Face Detection: An Effort to Accomplish an Analysis in the Archaeological Field

Ishani Sengupta, Subhashree Mishra, Bhabani Shankar Prasad Mishra, and Manoj Kumar Mishra

1 Introduction

Face plays a key role in human being's interactions. By identifying the facial expressions from the images of face, a number of applications in the human–computer interaction area will get simplified. In the past, many research works had been carried out on the problems of the different facial expressions of the modern human being in FR analysis [1, 2]. The pioneer studies of Ekman [3] in late 70s have given a proof to the classification of the basic facial expression. Face detection (FD) is stated as the process of obtaining faces from scenes. So, in a positive way the system captures a certain region in the image as a face. This procedure has many implementations on face detection and poses estimation. Face location is an interpreted approach of face detection (FD). Its aim is to establish the position of a face where there is only one face in the image. Current works on facial expression and recognition vary mainly in the selected facial features and the classifiers that are used to discriminate amongst the various facial expressions. There are many techniques which are planned for modern human face appearance identification from still pictures (database of images) to image scenes (video recorder).

In the literature survey, most of the researchers attempt to classify basic facial expressions by using different algorithms such as Haar cascade [4], multi-task

I. Sengupta · B. S. P. Mishra (✉) · M. K. Mishra
School of Computer Engineering, KIIT Deemed to be University, Bhubaneswar 751024, India
e-mail: bsmishrafcs@kiit.ac.in

I. Sengupta
e-mail: ishanisengupta2017@gmail.com

S. Mishra
School of Electronics Engineering, KIIT Deemed to be University, Bhubaneswar 751024, India
e-mail: subhashreeomm@gmail.com

N. Priyadarshi et al. (eds.), *Advances in Power Systems and Energy Management*,
Lecture Notes in Electrical Engineering 690,
https://doi.org/10.1007/978-981-15-7504-4_20

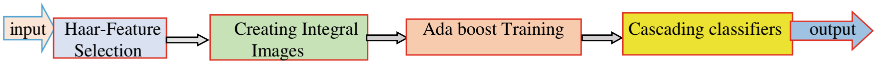


Fig. 1 Haar cascade algorithm

convolutional neural network (MTCNN) [5], Naive Bayes [6], SVM [7], HMM [8]etc.

The target of our paper is

- To identify and track face from a static image of ancient skulls.
- To recognize an early man's face.
- A comparative analysis of different machine learning-based classification approach for face detection in the area of archaeological field.

2 Details of Facial Detection Techniques

2.1 *Haar Cascade*

Haar cascade is an algorithm used in detecting objects in the artificial intelligence (AI) field to detect matter in an representation or videocassette which is based on the domain projected by Viola–Jones in 2001 [9]. A Haar cascade is basically a classifier detecting objects as it has been trained for. In this machine learning (ML) technique, a cascade function is skilled here by overlaying the positive images over a collection of negative images. Now the Haar-like features are different image features, and they owe their name to their inherent Haar wavelets. Cascading is a specific case of the whole learning based on a series of interconnected several classifiers using all information that gets collected from the output, from a given classifier which becomes an additional information for the next classifiers in the cascade.

The four levels of Haar Cascade algorithm have been shown in Fig. 1.

Input Haar feature creating integral AdaBoost training cascading classifiers output.

Selection images.

It is popular about Haar Cascade algorithm that it can detect faces in an image, but can be trained to identify almost any type of object.

2.2 *Multitask Cascaded Convolutional Neural Network (MTCNN)*

One of the popular approaches is MTCNN, described by Kaipeng Zhang et al. [10]. The MTCNN is well-known as it is achieved then state-of-the-art resulting on a range of benchmark data sets and also popularly called landmark detection because of its capability to recognize other facial feature types like eyes and mouth. The system uses a cascade structure consisting three networks.

2.3 *Analysing Face Detection Depending on Facial Features*

Various performances applied on the facial features detecting modern human being by using different classification techniques to recognize a face, emotions, age-gender, etc. The face detection process has been shown in Fig. 2.

Captured Extracting Matching Comparing Graphically Representing

2.3.1 Captured

Algorithms of face detection spotlight on the detection of front human faces. The first step is face exposure, i.e. capturing. Capturing means record accurately in words or pictures. Face capturing means obtaining or trapping only the facial part from the taken data. In this paper, we have captured face of early man, skull, and mummies using Haar cascade classifier and MTCNN classifier.

