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Fake Biometric Detection for Face and Fingerprint

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Abstract: ***Face and Fingerprint acknowledgment is most popular and generally utilized as a biometric innovation as a result of their high ampleness and peculiarity. Besides the recognizing the user the present biometric systems have to face up with the new troubles like the spoofing attacks, like presenting a photo of the person to the camera. We study the anti-spoofing solutions for distinguishing between original and fake ones in both face and fingerprint in this paper. Generally, the face arrangement and portrayal that exhibits enhancements in coordinating execution over the more typical all-encompassing way to deal with face arrangement and depiction. Face detection, introduced in this paper, comprises the accompanying significant advances like facial features locating using Active Shape Models (ASM), Local Binary Pattern for feature extraction which is known for its texture classification, and Random Forest is used for classification. a fingerprint comprises of edges and valleys design otherwise called furrows. For Fingerprint detection, introduced in this paper includes the accompanying significant advances like Minutiae based local patches, SURF, and PHOG for feature extraction, and Random Forest is used for classification. The proposed methodologies are profoundly seriously contrasted and different as the investigation of the general picture nature of real biometric tests uncovers essential data for both face and fingerprints that might be productively used to segregate them from fake attributes.***

Keywords : Active Shape Models(ASM), Local Binary Patterns(LBP), Pyramid Histogram of Oriented Gradients(PHOG), Random Forest(RF), Speeded-Up Robust Features(SURF).

I. INTRODUCTION

Security is the central aspect of any organization, to improve safety and protection now daily's programmed access of people to administrations is getting progressively significant. This prompts another innovation known as biometric acknowledgment. In a recent couple of years, Face and Fingerprint's acknowledgment investigates have quickened mechanical advancement in recognizable human proof for security and wellbeing measures.

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A face recognition framework that fundamentally plays out the elements of the face identification, social validation, lastly, individual acknowledgment has endless applications in safeguard, security, and programming get to control, human-PC interface. Among the various dangers broke down, the direct or satirizing assaults have roused the biometric network to consider the vulnerabilities against this sort of deceitful activity in modalities, for example, the iris, the finger impression, the face, the mark, and multimodal approaches. In these assaults, the interloper utilizes some sort of artificially created relic (e.g., gummy finger, printed iris picture or face veil), or attempts to copy the conduct of the certifiable client (e.g., signature), to falsely get to the biometric framework. As these kinds of assaults are acted in an unaffected area, and the association with the gadget is finished after the usual convention, the standard computerized assurance instrument (e.g., encryption, advanced mark, or watermarking) is not viable.

Among the different techniques created by specialists, appearance-based methodologies for face and fingerprint acknowledgment yielded excellent outcomes, which by and large work straight and henceforth prepared it as two-dimensional examples. The test results show this new way to deal with be a promising strategy for making acknowledgment frameworks increasingly powerful against counterfeit spoofing endeavors.

II. PREVIOUS WORK

There was significant research in the fields of these biometric traits, and there are many anti-spoofing techniques followed around the globe. Here we will go through some work done in this field. Quoc-Tin Phan, Duc-Tien Dang-Nguyen, Giulia Boato and Francesco G. B. De Natale [1] contributed towards an anti-spoofing solution with their work on face spoofing with help of high-order Local Derivative Pattern from Three Orthogonal Planes. Their innovation was exploiting the facial dynamics by considering the abstruse movements of face. Here the classification is done using SVM. This system can be applied on the cross-datasets. This system shows some over-fitting problems for the data driven methods. Tanvi Dhawanpatil, Bela Joglekar [5] provided an anti-spoofing solution with help of histograms obtained using Multiscale Local Binary Pattern and Scale Invariant Fourier Transform descriptor. A Moire pattern is obtained using MLBP and SIFT algorithms and then the histogram is made using the training data and testing data. Thereby using the Rule based classifier, we can know whether image is a spoof or a real one.

Taiamiti Edmunds and Alice Caplier [2] did the face spoofing detection by using the color distortions. In this system, for a given testing image the radiometric distortions obtained with the help of the recapturing process and the real face image is considered, then a color transformation is done between these two.

