three major ideas, the integral image, AdaBoost classifier learning, and lastly the attentional cascade structure.

4.1 The Integral Image

The first step of the proposed algorithm is to convert an input image into an integral image. It is done by making each input pixel equal to the total sum of all the pixels from left to right and from top to bottom of its adjacency pixels. It is shown in Fig. 2.

1	1	1
1	1	1
1	1	1

Input image

1	2	3
2	4	6
3	6	9

Integral image

Fig. 2. Integral Image

At the point (x, y) the integral image is expressed as,

$$t(x,y) = \sum_{x' \le x, y' \le y} t(x', y') \quad (1)$$

Therefore the computation of the integral image over the original image used the below recursive equations:

$$s(x,y) = s(x, y-1) + t(x,y) \quad (2)$$

$$t(x,y) = t(x-1, y) + s(x,y) \quad (3)$$

Here, $s(x, y)$ = means of the cumulative rows sum.

The rectangle D with four arrays the sum of integral image is calculated with the pixel in rectangle A assigned at location 1 as the integral image. The process is shown in Fig. 3. For, A + B assigned value at location 2. For A+ C assigned value at location 3. And for A+B+C+D value assigned at location 4. Therefore, for the grey rectangle, the computation sum calculated as,

$$\mathrm{D} - (\mathrm{B} + \mathrm{C}) + \mathrm{A} = 4 - (2 + 3) + 1$$

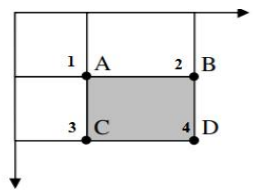


Fig. 3. The Integral Image sum calculation

4.2 Adaboost Classifier (Modified)

The main objective of the proposed method is to reduce the number of false-positive results. It reduces the number of regions in the image that are classified falsely as faces. Therefore, it changes the weighting system of the original Adaboost algorithm based.

As in the Viola–Jones method, the training data made of positive (cropped face) and negative (random images without faces) images. It used Haar-like features to build the full dictionary of weak classifiers. Note that weight was normalized in the Adaboost learning algorithm, which makes the total weighted error sum to 1.

The modified AdaBoost Classifier used to select the best features, polarity, and threshold of an input image. According to the algorithm this classifier,

Given sample images say (x_1, y_1) to (x_n, y_n), where y_1 = 0, 1 for negative and positive examples.

Initialize the weights $w_{1,i} = \frac{1}{2m}, \frac{1}{2l}$; where m = 0 and l positive and negative examples.

Now for t = 1 to T

Calculate the normalized weight,

$$w_{t,i} \leftarrow \frac{w_{t,i}}{\sum_{j=1}^{n} w_{t,j}}$$

Select the best weak classifier based on weight error, $\varepsilon_t = min_{f,t,\theta} \sum_i w_i \, |h(x_i, f, p, \theta) - y_i|$

Calculate the weak classifier,

$$h_t(x) = h(x_i, f, p, \theta) - y_i = \begin{cases} 1 & (if pf > p\theta \\ 0 & Otherwise \end{cases}$$

Update the weights

$$w_{t+1,i} = w_{t,i} \beta^{1-e_i} ,$$

Where,

$$e_i = 0 \quad for correct classify and\ 1\ for wrong$$

The final strong classifier is:

$$C(x) = \begin{cases} 1 & if \sum_{t=1}^{T} log \frac{1}{\beta^t} h_t(x) > \frac{1}{2} \sum_{t=1}^{T} log \frac{1}{\beta^t} \\ 0 & Otherwise \end{cases}$$

This classifier gives its best performance by choosing weak classifiers and modified them into strong ones based on weights error.

4.3 The Cascade Classifier

The basic principle of the Viola-Jones algorithm is to scan the detector again and again over the same image until the final result but each time with a new size. After the above classifier when the strong classifier is generated then the one strong classifier is insufficient for the final result. Because time is constant. Here the cascade classifier needs to composed each stage containing a strong classifier. The main goal is to determine whether a sub-window contains a human face or not. If it is not then it discards the window. The cascade classifier is presented in Fig. 4.

At the final stage, this classifier discarded all the false-positive samples and accept all false-negative. Therefore, in the end, only true-positive results get as an output. It is shown in Fig. 4.