2.3.2 Extracting

Face features extraction is the action of extracting face fundamental character like the left side of eye and right side of eye, nose, left side of mouth and right side of mouth etc.from face images. It is very significant for the initialization procedure methods such as face identifying, face appearance detection, or face identification. In this paper, while using Haar cascade, we extracted eyes from face images and while using MTCNN, we extracted eyes, nose, and mouth.

2.3.3 Matching

A face matching algorithm is a set of systems that a computer uses to identify a face in an image and then to match up to that face to another face (or features) to establish whether there is a match. In this paper, we have tried matching the face of an early man to the human face (i.e., reconstructed or a 3D model made), skull to an early man or human (reconstructed).

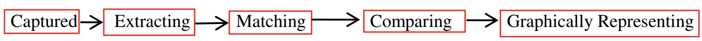


Fig. 2 Face detection process

2.3.4 Comparing

When we make a comparison, we consider two or more things and discover the differences. In this paper, once collected results by using Haar cascade classifier and MTCNN classifier, we compared them and tried getting better results which would give us a good collection of information regarding early men, skulls and mummies.

2.3.5 Graphically Representing

Representing data graphically is one of the most commonly used approaches of presentation. The idea of graphical communication is to deliver message or information to the receiver in a valid way.

In this paper, the parameters of both eyes, nose, both sides of mouth based on the feature extraction of skull, group of early men by MTCNN classifier has been represented graphically (Fig. 3).

2.3.6 Face Detection PseudoCodes

3 Discussion of Proposed Work

We collected facial images of different categories like early man, ancient skull, mummy's (ancient) face and ancient sculptures, to detect facial features. We used OpenCV software version-4.1.2 and two classifiers, namely Haar cascade classifiers and MTCNN classifier, and compared the results.

3.1 Haar Cascade Classifier

A Viola–Jones detection algorithm-based classifier, i.e. Haar cascade classifier, flowchart has been shown in Fig. 4.

A very basic line up used to exhibit an image using Haar-like features and OpenCV can be written as follows:

```
import numpy as np
import cv2
cv2.imshow ('img',img)
cv2.waitKey ()
cv2.destroy All Windows ()
```

```
This program of Open CV is to detect faces from images as input
INPUT:
Assign "haar cascade_frontal faces_default.xml" to faces_cascade
Assign "haar cascade_eyes.xml" to eyes_cascade
#Reading frames from images
Assign the name of the picture file in .jpg format to img
#Converting to gray scale of each frames
Assign gray the two parameters img and 'CV2.COLOR_BGR2GRAY'
#Detecting faces of different sizes in the input images
Assign the different sizes to faces as gray,1.3,5
PROCESS:
FOR (x,y,wi,hei) IN faces
        Draw a rectangular box on a face, taking the region of interest
        Assign eyes the different sizes of the input image
        FOR (eyx,eyy,eywi,eyh) IN eyes
                Draw rectangle in eyes
        ENDFOR
ENDFOR
OUTPUT:
Display image in a window
```

```
This program of deep learning is using to detect faces
INPUT:
#This functions show the picture and then draws a box around each bounding
box that was detected
Function draws_images(Argument one,Argument two)
            #loading the images
            Assign Argument one to load the image to data
            #ploting the image
              Plot the image using data
            Assign ax the context for drawing boxes
            #plotting each box
            FOR results IN Argument two
                  #To get the coordinates
                  Assign results to x,y,wid,hei
                  Assign the rectangular shapes to rect and create
                  Creating box using rect
                  #Draw the dots then
                  FOR keys, values IN results
                        Assign dot with value to create and draw dot
                  ENDFOR
            ENDFOR
            Showing the plotting
Assign Argument one the file name of the image like in .jpg format
Assign pixels the loaded image from file
Assign detector using weights and create it
Once the model has been shaped and loaded , it can now be used precisely to
detect respective faces in pictures
Assign faces the detector function which will return a list of objects, each giving
number of keys together with: 'box', 'confidence', 'key points'
#Display faces on the original photo
Call the draws_images(Argument one,faces)
FOR face IN faces
        OUTPUT face
ENDFOR
```