The radiometric transformations are done and those features are considered for the classification. The major drawback of this system is the unknown illuminations caused due to the color distortions.

Tarang Chugh, Kai Cao and Anil K. Jain[9] proposed an anti-spoofing solution using the neural networks. Firstly the minutiae of the fingerprint is detected and then the local patch extraction is done for the minutiae points. The CNN model is trained on the features extracted. While testing, the CNN gives a score for the testing image and according to the score we can know whether the image is real one or a fake one. This system is able to reduce the classification error by 69%.

Samruddhi S. Kulkarni, Hemprasad Y. Patil[11] proposed a solution towards the spoofing of fingerprints by using local binary patterns and the discrete shearlet transform for the feature extraction, so that we can categorize the fingerprint into real or a spoof. In this system, first the preprocessing is done in five stages and then LBP extracts the features of fingerprint with the help of histogram and shearlet transform is used for its efficiency in edge analyzing and thereby the classification is done using the SVM classifier.

Gustavo B. Souza, Daniel F. S. Santos, Rafael G. Pires, Aparecido N. Marana and João P.[13] contributed a solution for the spoofing of fingerprints with help of deep learning model. Here deep botzmann machines extracts the features from the training data and then DBM and MLP are trained on the given dataset then for a given testing image the trained model gives a matching score which help us know whether the fingerprint is a real or a spoof. This system gave a high accuracy in the detection of the attack.

III. PROPOSED SYSTEM

As there are many techniques available to track and stop the biometric traits, here we used a new strategy for making acknowledgment frameworks increasingly powerful against counterfeit spoofing endeavors.

Firstly, in the biometrics of face, when a user presents an image, we need to authenticate whether the given face is an original one or just a spoofed image to bypass the system. Thereby, we use some effective appearance-based strategies like Principal Component Analysis, Active shape models, and local binary patterns. PCA gives class portrayals that are in a symmetrical direct space. Anyway, ASM joins shape earlier and neighborhood appearances while twofold examples for surface portrayal. These strategies under changing condition are getting excellent outcomes will be characterized under Random Forest Classification for recognizing the original and fake one. The block diagram for the above-mentioned process is given in figure (1).

Similarly, in the biometrics of fingerprint, we need to authenticate whether the given input is an original one or just a spoofed fingerprint formed using gelatin, silicon, etc.

To detect these, we present a novel technique for separating counterfeit fingerprints from genuine ones, in light of the investigation of an impossible to miss attributes, i.e., the edges and the extensions on the skin. The extricated unique mark picture features the edges and the scaffolds on the skin surface. There are some successful appearance-based systems like minutiae extraction, Random forest classification for perceiving the first, and the phony one. The block diagram for this process is given in the figure (2).