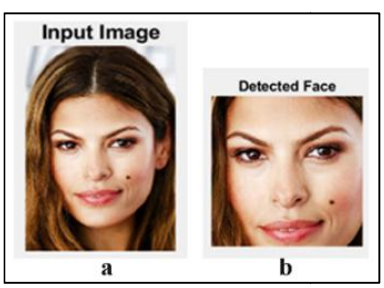


Fig. 4. a) Input Image, b) Detected face after applying the Viola-Jones algorithm

4.4 Facial Parts Detection

After detecting the face using the Viola-Jones algorithm it is necessary to detect every facial part, both left, and right eye, nose, and mouth. For detecting those parts also viola-jones algorithm is used here [15].

4.4.1 Eye pair detection algorithm

The eye is the darkest region in a face. So detecting the eye region is based on the segmentation of the small darker region in a face image. After the selection of the dark region, the histogram analysis method applied for detecting the biggest peak regions. For eyebrows, only one peak appeared but for eye two. The two major axes have alignment in the same region for the two eyes. Therefore, eyebrows can differentiate with eye pairs.

After detecting the eye pair easily separated the left and right eye by calculating their position as shown in Fig. 5.

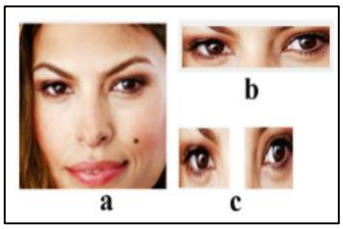


Fig. 5. a) Detected face after applying the Viola-Jones algorithm, b) Eye Pair Detection using Viola-Jones Algorithm, c) left and right eye crop

4.4.2 Nose detection algorithm

When an image is taken then it consists full of light and dark pixels. The nose is the peak region of a face. So the light and dark pixels mostly affected this area. The nostril region mostly consisted of light or white pixels and the two-hole on the nose consisted of dark pixels. Based on this the nose area identified easily as seen in Fig. 6.

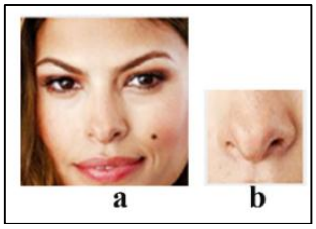


Fig. 6. a) Detected face after applying the Viola-Jones algorithm, b) Nose Detection using Viola-Jones Algorithm

4.4.3 Mouth detection algorithm

For detecting the mouth region first, the weak classifiers try to detect all possible regions and

extracted features from those regions. Then Haar features used to compare them and detect the actual mouth region. It is shown in Fig. 7.

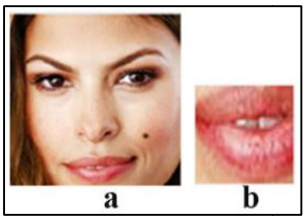


Fig. 7. a) Detected face after applying the Viola-Jones algorithm, b) Mouth Detection using Viola-Jones Algorithm

4.5 Facial Parts Identification

After detecting the facial parts now it is needed to identify them. For identification of those parts, eyes, nose, and mouth regions, a convolution neural network is used.

4.5.1 Convolution Neural Network (CNN)

In the classification process, based on the features the images are categorized. For classifying an unknown image lots of data needs to train by machine to reduce the gap between human vision and computer vision. In the Artificial Intelligence field sometimes the feature extraction method by machine learning not sufficient to differentiate perfectly between training and unknown samples. Therefore to solve this kind of problems another learning technique used, known as Deep Learning Network. To create a deep learning network several layered structures created with the help of several algorithms. This kind of deep neural network is called the Artificial Neural Network (ANN) [18]. The architecture of ANN, as in Fig. 8, created the human brain like structure to classify and identify unknown objects.

Convolution Neural Network [16-17] or Covsnet is one of the most powerful Artificial Neural Network. In CNN, the input images pass through several stages for processing, then based on its resolution $(height[h] \times width\,[w] \times dimension\,[d])$, the input image classifies into its proper class [19].

According to the CNN architecture, for classifying an input image, the input image passes through several convolution neural layers with filtering (kernel), pooling, fully connected layers (fc), and finally apply the Softmax layer to classify the input image with a probability between 0 and 1. The structure of CNN is shown in Fig. 9.

