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# AN ARTIFICIAL NEURAL NETWORK-BASED SECURITY MODEL FOR FACE RECOGNITIONUTILIZING HAAR CLASSIFIER TECHNIQUE

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***Abstract***:A facial recognition system is a computer program that uses a digital image or a video frame from a video source to automatically recognize or confirm a person.An amicable approach to achieving thedesired result in facialsby comparing certain facial traits from the image with a facial database, biometrics. This paper developed an ANN-based secure facial recognition model that will accurately and efficiently record all data and information about an individual. This system uses Haar Classifier Technique; face detection algorithms, Opencv, Visual C++, Haar-like Features the Canny Edge Detection and OPenCV. The results, therefore, demonstrate that the system successfully allows user to log in using credentials, enrols, registers, logs, and save captures data and facial biometrics. The system authenticates by analysing the upper position of the two eyebrows vertically. The method searches from w/8 to mid for the left eye and from mid to w - w/8 for the right eye. Thus, w denotes the image's width, while mid designates where the two eyes are cantered. For the left eye, the black pixel lines are between mid/2 and mid/4, while for the right eye, they are between mid+(w-mid)/4 and mid-+3*(w-mid)/4. From the initial height of the eyebrows until (h- eyebrow starting position)/4, the black pixel lines' height is calculated.

***Keywords***: Artificial Neural Network, Face Recognition, Security

## 1. INTRODUCTION

Using a digital image or a video frame from a video source, a facial recognition system can automatically recognize or confirm a person.(John, Christopher, Julius, Thomas, 2003**)**. Comparing specific face traits from the image and a facial database is one method for doing this. It can be comparable to other biometrics like fingerprint or eye iris recognition systems and is frequently utilized in security systems. Nowadays, there is a lot of focus on the interface and interaction between humans and computers, with the goal of creating a natural human-to-human connection that is based on everyday human behaviour. It is common knowledge that the most expressive way that people communicate emotion is through their faces. Humans are able to quickly recognize the indications of faces and facial expressions in a natural interpretation. Yet, creating an automatic system to recognize objects is challenging in the realm of computers and recognition.

This is mostly because of a number of issues, including:

i) I Segmenting and detect faces in the acquired image,

ii) Extracting the data pertaining to facial expression, and

iii) The method of identifying an emotional state from a facial expression.

Consequently, creating a real-time system to resolve these issues with precise operations to carry out human-like interaction between man and machine is the true problem. According to previously published research (Pantic&Rothkrantz, 2000), the terms "face-to-face" and "interface" typically clarify the crucial role in interpersonal communication. In human behaviour, the face serves as the primary means of identifying other species members, as it can be used to read lips to decipher spoken words, and it can also be used to infer an individual's emotional state from their facial expressions.

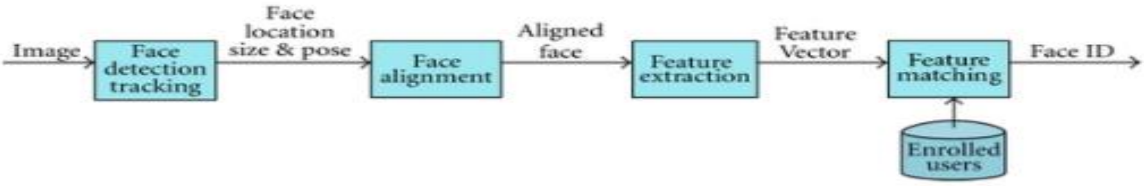



Figure 1: Structure of a face recognition system

Face recognition is biometric which uses computer software to determine the identity of the individual. Face recognition falls into the category of biometrics which is "the automatic recognition of a person using distinguishing traits. (John, Christopher, Julius, and Thomas, 2003**)**. The use of fingerprints, retinal scans, and iris scans are other biometric techniques. One of the first varieties of face recognition is 2D face recognition using Eigenfaces. The groundbreaking "Face Recognition Using Eigenfaces" by Turk and Pentland was released in 1991. The approach computes Eigen faces—

faces made up of eigenvectors—by analyzing face photos. To determine whether a face is present and to determine its identity, Eigenfaces are compared. The system created by Turk and Pentland has a five-step process (1991). The system must first be activated by being fed a set of practice face photos.This is used to define the face space, a collection of like-faced images. Then, it computes an Eigenface for each face it encounters. It is possible to establish whether the image being presented is even a face by comparing it to recognized faces and performing some statistical analysis. The algorithm will next decide if it recognizes the face in the image if it is judged to be a face. The optional final stage is for the system to learn to recognize an unfamiliar face if it is repeatedly observed.The Eigen face method is straightforward, effective, and produces generally positive outcomes under regulated conditions (Matthew and Alex, 2001). Even tracking faces on video was tested with the technique. Nevertheless, Eigen has significant drawbacks. Little resistance to changes in distance, angle, and lighting (RAND, 2003).A key issue with 2D recognition systems is that they fail to record the face's actual size (Trina, Mark, Charles, 2004). Due to the inability to rely on frontal pictures and steady lighting, the technique cannot be used with security cameras.