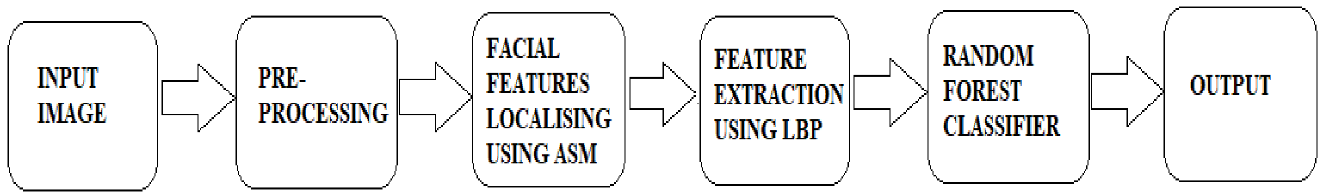

Figure (1): Block diagram of fake face detection

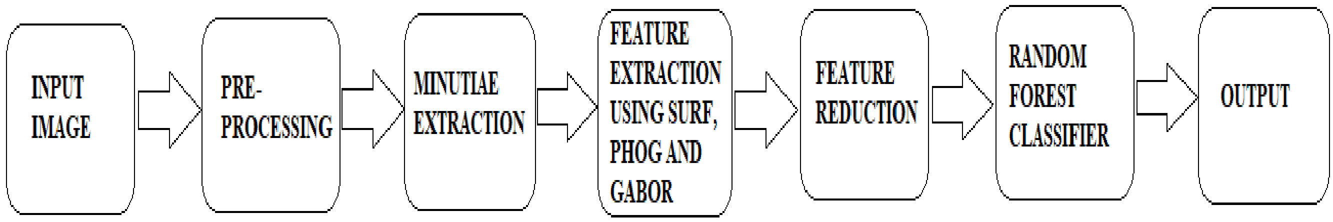

Figure (2): Block diagram of fake fingerprint detection

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IV. METHODOLOGY

4.1 FOR FACE

4.1.1 VIOLA-JONES ALGORITHM: The face region is known with help of this algorithm. The main reason we go for this algorithm is to recognize the face at first as we cannot use Stasm for the inputs with huge pictures with a small face in it. So, to locate the correct of the face we use this algorithm as it is really great in face identification with any image that has face images [4].

4.1.2 ACTIVE SHAPE MODELS: For localizing the facial features for a given input image, we use ASM. Here we use the Stasm to find the postion of the eyes so that we can localize the face region. ASM is prominent in finding the region of eyes, nose and mouth. We then make histograms of the these which is helpful in the classification.

4.1.3 FACE NORMALISATION: We compute the separating distance of the eyes in-order to crop and modify the face. Then the cropped face is normalized to 64 x 64 pixels. In a standardized face picture, we utilized the histogram balance, for modifying picture forces to improve and differentiate.

Later we de-noise the image using salt and pepper filter and functionalized the middle channel to disengage nearby highlights in the image, we apportioned the image it to squares covering all the areas and LBP is applied on each square.

4.1.4 FEATURE EXTRACTION USING LOCAL BINARY PATTERNS: We use LBP because it gives an increased detailing of an input. This methodology is mainly used for texture description. This is Computational, efficient, and fast. [3]

A image is made into 3x3 pixel blocks. The pixels corresponding to each square are limit by its inside pixel esteem, increased with the forces of two, and afterward it is added to acquire a mark for a pixel in the centre. We know that the local neighborhood contains 8 pixels, i.e., (2^8), based on the centre pixel and neighboring pixel grey values various labels are generated [6].

With the help of local binary patterns we obtain the histogram for a given input image and this histogram is used for the classification process which is processed using the RF classifier.

4.1.5 RANDOM FOREST CLASSIFICATION: The ensemble learning [18] alludes to the calculations that produce assortments or gatherings of classifiers that figure out how to characterize via preparing singular learners and combining the predictions of them. A decent improvement in the precision of classification has been obtained by growing the ensemble trees and getting them to decide in favor of the popular class.

Regularly, arbitrary vectors are assembled that control the development of each ensemble tree. Bagging and Boosting are the two kinds of learning methods. In the bagging method, the models will acclimatize equal where the progressive trees don't rely upon the past trees. Utilizing the bootstrap of dataset, every tree is a freely fabricated. In the boosting method, the models are consequently fit so that progressive trees dole out an extra weight to those perceptions ineffectively anticipated by the past model.

The Random Forest (RF) classifier is an innovation that speaks to a lot of learning techniques for arbitrary order that working by settling on choices utilizing a large number of trees casts a ballot and anticipating the highlights of the information by considering the output from each and every tree is gathered for a given input image and then the dominant part casting a ballot is accumulated to give a subsequent class name [14]. The RF classifier is worked by considering a random feature as the subset and sampling it for every available decision tree and then considering the training a data subset and sampling it over every decision tree available.

RF classifier is a technique of characterizing the information and displaying. In the RF classifier, the feature vectors obtained from the training data and the feature vectors obtained from the testing data are compared to know whether the given input is real one or just a spoofing.

Generally, in a RF classifier the error in dependent on the robustness of every decision tree and the correlation among the decision trees. We get the error rates based on the arbitrary determination of features that get chop at every node[15]. In the light of the training dataset, estimation on the error rate can be acquired as given below:

• From every decision tree developed with bootstrap sample, we get the out of bag data for each bootstrap emphasis.

• We calculate the out of bag every rate by valuating each and every out of bag consideration [16].

4.1.6 Comparing the accuracy of RF classifier with other classifiers: To know the accuracy of the RF classifier with SVM, KNN, MLP we using the same feature extraction with all the classifiers. The obtained results are shown in the below table.