Fig. 3 Commands using two classifiers to detect face

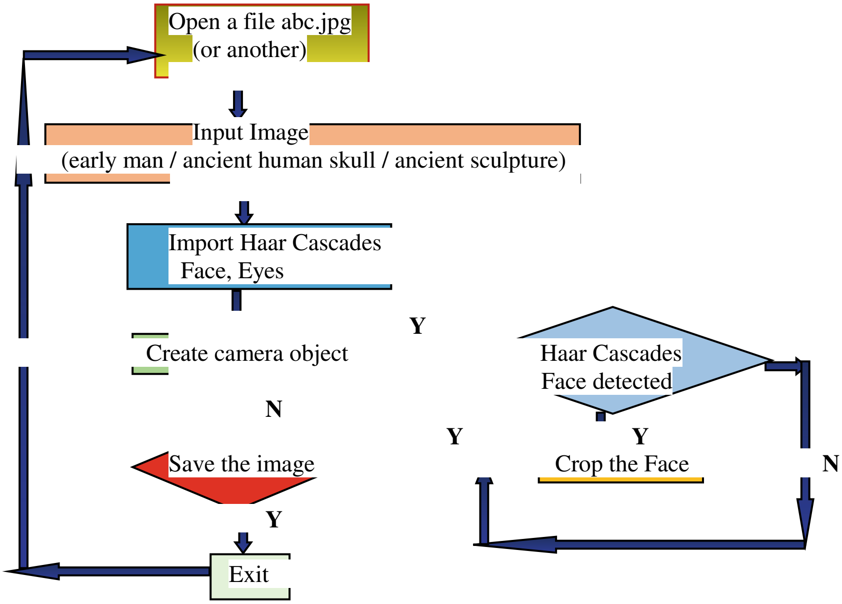


Fig. 4 A flowchart showing Haar cascade classifier mechanism

3.2 MTCNN Classifier

The multitask cascaded convolutional neural network (MTCNN) algorithm works in three steps where one neural network is used for each.

Steps are:

I. Firstly, it will figure the possible face location and their rectangular region like an attention network in faster regional convolutional neural networks (RCNN). The outcome of this stage is tones of face detection and large number of fake detection.
II. Here, the images and outcomes that were predicted at first are used. It creates a clarification of the obtained consequence to erase mainly fake detection and aggregate rectangular region.
III. This is the last stage, which purifies even more the forecast and adds facial marker predictions.

Now, a very basic line up used to demonstrate an image and its plotting using OpenCV, matplotlib can be written as follows:

```
import tensorflow as if
import cv2
import mtcnn
import matplotlib
From matplotlib import pyplot
From matplotlib patches import Rectangle
From matplotlib patches import Circle
From mtcnn.mtcnn import MTCNN
```

3.3 Details of the Images

See Table 1.

3.4 Comparison Analysis I

Table 2 summarizes the difference between the observations obtained from the ancient skulls, fossils, early man, 3D model (face reconstruction), mummy (Egypt), sculptures face images using the two classifiers, viz. cascade classifier and MTCNN.

3.5 Comparison Analysis II

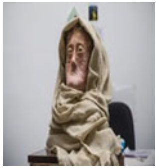
Very few facial images are detected by cascade classifier only but they are not detected by MTCNN. Again most of the facial images are detected by MTCNN only. This comparison analysis has been shown in Table 3.

3.6 Graphical Representation Analysis

In this paper, it has been shown that only MTCNN provides different parameters of the facial images obtained from various ancient skulls, early men, mummy and sculpture. The parameters (left side of eye (LE), right side of eye (RE), nose (N), left side of mouth (ML), right side of mouth (MR)) of two images are described graphically in Table 4.

In the first picture, only one skull's face image has been taken which is detected using MTCNN classifier, whereas in the second picture, a group of eight early men face images has been taken, but only seven face images are detected. So graphically, the parameters of seven face images are plotted together. Also graphically the

Table 1 Description of various early man, ancient skull, sculpture and mummy's images

	This picture belongs to an early man's face reconstruction		Adivans who roamed the savannah plains of Africa ate grass like cows 3.5 million years ago		This picture is an early human fossil, found out of an African cave
	The face of one of Scotland's oldest woman, nicknamed Hilda died 2000 years ago		This is the mask of Tutankhamun which was made of gold		This is a remarkable skull of human ancestor of the genus *Australopithecus*
	This picture belongs to a caveman which was sculpted over a plaster cast of an actual Neanderthal skull		A skull of an Egyptian mummy of a child was around 1000 B		A plastic cast of Kennewick Man's skull, A New History of the First Peoples in the Americas

(continued)

Table 1 (continued)