## 2. ANN FOR FACE DETECTION

The face recognition system's face detection processing is its initial stage. The phase is the most crucial one in the recognition process because it determines how well the system performs.

system. A variety of strategies have been suggested by numerous researchers to carry it out effectively. There are generally four categories of face detection techniques (Yang et al, 2002)

(1) Methods based on knowledge;
(2) techniques using invariant characteristics;
(3) methods that are used in template matching;and
(4) approaches based on machine learning.

We exclusively employ machine learning techniques in this paper since they take the subjective thinking components out of the human experience. Additionally, they exclusively base their decisions on training data. So, if training data is organized and sufficient, these systems will function well without the need for human elements.

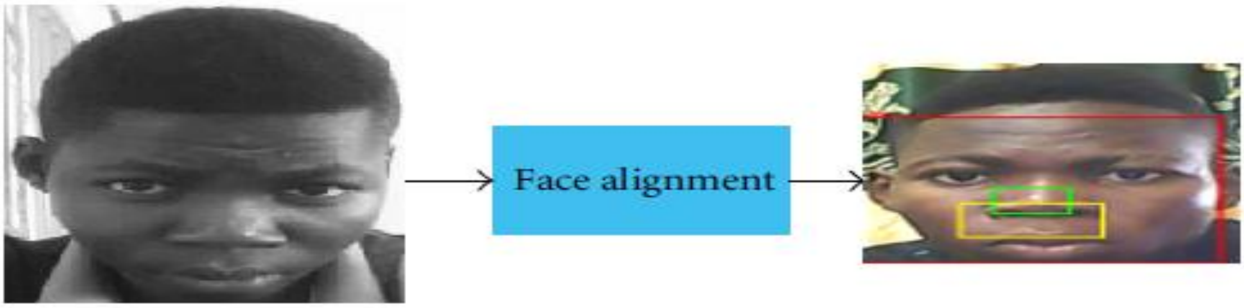
AdaBoost technique (Viola and Jones, 2001) designed a quick, reliable face identification system where AdaBoost learning is used to generate nonlinear classifiers. It is one of the most well-known and effective learning machine-based approaches for detecting faces. AdaBoost is used to address the three main issues listed below:

(1) discovering useful traits from a broad feature set;
(2) building weak classifiers based on a single one of the chosen features;
(3)constructing a strong classifier by boosting the weak classifiers.

For the efficient computation of numerous such features at various scales and locations, which is crucial for real-time performance, Viola and Jones employ a variety of strategies. Additionally, the calculation will be significantly more effective thanks to the cascade of powerful classifiers that makes up a cascade tree.

**Local Texture Classifiers Based onMultilayer Perceptron for Face Alignment**

One of the crucial phases of face recognition is facial alignment. Moreover, face alignment is employed in face modeling and synthesis, two additional face processing applications. Its goal is to identify the feature points, such as the contour points of the face, nose, and mouth, on photographs of faces.




**Figurement2: Face Alignment**

There are numerous techniques for face alignment. Two popular face alignment methods are the active shape model (ASM) and the active appearance model (AAM), both proposed by Cootes. The two methods parameterize a facial form using a statistical model by employing the PCA method.However, their feature model and optimization are different. Given the initial labels, each label point in its local region is searched for a new position in the first stage of the ASM algorithm that best matches the associated local 1D profile texture model. The shape parameters that best fit these new label positions are then modified in the second stage.

