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Biometric Face Identification: Utilizing Soft Computing Methods for Feature-Based Recognition

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ABSTRACT

Biometric facial identification presents a distinct and reliable method for distinguishing individuals based on unique physical or behavioral characteristics. Unlike traditional security measures such as passwords, facial features offer a level of security that cannot be shared, replicated, or forgotten. This study focuses on the application of facial biometrics for person identification, leveraging the advantages of non-contact biometrics like facial features over other methods such as fingerprint or palm recognition. Facial recognition in this work is predicated on the geometric shapes or facial characteristics. Emphasis is placed on three fundamental views of the face: upward, frontal, and downward. For each of these views, specific regions are extracted for processing, including the right-eye region and its width. Simultaneously, the dimensions of the mouth, both height and width, are extracted in a similar manner. Training and evaluation of the proposed system are accomplished using three soft computing models: an Artificial Neural Network (ANN), a Particle Swarm Optimization Neural Network (PSO-NN) model, and an Adaptive Neuro-Fuzzy Inference System (ANFIS) model. Each model employs a dataset constructed for each view. Optimization of the models is achieved by adjusting parameters like the number of neurons used in the hidden layer for recognition in neural network-based procedures. Performance evaluation of the proposed system is conducted by computing the mean square error, obtained by random data division. The models demonstrated a training set accuracy of 97.20% and a testing data set accuracy of 90.86%. These results indicate the effectiveness of the proposed system for both individual and combined face views, underscoring the potential of facial biometrics in secure identification applications.

1. INTRODUCTION

Personality can be ascertained through an extensive array of physiological and behavioral traits. Physiological methods often consider features such as the face, iris, retina, hand geometry, and ear, while behavioral methodologies take into account aspects like voice, gait, and keystroke patterns [1].

1.1 Background work

This research focuses on utilizing biometric features from facial images for identification purposes. Given the substantial efforts by government agencies to enhance security mechanisms, vulnerabilities in the latest technologies have been exposed. To circumvent potential hacking, it is prudent to incorporate a unique marker or password throughout the authentication process. While biometrics is a prevalent choice, it presents certain limitations. For instance, iris scanning, despite its effectiveness, is often deemed intrusive, whereas fingerprint matching, though socially acceptable, is inappropriate for individuals without their consent [2].

Remarkably, under supervised conditions, face recognition showcases an impressive balance between social acceptability and accuracy. As a biometric method, face recognition is employed to identify and authenticate individuals in both still and moving visual media. Faces are identified by isolating and examining specific features from the target facial image [3].

Figure 1. A different view of the face

1.2 Problem statement

A Particle Swarm Optimization Neural Network (PSO-NN) technique has been proposed for recognizing various viewpoints of a face using morphological indicators. Multi-view face recognition has recently garnered attention, attributed to the fact that over 80% of faces in authentic images are presented in non-top views [4]. Unforeseen circumstances can lead to varying viewpoints of the same individual, whereas certain morphological aspects such as expressions, emotions, lighting conditions, background settings, and occlusions tend to have marginal impact. Figure 1 showcases three distinct views captured for this study: upward, frontal, and downward [5].

1.3 Face recognition

Facial recognition, while less stable than fingerprint or iris identification, offers certain unique advantages, despite the challenges in achieving high authentication accuracy. Unlike most biometric methods, facial images can be acquired without the subject's knowledge or consent [6]. In human-to-human identification, faces are the most frequently used biometric. This ubiquity is reflected in the use of facial images on various official documents such as driver's licenses and passports. In many Western cultures, concealing one's face is often associated with mistrust or guilt, further promoting the use of facial recognition. Consequently, despite its comparative inaccuracy to iris and fingerprint scanning, facial recognition is extensively employed.

However, this widespread use of facial recognition introduces a significant drawback: it facilitates identity theft [7]. Capturing someone's image without their knowledge is straightforward, whereas gathering other biometric data covertly necessitates specialized equipment. As such, facial recognition may not be the optimal biometric for access applications. Nevertheless, it remains one of the few biometrics suitable for camera surveillance systems, with the added advantage that human observers can easily verify the results of automatic analysis [8].

Figure 2 illustrates the comprehensive process of facial recognition. Initially, faces are photographed, followed by the extraction of specific facial characteristics. Facial images with these distinguishable features can then be used to differentiate between individuals. Upon the creation of the dataset, the selected model is utilized to design the network architecture. The network's ability to identify individuals is subsequently tested using a new set of facial images.