Classifier	Accuracy
SVM	95.687%
Random Forest	97.982%
KNN	88.569%
MLP	78.635%

From this, we can say that the RF classifier has the higher accuracy which in deed helps in the better classification.

4.1.7 No. of decision trees to be used in RF classifier: For distinguishing the data between the real and spoofing, we need a better accuracy for the system. Therefore, we trained the classifier with a variant number of decision trees. From below table, we can conclude that the tree count proportional to the performance of the proposed system.

Number of Trees	60	80	100
Accuracy of Detection	84.325%	93.618%	98.256%

4.2 FOR FINGERPRINT

4.2.1 IMAGE PREPROCESSING: A fingerprint usually consists of a plethora of furrows and as well as ridges.

Furrows are also known as valleys. There are small points on the ridges of the Fingerprint known as minutiae. When you consider a Fingerprint image, it has some noise and unclear lines, and you might even have unclear ridges and Furrows as well. All these errors may occur during the capture of the fingerprint images. It may be because of several reasons such as moist or dehydrated fingers. So from this, we came to know that image capturing stage doesn't always provide you with high-quality fingerprints. So, we need to use processes like Image Enhancement, noise removal, thinning to get the desired region in the acquired fingerprint.

4.2.2 IMAGE ENHANCEMENT: This procedure is adjusting the digital images to get a clear separation between the wanted and unwanted attributes of the fingerprint image and further used for image analysis. For instance, removal of noise sharpens, or brighten a picture, etc.

4.2.3 REDUCTION OF NOISE: This stage comes under Image Enhancement**.** Here, we use the median filter to get an enhanced image. The Median Filter is used for removing noise from an image. The improved image after the Median filter has improved, attaching some points on the ridges that are not connected and getting rid of the false connections between ridges. After this, ridge segmentation is completed where it identifies ridge-like segments of a fingerprint image and also normalizes the intensity value of the image. Working of the Median filter is as follows Read a 2d image. Enter the matrix with zeros on all sides. Copy the first image matrix to a padded matrix. Then a matrix of size 3-by-3 is formed. In this matrix, we have the values of the input matrix. Then this matrix is converted into an array, and we finally find the center value.

4.2.4 BINARY IMAGE: Ridge orientation is done, and the local ridge frequency of a fingerprint image is determined. Subsequently, by applying the ridge filter, we enhance a fingerprint image by using oriented filters. After this filter application, we get a binary image. Now finally, a 1bit binary image is generated from an 8bit grayscale image.

4.2.5 THINNING OF THE IMAGE: Thinning is performed to remove the chosen forefront pixels from binary images; it is similar to opening or erosion. As to remove unwanted information and noise from the image, the undesirable ridges are removed. So the region acquired undergoes further operations. Finally, we obtain the skeleton of the image, in which all the ridges have only one-pixel value in width. After this process further reduction of pixels will not be possible.

4.2.6 MINUTIAE EXTRACTION: The minutiae extraction process's primary objective is to identify ridge ending and Bifurcation points, and the rest of the points on the Fingerprint are not considered minutiae. To extract these points, we use the process of Crossing Number (Cnbr). The crossing number concept works on continuously acquiring the neighborhood pixels of the ridge pixel in the preprocessed image. All these pixels are taken into the form of three into three matrixes, if the middle pixel is one and surrounded by another three neighbors with their values as one, then the middle pixel is a Bifurcation point. If the middle pixel is one and surrounded by only one neighbor with its value as one, then the middle pixel may be a ridge ending for a pixel px. If Cnbr(px) is equal to one, then it is a ridge ending, and if Cnbr(px) is equal to three, then it is a ridge bifurcation point in the image, a branch is counted thrice [7].

4.2.7 FEATURE EXTRACTION: After the minutiae extraction, we also extract features from SURF, PHOG, and GABOR, and all these features are reduced using PCA analysis to get better classification, which improves the accuracy of the system. We can acquire fingerprint images using different types of sensors like optical, capacitive, ultrasound, thermal. So, the fingerprint images from various sensors have different rotation as well as scales. So to get rid of these problems, we use speeded up robust features technique known as SURF.