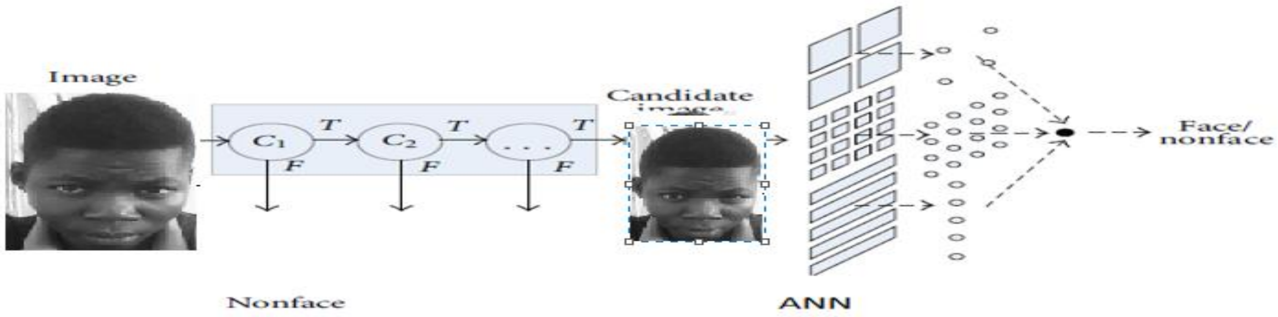



Figure 3(a): The process of detecting faces of ANN

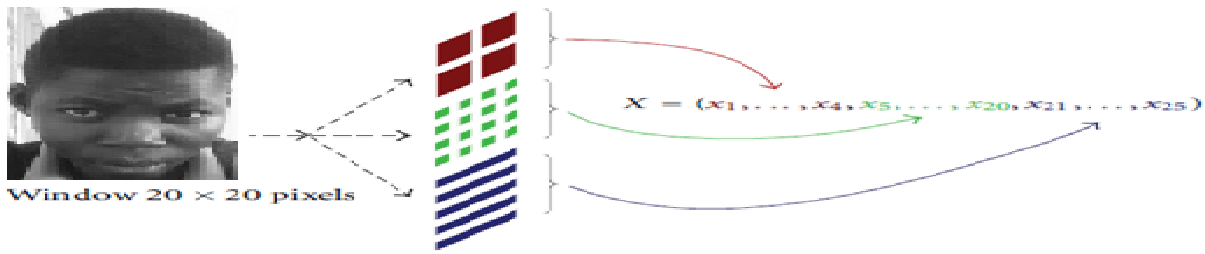



Figure 3(b): Neural network's input.

**3.1. Models of statistical shapes.** A 2n-element vector with n points, X = (x1, y1,..., xn, yn)T, can be used to depict a facial form (xi, yi). s shape vectors (Xi) are present when a collection of practice face photos is used. Before we can statistically examine these vectors, it is essential that the shapes they represent are in the same coordinate system. In Figure 4, the form model is displayed.

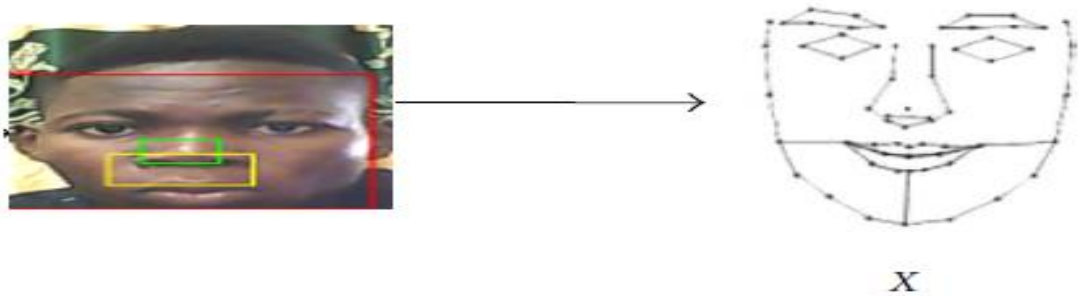



Figure 4: Model of an image's shape.

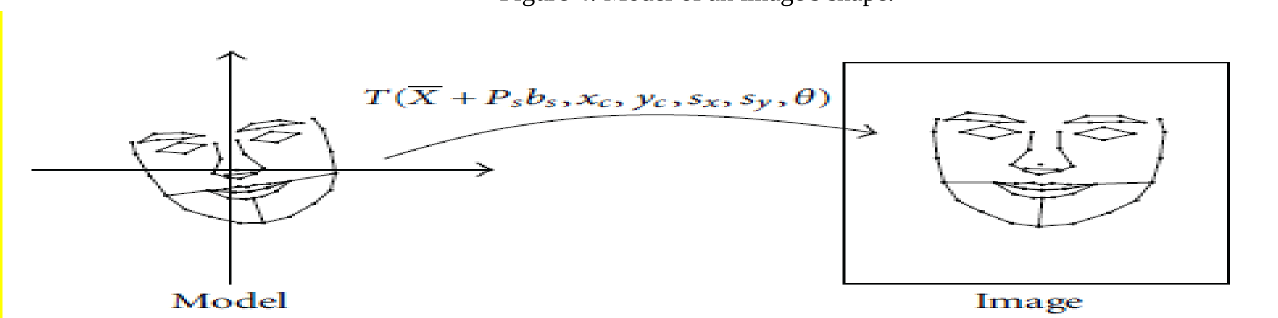



Figure 5: Picture transformation using a model.

Step 1 is to calculate the data set's mean.

$$\overline{X} = \frac{1}{s}\sum_{i=1}^{s} X_i. \qquad (1)$$

Step 2. Calculate the data set's covariance matrix.

$$S = \frac{1}{s-1}\sum_{i=1}^{s}\left(X_i - \overline{X}\right)\left(X_i - \overline{X}\right)^T. \qquad (2)$$

Step 3. Compute the eigenvectors, $p_j$ , and correspondingeigenvalues, $\lambda_j$ , of the data set S (sorted so $\lambda_j \geq \lambda_j+1$).