	The archaeological record shows that this image is 35,000 years old		This picture belongs to Nefertiti who was Egyptian queen around the mid of 1300s B.C.		The pictures of skulls are around 92,000 years old
	This is a sculpture which shows the face of Homo floresiensis, from the Indonesian island of Flores		This picture belongs to a woman who lived in Greece around 7000 B.C.		The mummy of Tutankhamun was over 3300 years old
	Early Humans—History—LibGuides at Loreto Mandeville Hall		This real Peruvian elongated mummy head was around 800–100 BCE		

Table 2 Comparison analysis I of various face images using cascade classifier and MTCNN

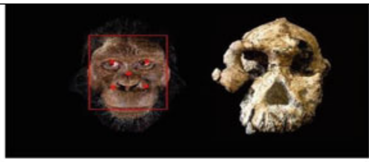
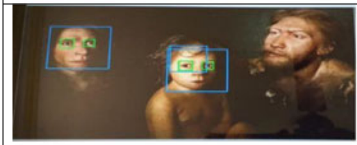
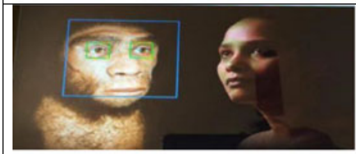
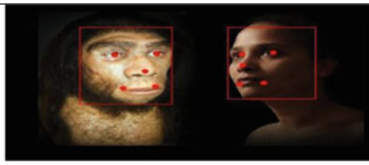
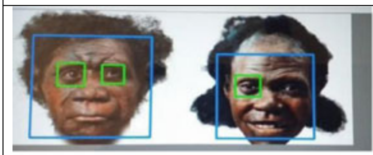
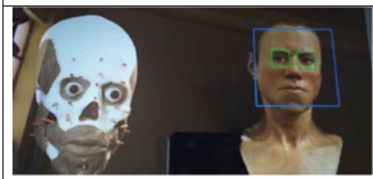
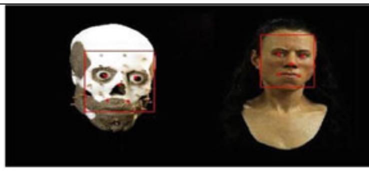
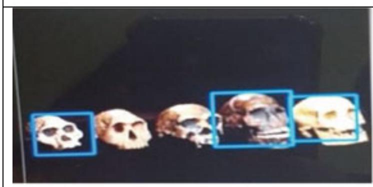
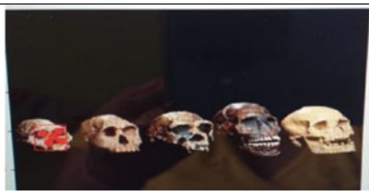
Face detect by Cascade Classifier	Face detect by MTCNN Classifier
	
	
	
Neither of the two were detected	
	
	
	

Table 3 Comparison analysis II of various face images using cascade classifier and MTCNN

Image detect by MTCNN Classifier only whereas Cascade classifier does not	**Image detect by Cascade Classifier only whereas MTCNN classifier does not**
	
	
	
	

parameters of one face image of first picture are plotted. This graphical representation analysis is described in Table 4.

4 Conclusion and Future Scope

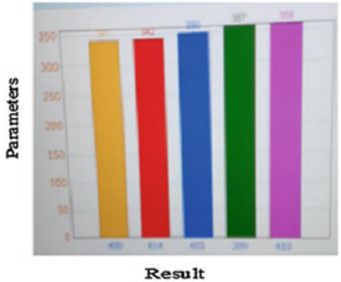
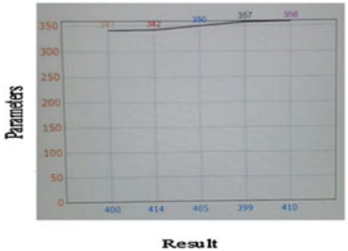
Face detection is the challenging aspects in the research area of artificial intelligence, computer vision (CV), where it analyses the present mankind's face images.

In this paper, we tried a new idea and implemented face detection methods on ancient skull images, early man, mummies (Egypt) face images, sculptures and 3D face models (i.e. reconstructed ancient faces).

The focus in the direction of the face detection has been increased in the previous years due to its vast applications in the real world. The research conducted in this field leads to encouraging results but still we are incapable to find the face detection technique which is able to execute resourcefully in the various situations of daily lives.

We hope that the study of this paper will help and opens a new gate for not only archaeologists with their research works [11], but also in computer vision field.