SURF is also useful in various other works such as in registration of the image and 3-D image reconstruction etc. A rotation descriptor and detector are present in SURF [8]. Basically, the descriptor helps in identifying unique features in the image. To overcome scale and rotation problems, SURF masks the axes and forms forty-five degrees angle with the axis. The approximate determinant of the hessian blob matrix is used in SURF is similar to scale-invariant feature transformation (SIFT), but the difference is details in those steps. The runtime is reduced because of the SURF's short descriptor length. So it is faster than SIFT [17]. But the fingerprint images susceptible to geometric transformations also in order to overcome this problem, we use a pyramid histogram of oriented gradients (PHOG).

A PHOG descriptor is a concatenation of histograms obtained from pixels of each cell. PHOG basically concentrates on the shapes which are locally present in the fingerprint. PHOG is derived from HOG. HOG works on cells that are locally present in the image, which helps in identifying the shape of the images and sometimes appearance also [10]. It uses the direction of the edges in the image and intensity gradients also, as the name suggests. PHOG technique also gives good results in problems such as analysis of static facial expressions. So in the fingerprint image, you may have phot5ometric transformations, but PHOG is invariant to those transformations also. The Algorithm of PHOG follows these stages that are Gradient Computation normalizing the gamma and color values in the image; Orientation binning is obtaining the histograms of each cell followed by Normalized blocks and at last object recognition. The problems like scale transformation, object orientation, geometric and photometric changes are solved using PHOG and SURF, but we are still left with textural issues of the image.

To eliminate these problems, we used a linear image processing filter known as a Gabor filter for analysis of texture in the image. This filter is used in the spatial domain and to get selective features from an image [12]. So in image processing, we use two-dimensional Gabor filters. If you take filters with different frequencies, we can obtain our selective features and also useful for texture analysis. Gabor is also used for segmentation. The frequency of the Gabor filter relates to spaces between the ridges in the image. The image is divided into M*M blocks, and each block is filtered with Gabor to extract distinctive features**.**

4.2.8 FEATURE REDUCTION: For feature reduction, we use the PCA analysis. It is a statistical analysis method to extract the essential contradicting features from multiple features [19]. The PCA analysis also contributes to the reduction of the dimensions of the feature vectors generated by SURF, PHOG, and Gabor filter. Using the PCA, we can retain most of the original data and can reduce the data redundancy. The feature vector generated here is used for the classification.

4.2.9 RANDOM FOREST CLASSIFICATION: As described in the **(A),** the same method of classification is followed here.

4.2.9 Comparing the RF classifier and SVM: We compare the accuracy of RF classifier with that of SVM by using SURF, PHOG, Gabor filter as a combination, and SURF, PHOG, Gabor filter individually as a feature extraction processes. The comparison is shown in the below table.

Method	Random Forest	SVM
SURF	92.368%	92.768%
PHOG	94.456%	93.82%
Gabor	91.236%	94.367%
SURF+PHOG+Gabor	97.432%	95.965%

With the combination of SURF, PHOG, and Gabor, the random forest gives higher accuracy.

4.2.10 Finding the count of decision trees to used with the RF classifier: For better distinguishing between real and spoofed fingerprints we need the system to be more accurate. So, we trained the classifier with a variant number of decision trees. From below table, we can conclude that the tree count proportional to the performance of the proposed system.

Number of Trees	50	70	80
Accuracy of Detection	88.715%	95.634%	97.506%

V. EXPERIMENTAL ANALYSIS

5.1 FOR FACE

When a given input image is processed, and the locations of the facial features are obtained using the ASM, and the features are extracted using the LBP and then it is processed to the random forest classifier where bagging process takes place, and we get the out of bag perceptions i.e., In training dataset, the perceptions that does not belong in are considered as "out-of-bag" and the graphical representation of prediction error versus decision tree count is given below figure (3).