4.5.2 Pre-trained Convolution Neural Network (CNN)

For recognizing object Convolution Neural Networks created a strong model that is easy to control and even easier to train. It uses millions of images to train and the performance is almost identical with the feed forward neural network. Only one problem it uses high-resolution images for training purpose. Therefore for optimize the GPUs performance and reduce the training time it is needed to scale the images.

The ORL Database [14] of used in the method has Faces contains different images. For some subjects, the images were taken at different times and under varying the lighting [20]. The face situation towards the camera angle is variable from top to bottom and left to right side. All the pictures are black and white with 112×92 pixels at the time of processing.

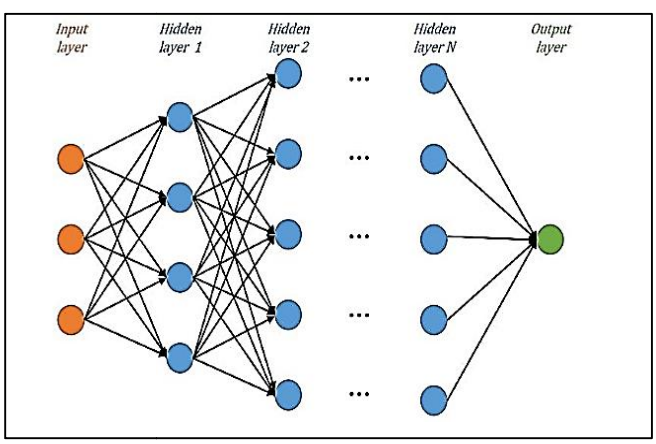


Fig. 8. Architecture of ANN

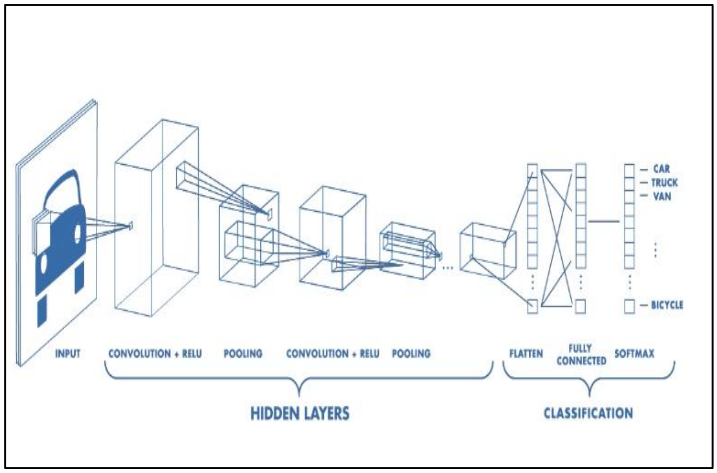


Fig. 9. Architecture of CNN

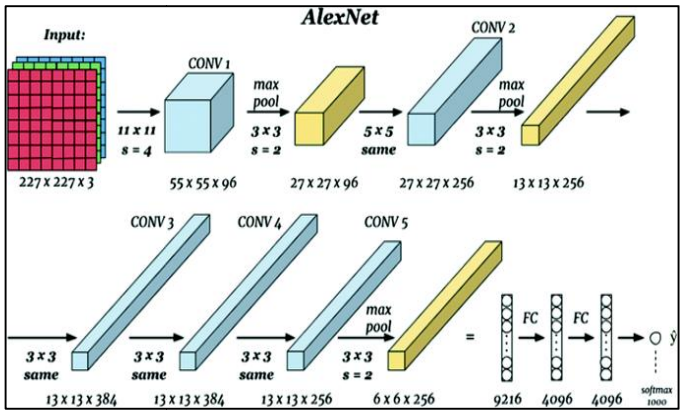


Fig. 10. Structure of AlexNet

The Image Net database consists of 15millions high-resolution images with 22 thousand label image classes. Alexnet [21-22] is one of the pre-trained CNN models used to classify objects. It used images for training from either Image Net or Places365 datasets. It has 22 layers and is also capable to classify more than 1000 images category. The number of layers used is 22 and it found best results with 5000 neurons in each phase of analysis.