Step 4. We can approximate X from the training set

$$X \approx \overline{X} + P_s b_s, \qquad (3)$$

where Ps = ($p_1|p_2| \cdot \cdot \cdot |pt$) (t, the number of modes, can bechosen to explain a given proportion of 98% of the variancein the training data set) and bs = ($b_1, b_2, . . . ,b_t$), shapemodel parameters, given by

$$b_s = P_s^T\left(X - \overline{X}\right), \qquad b_i \in \left\{-3\sqrt{\lambda_i} + 3\sqrt{\lambda_i}\right\}. \qquad (4)$$

A real shape X of images can be generated by applying asuitable transformation T to the points X:

$$X = T\left(\overline{X} + P_s b_s, x_c, y_c, s_x, s_y, \theta\right). \qquad (5)$$

*3.2. ASM Algorithm.*The parameters of a model instance can be changed, given a rough starting approximation, to improve the model's fit to a fresh image.

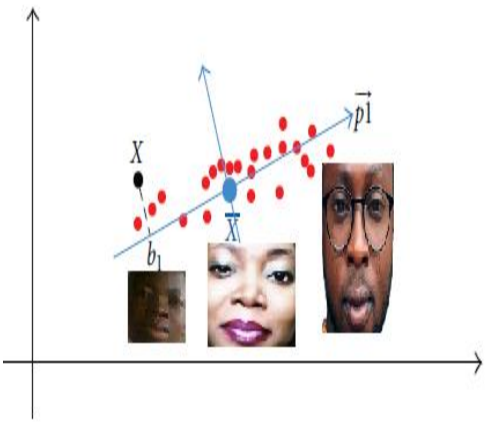



Figure 6: Using PCA to compute statistical shape model.

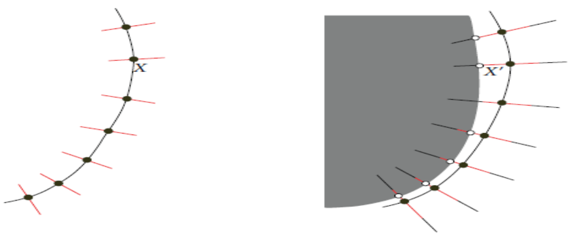



Figure 7: 1D profile texture model.

In a coordinate system that is centered on the object, we determine its shape. By specifying the location ($x_c$, $y_c$), orientation (), and scale ($s_x$, $s_y$) parameters, we may produce an instance X of the model in the image frame. Following is an iterative process to enhance the instance's fit to a picture, T(X + Psbs, xc, yc, sx, sy, ) (Figure 7).

*Step 1.* To locate the ideal neighboring match for the points X', examine the area of the image surrounding each point of X'.

Step 2. till convergence, repeat. In order to minimize the sum of square distances between corresponding model and image points, update the parameters ($b_s$, $x_c$, $y_c$, $s_x$, $s_y$) to best fit the newly discovered points X':

$$E\left(b_s, x_c, y_c, s_x, s_y, \theta\right) = \left|X' - T\left(\overline{X} + P_s b_s, x_c, y_c, s_x, s_y, \theta\right)\right|^2.$$

**----------(6)**

Classical Local Texture Model. To find a local match for each point is the goal (illustrated in Figure 8). It is presumable that the model has the best edge, correlation, and statistical profile model.

Step 1. Computing normal vector at point ($x_i$, $y_i$) and calculatingtangent vector t,

$$t_x = x_{i+1} - x_{i-1}, \qquad t_y = y_{i+1} - y_{i-1}. \qquad (7)$$

Normalize tangent vector t,

$$t_x = \frac{t_x}{|t|}, \qquad t_y = \frac{t_y}{|t|}. \qquad (8)$$

Calculate normal vector n,

$$n_x = -t_y, \qquad n_y = t_x. \qquad (9)$$

Step 2. Calculate g(k) by sampling along the 1D profile ofpoint ($x_i$, $y_i$),

$$G(k) = \text{image}\left[x_i + kn_x, y_i + kn_y\right], \quad k \in [\ldots, -2, -1, 0, 1, 2, \ldots]. \qquad (10)$$

To noise images, The average orthogonal to the 1D profile.

$$g(k) = \frac{g_{kl}}{4} + \frac{g_{kc}}{2} + \frac{g_{kr}}{4}. \qquad (11)$$

We can choose the location at the strongest edge by using image derivation to make the edges of images obvious. The real point, however, may not always be at the sharpest edge. To find the spot, we employ the local probability model. In order to find the proper point, we estimate the probability density function (p.d.f.) on the 1D profile for each point using the training data set.

3.4. Multilayer Perceptron Model forLocal Texture Classification

3.4.1. Structure of Multilayer Perceptron (Bishop, 2006). A multi-layerperceptron (MLP) is a function

$$\hat{y} = \mathrm{MLP}(x, W); \quad x = (x_1, x_2, \ldots, x_n); \quad \hat{y}(\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_m), \qquad (12)$$

For each unit *i*of layer *L* of the MLP,Integration:

$$s = \sum_j y_j^{L-1} w_{ij}^L + w_{i0}^L. \qquad (13)$$

Transfer: $y_j^L = f(s)$, where

$$f(x) = \begin{cases} -1 & x \le -\frac{1}{a}, \\ a \cdot x & -\frac{1}{a} < x < +\frac{1}{a}, \\ 1 & x \ge +\frac{1}{a}. \end{cases} \qquad (14)$$

### 3. HAAR LIKE FEATURES

Digital image properties that resemble Haar are employed for object detection. Any position and scale inside the original Picture can be used to generate a basic rectangular Haar-like feature, which is defined as the difference of the sum of pixels of areas inside the rectangle.