1.4 Motivation for the face recognition process

Facial recognition has superseded fingerprints as the most frequently utilized biometric technology, largely due to the proliferation of devices such as smartphones, tablets, and webcams. Simulations of face recognition are integral to the development of truly intelligent and autonomous devices [9]. In comparison to other biometric identifiers, facial recognition technology offers several advantages, including low resource requirements, non-intrusiveness, and ease of data collection and deployment [10]. Real-world applications of this technology span across electronic and physical access control, biometric authentication, surveillance, human-computer interaction, multimedia management, and more.

Soft computing (SC), which yields outcomes that are probabilistic, imprecise, and range between 0 and 1, was formally acknowledged as a branch of computer science in the early 1990s [11]. Historically, modeling and analysis of systems using conventional computer techniques were only successful for relatively simple systems [12]. Complex systems in domains such as biology, medicine, humanities, and management traditionally defied solutions using standard mathematical and analytical techniques. It is important to remember that the complexity or simplicity of a system is relative, and many proven mathematical models have demonstrated both robustness and high effectiveness.

Soft computing addresses issues of imperfection, uncertainty, partial truth, and approximation to achieve practicality, resilience, and cost-effective solutions [13]. As a result, it forms the foundation for many machine learning techniques. Recently, computational techniques inspired by evolutionary and swarm intelligence approaches have gained traction. Although soft computing and possibility theory share similarities, they also exhibit significant differences. Possibility theory is employed when there is insufficient knowledge about a problem to solve it, whereas soft computing is used when the problem itself is not well-understood. These issues often stem from the human mind, with its inherent uncertainties, subjectivity, and emotional influences; for example, choosing an appropriate room temperature is a good illustration of this.

Three models utilized in facial recognition are the Artificial Neural Network (ANN) model, the Particle Swarm Optimization Neural Network (PSO-NN) model, and the Adaptive Neuro-Fuzzy Inference System (ANFIS) model [14]. The ability to recognize a person's face from various angles is becoming increasingly crucial for a range of applications, including surveillance, human-machine interaction, and entertainment [15]. This paper discusses methods for learning and recognizing different viewpoints of a person's face using artificial neural networks, adaptive neuro-fuzzy inference systems, and particle swarm optimization-neural networks, all of which draw inspiration from biological neurons.

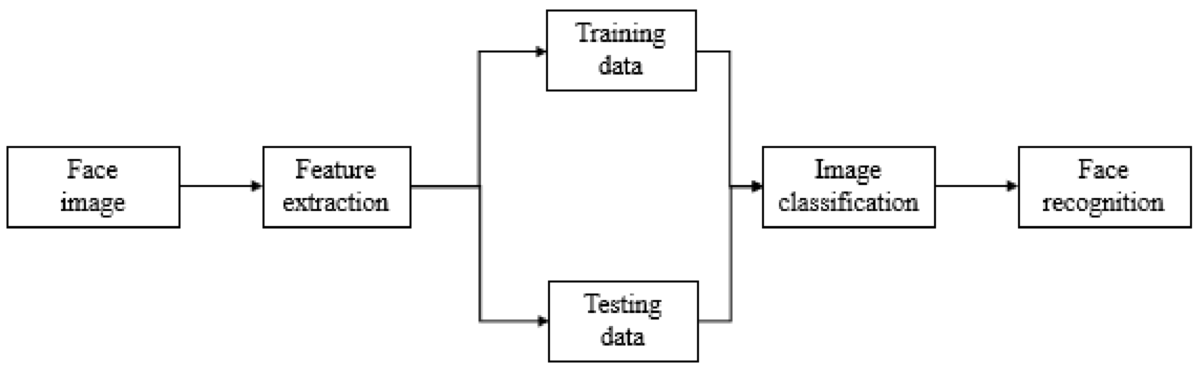

Figure 2. Face recognition process

1.5 Objective

Neural networks prove advantageous when an algorithmic solution is elusive and there's a need to extract structure from pre-existing data. In this context, multi-view face recognition becomes pivotal, offering enhanced usability and reliability compared to single-view face recognition. A key benefit of this soft computing approach is that it facilitates personal identification and recognition without requiring active participation from the users. Given the interest from the image recognition community, the public sector, and private industry, facial recognition has emerged as a challenge well-suited for computational solutions.

2. RELATED WORKS FOR BIOMETRIC FACE RECOGNITION

For a conventional facial recognition system to work, it needs to be able to identify the same face in different shots. An agreed-upon approach for compensating for visual disparities has been proposed. An experimental study claims that these characterizations are sensitive to changes in illumination, viewpoint, and facial expression. According to this research, none of the considered descriptors is adequate on its own to address the difficulty posed by image modifications due to changes in light direction. A similar viewpoint and expression outcome was achieved when the changes were made. Horizontal picture features were less susceptible to directional shifts in lighting. Research using only these representations found that less than 20% of the faces in the database were recognized. Human performance was noticeably higher in the same conditions [16].