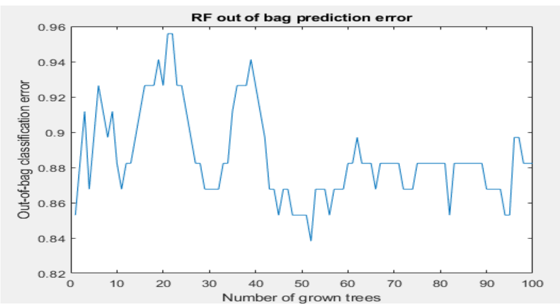

Figure (3): The RF out of bag prediction error graph for fake face detection

After the bagging process, the decision trees are made accordingly, and the classification is done, and the classification tree is shown below figure (4).

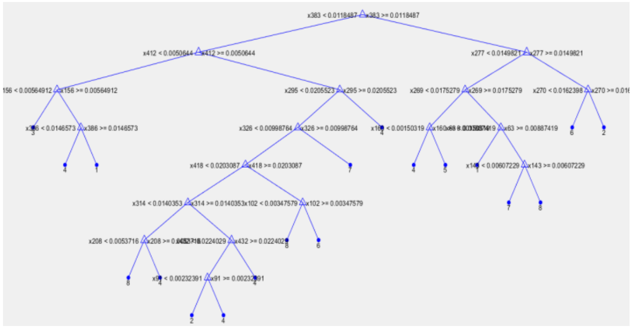

Figure (4): The Classification tree for fake face detection

From the above classification tree, we can conclude whether the given input face is a fake face or a real face.

5.2 FOR FINGERPRINT

For a given fingerprint image, first, we extract the minutiae from the image, and it is shown in figure (5).

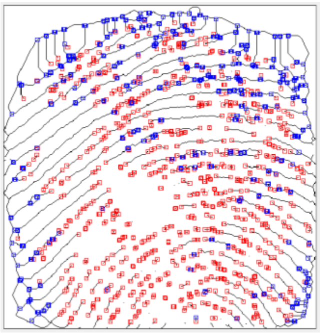

Figure (5): Minutiae extraction for the given fingerprint

Then the feature extraction is taken place and then it is processed to the random forest classifier where bagging process takes place, and we get the out of bag perceptions i.e., In training dataset, the perceptions that does not belong in are considered as "out-of-bag" and the graphical representation of prediction error versus decision tree count is given below figure (6).

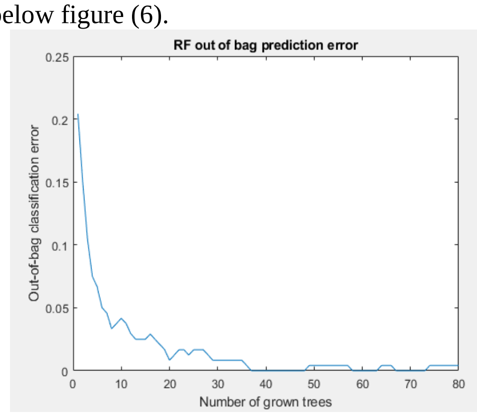

Figure (6): The RF out of bag prediction error graph for fake fingerprint detection

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After the bagging process, the decision trees are made accordingly, and the classification is done, and the classification tree is shown below figure (7).

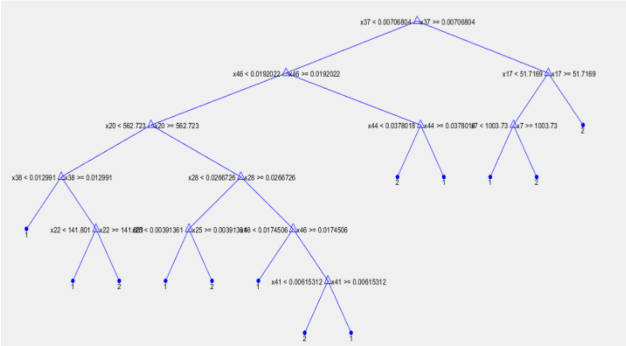

Figure (7): The Classification tree for fake fingerprint detection

From the above classification tree, we can conclude whether the given input fingerprint is a real or fake fingerprint.