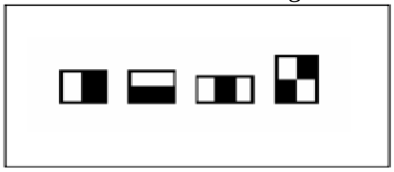


Figure 8: A set of basic of Haar like Feature. (Center)

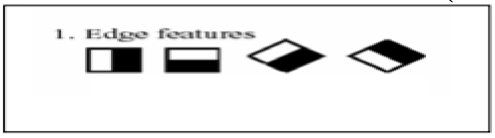



Figure 9: A set of extended Haar Like Feature (edge features)

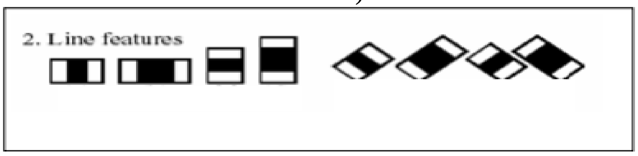



Figure 10: A set of extended Haar like Feature (Line features)

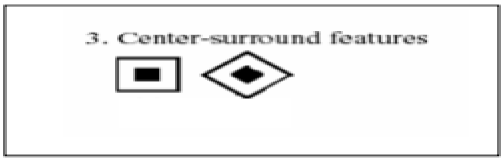



Figure 11: A set of extended Haar like Feature (center-surrounded features).

By comparing them, 3D systems create 3D models of faces. Because these systems capture the true shape of faces, they are more accurate. (2004) Trina, Mark, and Charles with the addition of skin texture analysis, face recognition accuracy can be increased by 20–25%. (Mark, 2007). One of the key issues with 3D systems is the collection of 3D data. It is crucial for researchers to be aware of the findings from human facial recognition investigations (Pawan Sinha, Benjamin Balas, Yuri Ostrovsky, and Richard Russell, "Face Recognition by Humans: Nineteen Results All Computer Vision Researchers Should Know About," Proceedings of the IEEE, Volume: 94, Issue: 11, 2006.)

Understanding these results might aid them in creating inno vative new techniques. After all, competition and research. Law enforcement is drawn to facial recognition. It can be utilized in conjunction with the currently installed infrastructure of security cameras to look for criminals. Comparing face recognition to other biometrics like fingerprints, retina scans, and iris scans, which are overt and obtrusive (RAND, 2003). Faces are regarded as public information, hence this is crucial in relation to the law. There are already extensive photo databases made from mug photographs or driver's licenses.

It is advantageous to try to get good-quality photos in relation to these characteristics because face recognition has issues with lighting, perspective, and other elements. Face traps are a concept where cameras are placed deliberately to get somewhat controlled pictures (RAND, 2003). Examples include placing cameras in front of doorways, close to objects that people tend to gaze at, at airport check-in counters, and elsewhere. These traps would help facial recognition software by making it easier to capture a frontal image in a straight line, increasing system accuracy. Despite their potential advantages, there doesn't seem to be much research on face traps.

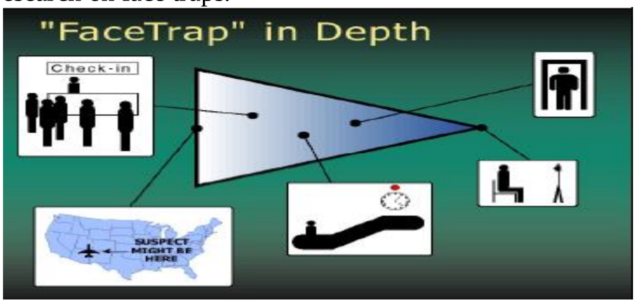



Figure 12:Increasingly controlled environments from left to right

Figure 12 shows, from left to right, situations that are more tightly managed. Suspect boarding a plane (no control), subject at a check-in desk, subject on an escalator gazing at a flashing red light, subject walking through a doorway, and subject seated in front of a camera (complete control), from left to right (RAND, 2003).

Some people have questioned the legality of face scanning and said that the use of such technology to track down criminals in public places violates people's privacy. Legally speaking, in the United States, there is no such thing as a right to privacy for things that are displayed in public (RAND, 2003). According to United States v. Miller, 425 U.S. 435, "What a person willingly discloses to the public.is not a subject of Fourth Amendment protection" (1976). According to United States v. Dionisio, 410 U.S. 1, "No person may have a reasonable expectation that others will not be aware of the sound of his voice, any more than he can fairly anticipate that his face will be a mystery to the world" (1973). These Supreme Court decisions' citations are beneficial.