AlexNet model used in which was the first deep convolutional neural network to successfully demonstrate performance outperforming the classical image object recognition procedures. The model consists of five sequentially connected convolutional layers of decreasing filter size, followed by three fully connected layers. One of the main characteristics of AlexNet (Fig. 10) is the very rapid down sampling of the intermediate representations through convolutions and max-pooling layers.

For this experiment, each image was scaled with 227 X 227 fixed pixel with required areas. Here four 4 label image classes were used and each class contains more than 700 images for training.

5. PROPOSED METHOD

5.1 Spot Detection

Face identification is one of the most significant biometric as it identified a person's identity very accurately. Because of this to make this identification more accurate it is needed to investigate several small details on the face including facial spots. There are several facial spots are available on the face, like a mole, scars, freckles, etc.

Mole: It is a typically pigmented spot formed by melanocytes. It is naturally black or dark brown in color. The size may vary from small to large to very large.

Scars: It is a mark produced by healing or cut the skin tissue due to an injury.

Freckles: It is the combination of several melanins. It is visible on fair skin, basically on the face. It is dark brown in color and it is genetic.

To detect such facial spots for identification, here Template Matching technique used. It is very much common in pattern recognition and a high-level machine vision technique.

5.2 Template Matching Technique

Template matching [23-26] is the high-level machine vision pattern recognition technique. In this technique, it is needed to find a piece of an image into the source of the image and the main goal is to detect the best-matched area. In this paper, for this experiment, the normalized cross-correlation template matching technique is used.

5.2.1 Normalized cross-correlation technique

The normalized cross-correlation technique[23-28] is the updated version of the cross-correlation template matching technique. The main of this version is,

i) It remains unchanged with the change of global brightness, the means there is no change in correlation matric due to the change of intensity of the image.
ii) It is very much easy to understand because the value of normalized cross-correlation tends to +1, whereas, Cross-correlation value varies from -1 to +1.

$$NormalizedCrossCorrelation(NCC) = \frac{\sum_{x,y}\left[f(x,y)-\bar{f}_{u,v}\right]\left[t(x-u,y-v)-\bar{t}\right]}{\left[\sum_{x,y}\left[f(x,y)-\bar{f}_{u,v}\right]^2\sum_{x,y}\left[t(x-u,y-v)-\bar{t}\right]^2\right]^{0.5}}$$

Here (x, y) is the original image; $\bar{f}$ is the mean of image intensity in the region under the template, t is the template and $\bar{t}$ represents the mean of image intensity in the template. Here (x, y) and (u, v) represent pixel coordinates.

5.3 Spot Identification

After detecting the spot on the face it is needed to identify the spot type, whereas it is mole, scar, or freckles. To identify the spot type here again the convolution neural network with a pre-train network is used. For this identification purpose, 3 spot classes and each class contain more than 100 images to train the network.

5.4 Working Steps of Proposed Scheme

In the system facial parts are initially isolated using CNN [18-28]. During the process there is possibilities of missing some parts. Template matching is ideal to detect all missing parts, if any. Next the process for identification of facial spots are done to select the type of the spots.

The below steps are the working steps of the proposed method:

Step 1: Accept the input image from the user.

Step 2: Using the Viola-Jones algorithm detects the face and its al facial parts. (Eye pair or Left and Right eye, Nose, and Mouth).

Step 3: Use the Convolution Neural Network to detect whether any facial parts absent or not. If yes, then identify the missing part and go to step 4. If no, directly go to the next step 4.

Step 4: Detect if any facial spots present on the face using a normalized cross-correlation template matching technique.

Step 5: If found, marked the location of the spot and go to step 6 to identify the spot type.

Step 6: Use the Convolution Neural Network to correctly identify the spot type.

5.5 Experimental Result and Performance Analysis

The result of each step of the following experiment is given below (Figs. 11-12):

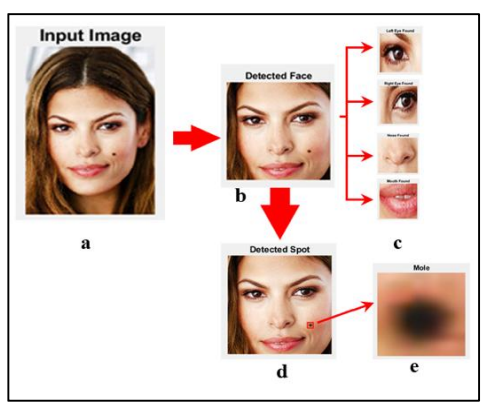


Fig. 11. a) Original input image, b) Detected Face using Viola-Jones algorithm, c) After all facial parts detection, d) After spot detection, e) After detecting the spot type (Here: Mole)