VI. RESULT

As discussed in the above detection processes for face and fingerprint. Based on the input image, the system processes the data and gives a result whether the given input is a spoof or real. For fake face detection, the facial features are located using ASM, and the feature extraction is done using LBP and the RF classifier is used for classification. For fake fingerprint detection, first the minutiae extraction is done and then the feature extraction is done using SURF, PHOG and Gabor. The feature dataset obtained here is then processed to feature reduction which is done using PCA analysis. The generated feature vector is sent to RF classifier for classification. The flow of the proposed system for a given input image is shown in the below figures.

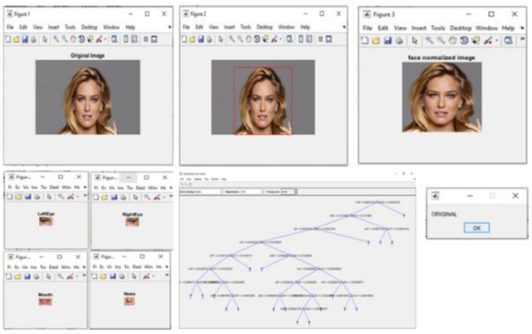

Figure (8): Detection of real face for a given input image

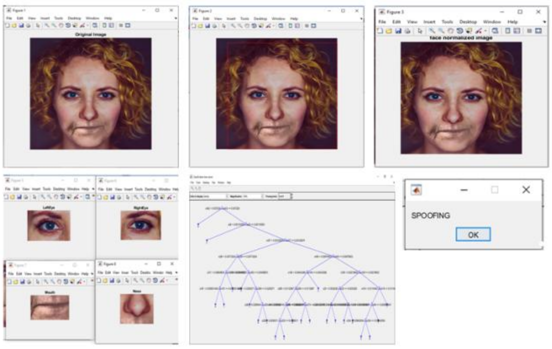

Figure (9): Detection of spoofed face for a given input image

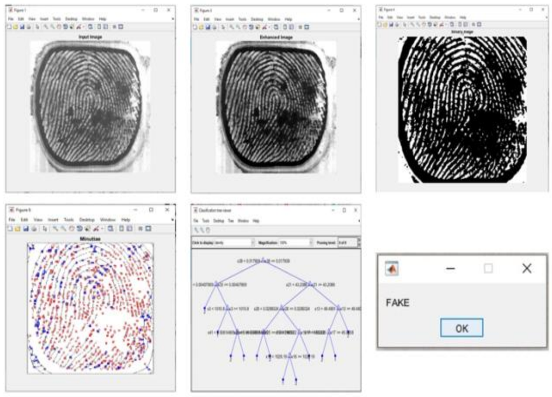

Figure (10): Detection of fake fingerprint for a given input image

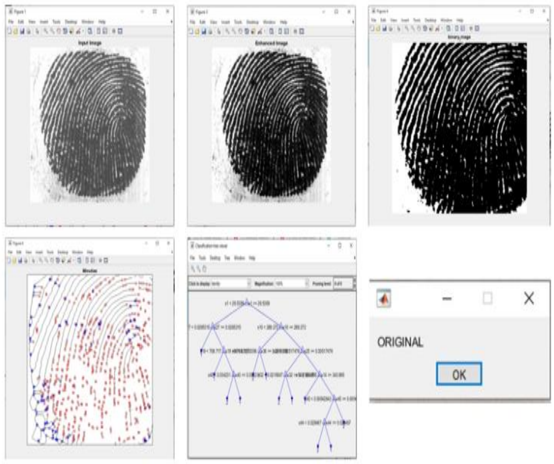

Figure (11): Detection of real fingerprint for a given input image

VII. CONCLUSION

Face and Fingerprint biometric systems are vulnerable to spoofing attacks. The proposed system provides an anti-spoofing solution by using the Active Shape Models for facial feature localizing and Local Binary Patterns for obtaining the histogram for the input image and then the RF classifier distinguishes it into real or spoof in fake face detection and in fake fingerprint detection, we use Local Binary patches for minutiae extraction and SURF, PHOG to extract gradient features and GABOR Filter to extract texture features and then Random Forest classification to differentiate real biometrics from fake ones. In this paper, we used the Random Forest classifier commonly in fake face detection and in fake fingerprint detection. Hence we are able to differentiate the original data from the fake or spoofed data provided by the user and increasing the integrity of the system.

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