In Tampa, Florida, and Newham, England, surveillance cameras are connected to face recognition systems (Michael Kraus 2002). Trials of the systems produced mediocre outcomes. The Newham system didn't result in any arrests during the course of three years. Logan Airport in Boston had two demonstrations using face recognition technology. The accuracy of the system was just 61.7% of the time (Ryan Johnson, Kevin Bonsor, "How Facial Recognition Systems Work," How Stuff Works, 2007).

Recently, Australian customs began using its SmartGate system to automatically verify faces in passport images. A secret component on Google's image search engine is being used to test facial recognition ("New: Google Image Search Categories," Google Blog scoped, 2007). Google plans to integrate Neven Vision's technology into Picasa after purchasing the computer vision business in 2006.

This work presents a safe, ANN-based facial recognition model that can swiftly and accurately record all personal data and information about an individual. The remaining sections of the paper discuss the literature review, the methodology used to create the facial recognition system, the results obtained, and recommendations for future research. Section three of the paper discusses the literature review, section four discusses the results, and section five concludes.

## 4. METHODOLOGY

An extensive explanation of the architectural planning and creation of the ANN facial recognition system is provided in this section. The technology only recognizes facial features, ignoring objects like bodies, trees, and buildings. The Haar Classifier Method, face identification techniques, OpenCV, Visual C++, Haar like Features, Canny Edge Detection, and OPenCV are all used by this system. A computer vision library, OpenCV primarily focuses on real-time image processing. OpenCV is a library of techniques and example programs addressing a range of computer vision issues.

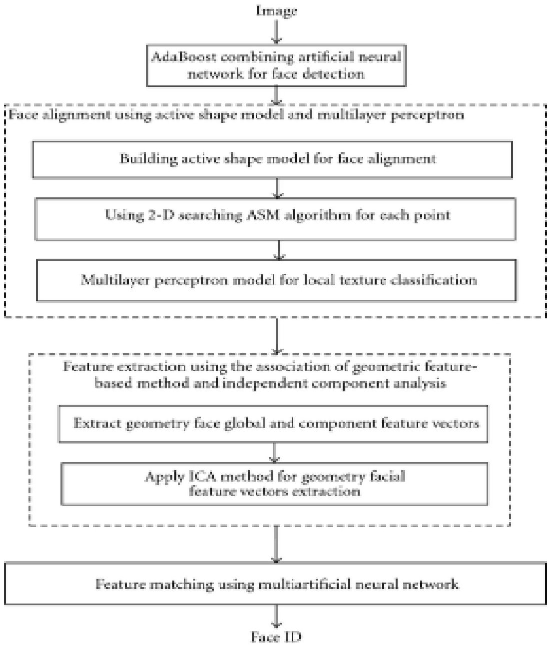



Figure 13: Proposed models for steps of a face recognition system.

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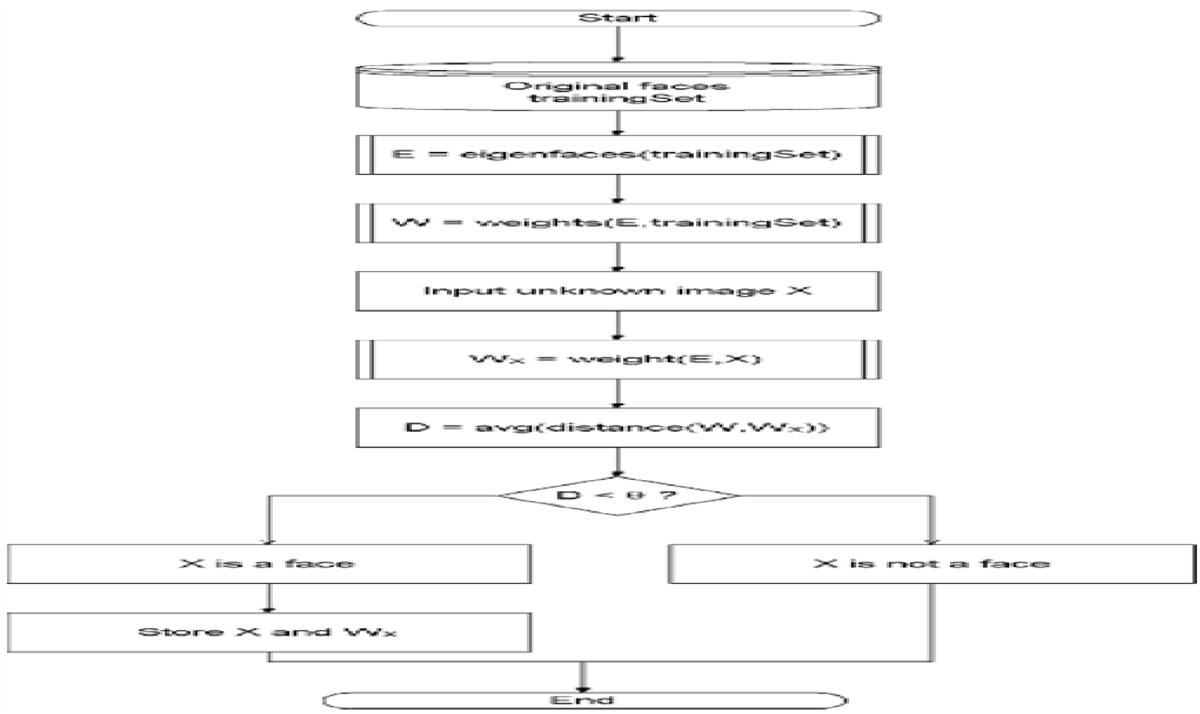


Figure 14: Flow chart of the Eigen face-based algorithm

 

Figure 14 illustrates the three stages of the ANN face biometric template matching process: preprocessing, feature extraction, and template fitting.