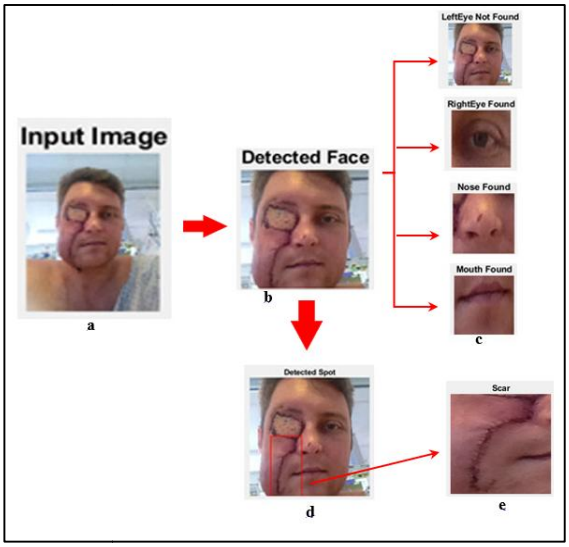
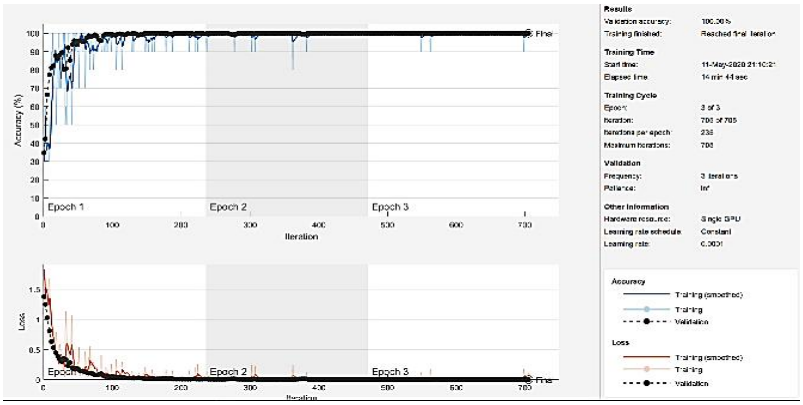
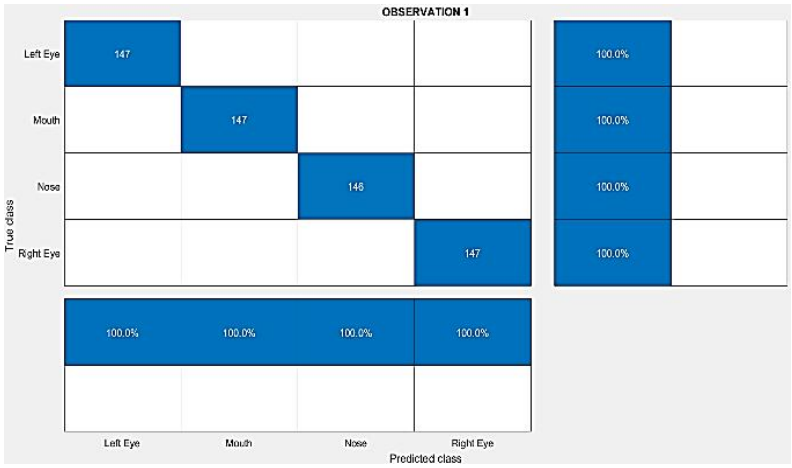


Fig. 12. a) Original input image, b) Detected Face using Viola-Jones algorithm, c) After all facial parts detection, d) After spot detection, e) After detecting the spot type (Here: Scar)