Table 4 Graphical Representation analysis

Parameters of first image: (LE): (400, 341), (RE): (414, 342), (N): (405, 350), (ML): (399, 357), (MR): (410,358)  Percentage value: LE: 19.5%, RE: 19.6%; N: 20%; ML: 20.4%; MR: 20.5%	 

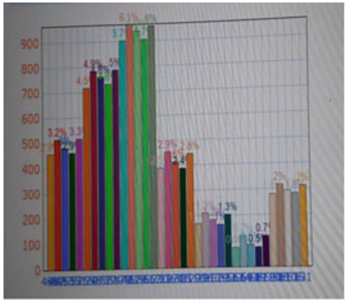
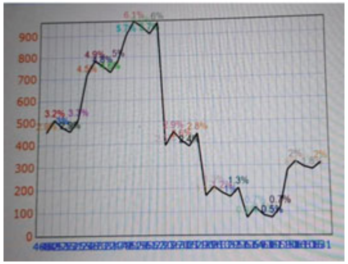
(continued)

Table 4 (continued)

Parameters of second image: (1) (LE): (456, 468), (RE): (513, 462), N: (479, 497), (ML): (459, 535), (MR): (515, 531); 2) (LE): (716, 255), RE: (782, 248), N: (759, 273), (ML): (729, 327), (MR): (786, 317); 3) (LE): (901, 479), (RE): (965, 481), N: (939, 529), (ML): (905, 561), (MR): (957, 562); 4) (LE): (391, 230), (RE): (453, 236), N: (413, 270), (ML): (387, 305), (MR): (444, 311); 5) (LE): (168, 290), (RE): (208, 296), N: (182, 313), (ML): (164, 329), (MR): (202, 333); 6) (LE): (74, 563), (RE): (118, 564), N: (85, 593), (ML): (75, 609), (MR): (118, 611); 7) (LE): (279, 590), (RE): (316, 586), N: (292, 610), (ML): (282, 635), (MR): (310, 631).	

(continued)

Table 4 (continued)

 	Percentage value: 1. LE: 2.99 %, RE: 3.2 %, N: 3 %, ML: 2.99 %, MR: 3.3 % 2. LE: 4.5 %, RE: 4.9 %, N: 4.8 %, ML: 4.6 %, MR: 5 % 3. LE: 5.7 %, RE: 6.1 %, N: 5.9 %, ML: 5.7 %, MR: 6 % 4. LE: 2.5 %, RE: 2.9 %, N: 2.6 %, ML: 2.4 %, MR: 2.8 % 5. LE: 1 %, RE: 1.3 %, N: 1.2 %, ML: 1 %, MR: 1.3 % 6. LE: 0.5 %, RE: 0.7 %, N: 0.5 %, ML: 0.5 %, MR: 0.7 % 7 LE: 1.8 %, RE: 2 %, N: 1.8 %, ML: 1.8 %, MR: 2 %

References

1. Bharati Dixit et al., Facial features based emotion recognition. IOSR J. Eng. **08**(8), 08–15 (2018)
2. S. Bhosale et al., Face detection and recognition techniques:a survey. Int. J. Adv. Res. Comput. Commun. Eng. **7**(11), (2018)
3. P. Ekman, W.V. Friesen, *Unmasking the Face* (Pren-tice Hall, New Jersey, 1975)
4. J. Huang et al., improved viola-Jones face detection algorithm based on Hololens. EURASIP J. Image Video Process. https://doi.org/10.1186/s13640-019-0435-6 (2019)
5. Y. Zhao et al., Joint face alignment and segmentation via deep multi-task learning. Muitimed. Tools Appl. (2018). https://doi.org/10.1007/s11042-018-5609-1
6. A. Devi et. al., Naive Bayes classification based facial expression recognition with kernel PCA features. Int. J. Eng. Dev. Res. **5**(3) (2017)
7. C. Rayani, K Rajakumar, Face detection and recognition using support vector machine. Int. J. Eng. Adv. Technol. **8**(4), 382–384 (2019)
8. S. Saxena et al., Face recognition using coupled the hidden markov model with an artificial neural network. IOSR J. Comput. Eng. **20**(1), Ver. III, 08–15 (2018)
9. P. Viola, M. Jones, rapid object detection using a boosted cascade of simple features, in *Proceedings of IEEE CVPR* (2001)
10. K. Zhang et al., Joint face detection and alignment using multitask cascaded Convolutional networks. IEEE Signal Process. Lett. **23**(10), 1499–1503 (2016)
11. H.A.Orengoa, A.Garcia-Molsos, A brave new world for archaeological survey: automated machine learning-based potsherd detection using high-resolution drone imagery. J. Archaeol. Sci. **112** (2019)