The segmented face image is transformed into a machine code or binary template during feature extraction, which provides specific information. In order to establish if a match is found or not, the binary templates must be created and then compared to each template that is recorded in the database.

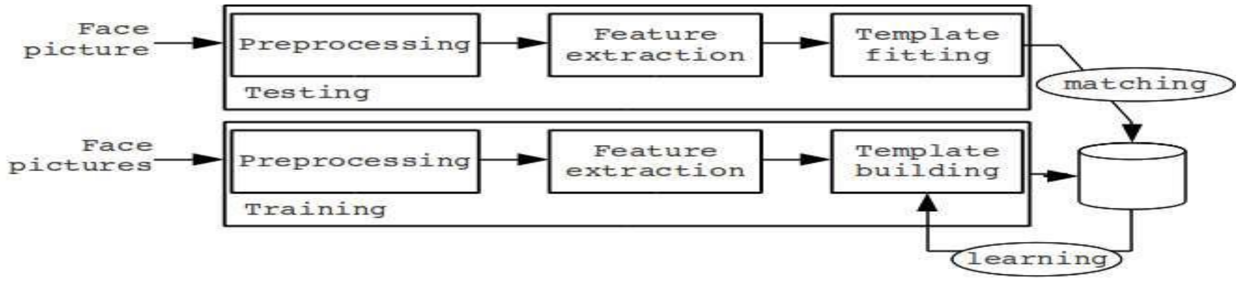


Figure 15: Template-matching algorithm diagram

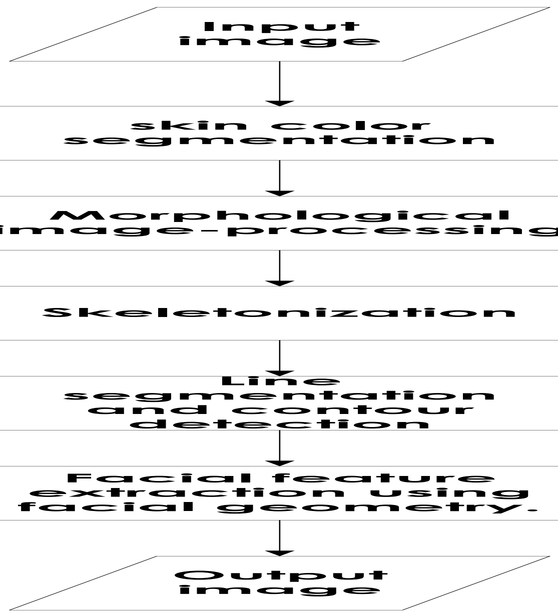


Figure 16: Program Flowchart

## 6. Experimental Results and Discussion

After successfully logging into the system, enter the student's information into the registration form, as shown in Figure 17, before capturing the face biometrics.

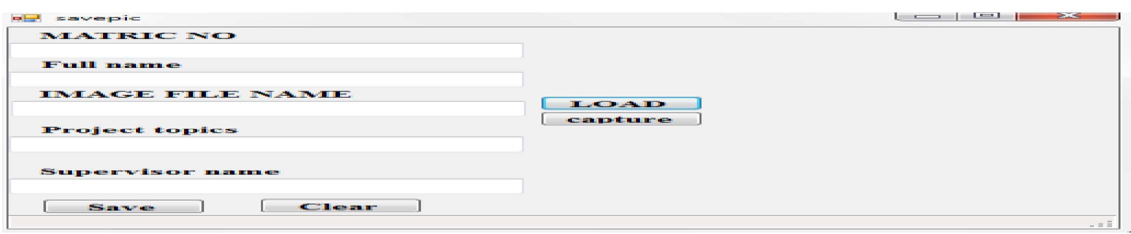


Figure 17: Registration form

The second step is to save after entering the student's necessary information by pressing the save button, as illustrated in Figure 9. The student's facial biometric will be taken as illustrated in Figure 18 after clicking the capture button.