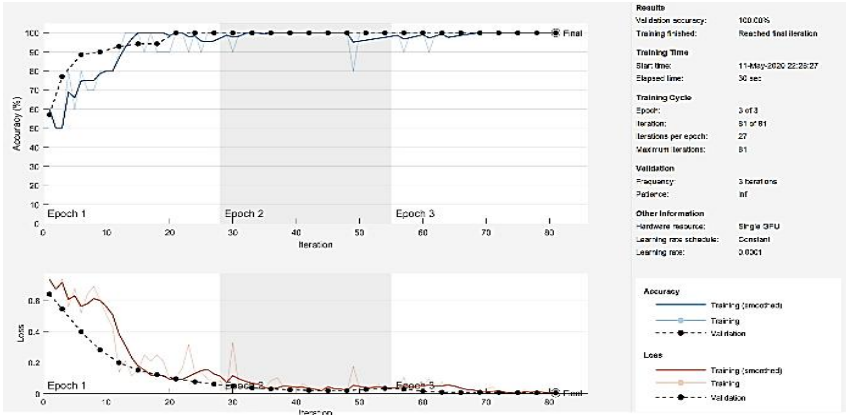


(a)

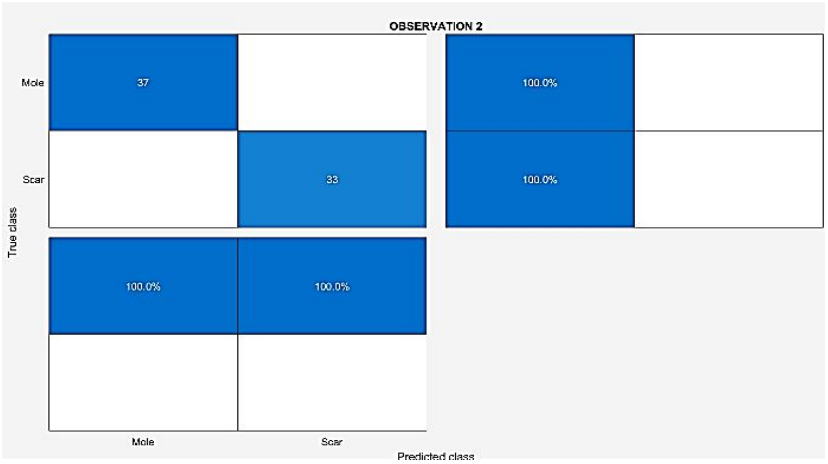


(b)

Fig. 13. Observation-1: a) Network analysis, b) Confusion matrix of the Convolution Neural network for identifying the facial parts



(c)



(d)

Fig. 14. Observation-2:c) Network Analysis, d) Confusion matrix of the Convolution Neural Network for identifying the spot type

Table 1. Metric for classification evaluation

Metrics	Formula	Evaluation measure
Accuracy	$\frac{Tp + Tn}{Tp + Tn + Fn + Fp}$	Accuracy metric measures the ratio of the correct prediction over the total number of samples
Specificity	$\frac{Tn}{Tn + Fp}$	Specificity used to measures the fraction of negative samples that are correctly classified
Sensitivity	$\frac{Tp}{Tp + Fn}$	Sensitivity used to measures the fraction of positive samples that are correctly classified
Precision	$\frac{Tp}{Tp + Fp}$	The precision used to measure the positive patterns that are correctly predicted from the total predicted patterns in a positive class
F-Measure	$\frac{2 \times Precision \times Sensitivity}{Precision + Sensitivity}$	It represents the harmonic mean between sensitivity and precision values.

In this paper, to perform the experiment part one, a facial parts database was created. This database contains four classes, left eye, right eye, nose and mouth. Each class contains more than 700 images to train an unknown image. The performance of the neural network for classifying the unknown image. For performing the second part of this experiment, spot detection, and identification, another facial spot database was created. This database contains two classes,

Table 2. Performance evaluation matric for classification

	Accuracy	Specificity	Sensitivity	Precision	F-Measure
Face and facial Parts Identification	93%	1	1	100%	1
Spots Identification	93%	1	1	100%	1

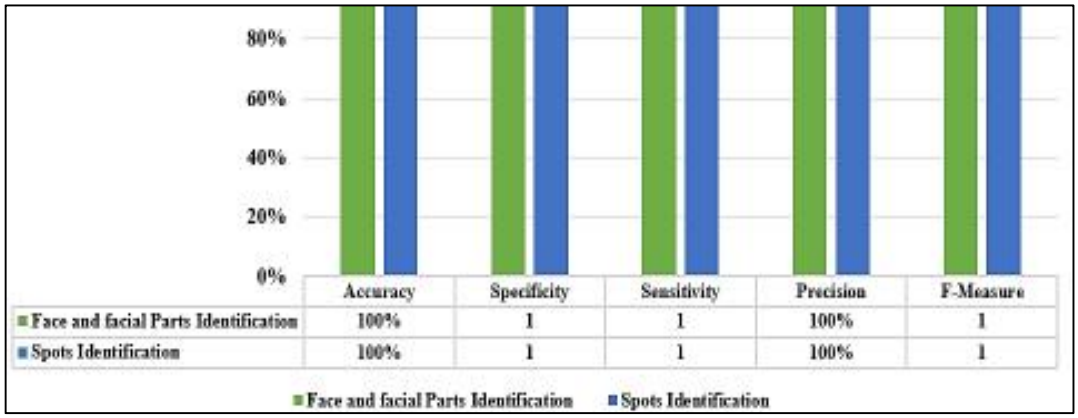


Fig. 15. Performance Metric Comparison between Observation 1 (Facial parts detection) and 2 (spot detection)

Table 3. Results of recent methods

Model	#parameter	Input size	Output size	#layers	FLOPS/fwd. pass
Alex Net [22]	58 282752	(3, 224, 224)	4096	7	1.1×10^9
VGG-Face [27]	117 479 232	(3, 224, 224)	4096	15	1.5×10^{10}
GoogLeNet [36]	21 577 728	(3, 299, 299)	2048	37	5.6×10^9
SqueezeNet [17]	3 753 856	(3, 224, 224)	2048	12	9.7×10^8

mole and scar. Each class contains more than 150 images. The performance analysis of this neural network is given in Fig. 13 and Fig. 14. The Observation -1 indicates confusion matrix of facial parts where as Observation-2 species confusion matric of facial spots.

The performance metrics of a classification measured from the confusion matric is described as follows Table 1.

The performance metric of this experiment is given below Table 2.

Comparisons between Observation-1 and Observation-2 (94%).

These results suggest that noise is an important factor affecting the performance of deep models and consequently. It needs sufficiently low levels of noise need to be assured for reliable verification performance. In the proposed method the results are about 93% which is higher than the recent methods.

6. DISCUSSION

The accurate identification of spots within facial images is an important step for facial recognition and facial expression analysis. it has taken decades of research, an increase in the availability of quality data sets, and a dramatic improvement in computational processing power to achieve near-human accuracy in spots localisation. The intent of this paper is to identify facial spots using deep neural network.

7. CONCLUSION

Face recognition is one of the most significant processes in biometric authentication and as well as in the cosmetological process. Due to the different global issues, the demand for the face recognition system is very high. In this paper, a technique is introduced, which helps to detect a face more accurately. In this process with detecting face different facial parts, say left eye, right eye, mouth, and nose also detect and check their validity. It also detects the spots on the face

and tries to identify the spot type. This whole process helps to detect the face more accurately than other processes. Here a convolution neural network is used to check the facial parts and the spot type, and a template matching technique is used to detect the spot on face. The whole process has taken an efficient amount of time to complete.

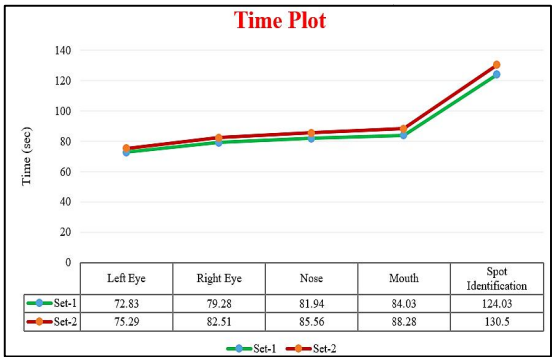


Fig. 16. Time series plot after detecting each part (two data series taken for the two results [Figs. 11,12])

From the performance analysis, it is cleared that the process is efficient to detect and check the validation of each human part very effectively. From the time plot (Fig. 16) it is also cleared that it takes an efficient amount of time to complete the whole process. This process has a drawback that, this process only applies to the frontal face and a certain amount of illuminated image. No side face or too illuminated face is applicable for this process. Therefore, the future work is to modify this system for side face and most illuminated image also. Finally, a graphical user interface was created for better use for all users.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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