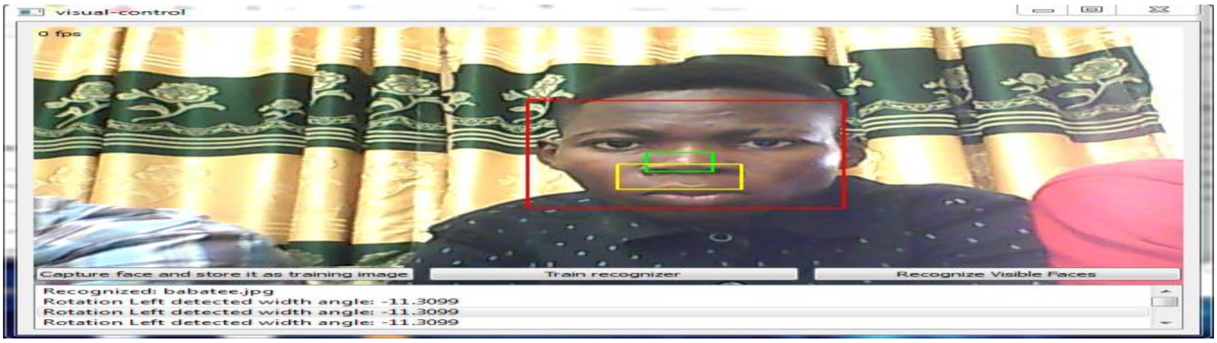


Figure 18:Face Detection

The results therefore demonstrate that the system successfully allows user to login using credentials, enrolls, registers, logs and save captures data and facial biometric. The system authenticates by analyzing the upper position of the two eyebrows vertically. For the left eye. The system looks for the right eye from mid to w - w/8 and the left eye from mid to w - w/8. Therefore, w stands for the width of the image, while mid means the center of the two eyes.

For the left eye, the black pixel lines are between mid/2 and mid/4, while for the right eye, they are between mid+(w-mid)/4 and mid-+3*(w-mid)/4. From the initial height of the eyebrows until (h- eyebrow starting position)/4, the black pixel-lines' height is calculated.

Thus, w stands for the image's width, mid for the two eyes' placement in the middle, and h for the image's height. Next, we may find where the two eyes are located at the bottom by scanning vertically for black pixels. Between mid-mid/4 and mid-mid-mid/4 breadth, we search for left eye.

And for the right eye, we seek for a width of mid + (w-mid)/ 4 to mid+3*(w-mid)/ 4 from the bottom of the image to the initial position of the eyebrow. We can therefore locate the right side of the left eye by starting from the middle of the left eye and proceeding horizontally to the starting position of the black pixels between the upper position and lower position of the left eye.

Next, we search for any black pixels on the left side of the right eye that are halfway between the upper position and lower position of the right eye. The left side of the left eye is where the image starts off, and the right side of the right eye is where it ends. The top position, bottom position, left side, and right side of the two eyes were then separated from the RGB image. The system compares the chosen facial features from the image and the database after analyzing all of the aforementioned features.

Table 1: The ANN structure for detecting faces.

| Name | Input Nodes | Hidden Nodes | Output Nodes | Learning Rate |
|---|---|---|---|---|
| ANN_Face | 35 | 35 | 1 | .5 |

Experimental Results of ANN-Based System. We used a trained ANN model for detecting faces (Table 1). We also tested the system on the HAAR [3] test set. Table 3presents the performance of ANN.

Table 2: Performance of detection on MIT + CMU test set of AdaBoost detector

| Method | Number of Stages | Number of Haar like features used | Faces detected | Missed faces | False detections | Detection rates | Average time to process an image |
|---|---|---|---|---|---|---|---|
| HAAR | 40 | 1800 | 767 | 30 | 302 | 96.11 | .15 |
| ABANN | 50 | 1900 | 352 | 75 | 70 | 59.15 | .302 |

Strong classification method ANN has been successfully used to the problem of face detection. The performance time is also not long. Since then, we have recommended a hybrid AdaBoost/ANN model. On the other side, we add ANN at the very end to produce a fully integrated hybrid system.

Table 3: Performance of detection on HAAR test set of ANN detector

| Method | Face Detected | Missed faces | False detection | Detection rate | Avg. time to process an image |
|---|---|---|---|---|---|
| ANN | 767 | 31 | 19 | 74.89 | 51.56 |

## 5. CONCLUSION AND RECOMMENDATION

**Efficiency**. A 2.0GHz Pentium IV CPU with 1 GB of RAM is used for all tests. Because to its extremely straightforward computation of the local texture model, the traditional ASM is the fastest. Although our approach is a little slower than the traditional ASM, it is still comparable.

 

The effective development and implementation of the ANN-based secure facial recognition model will efficiently and accurately record all data and information about an individual using facial biometrics. Every company or school can utilize the system to manage student and staff data instead of using outdated methods. It will take less time and effort to manage, update, secure, and monitor information.

As a conclusion, we showed our reliable face alignment method that makes use of a local texture model (MLP ASM). Instead of simulating a local feature by a 1D profile texture, our classifier is trained by comparing its 2D profile texture patterns to those of its neighbors. The classifier is an effective tool for the local search of feature points because to its high discriminative capacity.Performance is ensured by the MLP method's generality and resilience. Our method therefore exhibits potential in real-world applications when contrasted to those now in use, which achieve their models in very limited training sets.

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