2.1 Feature extraction model

New and effective face image representation using texture data from local binary patterns (LBPs). A better feature vector that can be used as a face descriptor is generated by concatenating the LBP feature distributions extracted from the various parts of the face image. The method's efficacy in the context of the face recognition problem has been assessed under a variety of conditions. Multiple data sets with substantial pose shifts necessitated the development of a clustering-based method. The low-dimensional unit of the dataset is the starting point for the formation of many, distinct clusters. An organizational structure in the shape of a tree is used for dispersal. The "Subclass Linear Discriminant Analysis (SLDA)" subspace-based linear identification approach was used to successfully identify the faces [17]. For later usage in identification tasks, the obtained set of sets is incorporated into a training set. The properties of the clusters created by the proposed grouping design are compared to those generated by the K-means clustering algorithm. When compared to K-means, the results show that the suggested grouping technique produces superior clusters. In 2006, B.B. Amor et al. introduced a groundbreaking method of facial recognition [18]. This new method is based on a tried-and-true method: dimensional surface matching. The advancement of numerous challenging issues, such as gesture, illumination, and face expression modification, is the center of a present cluster of methods. The relevant matching method is based on ICP (iterative closest point), which aligns a single given prototype to a 3D face model from the set of data sets and provides a precise depiction of the posture. A significant obstacle in the field of face recognition is the need to locate a narrator who is adept at describing facial presentation [19].

The picture of the face looks like a collection of individual face parts. Using a dependency matrix between spatial features, a novel approach has been developed for face characterization (SFIM). By employing a method that encrypts feature interdependence-based connections inside local space, SFIM transforms the facial picture into a random connected network. They determine the match-wise interdependence strong point as the removed weighted conflict between two trait units in a hybrid trait space consisting of force histograms, oriented gradients, and the local region of binary patterns [20]. Three recognition frameworks are used by the SFIM-based face descriptor for face identification: closest neighbor search, subspace-based classification, and linear optimization-based classification. Significant matching with the advanced outcome and thorough trial results on four beautiful face datasets are saved to demonstrate the efficacy of the newly provided SFIM-based descriptor. Human face recognition is one of the most difficult problems in the field of pattern recognition. The variations in face images brought on by changes in expression, position, and illumination are among the most significant challenges to be overcome when creating a face recognition system [21].

A novel distance metric, the grey Harsdorf distance (pg), is introduced to directly compare greyscale images of faces. An efficient approach is developed that can compute the new metric. In other words, the processing time grows proportionally with the size of the image. The effectiveness of this metric is examined using standard face databases as benchmarks. It is found that the novel metric-based face recognition system is robust against changes in posture, facial expression, and illumination. Analyses comparing the proposed method to those already in place show that it routinely produces better results. Shown how there has been much research effort put into facial recognition recently. Unfortunately, when put into an unconstrained environment, some systems' generalization abilities suffer. Only a handful of the currently employed solutions have shown any real promise outside of a small number of relatively easy-to-solve examples. Inevitably, this will limit the usefulness of such methods on mobile devices due to their limited processing capacity and rigorous power consumption constraints [22].

2.2 Feature matching technique

The author-provided face is a complex multidimensional visual image, making it difficult to develop a computational model for face matching technique. Face matching is based on the information theory of encoding and decoding facial features. The proposed method is built from a combination of two interconnected steps. In the first phase, use a back propagation feed-forward neural network, and in the second, it is employed feature extraction based on principal component analysis. The desired outcome was achieved when 400 photographs were subjected to algorithmic testing. To acquire a recognition result for the test batch, it is necessary to take into account all technical aspects of feature extraction. The recognition rate in the test was very high, at 97.20%. Using sinusoidal projection, it can successfully extract facial features. The basic idea is to immediately multiply the image matrix by a projection matrix, which is generated by stacking vectors with sinusoidal values at different frequencies, to extract weighted features from the image. The sinusoidal projection matrix exhibits orthogonality between its vector components when the frequencies are chosen as multiples of the fundamental frequency [23].

The proposed method shows promising verification performance across three face databases. It has been reported that face verification and identification in different positions and lighting situations remains a challenging subject. A unique artificial neural network-based approach is proposed for pose-invariant face detection in similar lighting circumstances. The neural network is taught the facial features with many poses and then interpolates the facial features for any unknown poses to establish a satisfactory match with the probing picture. The findings of the simple simulation experiment performed on the HOIP data set are promising. Human face recognition is a promising biometric authentication method. A system for recognizing persons' faces that uses principal component analysis and a back-propagation neural network in conjunction with face detection and edge detection algorithms. The efficiency of this system has been evaluated in light of the proposed feature fusion method. The most important feature was initially extracted using principal component analysis, which also reduced the overall dimension of the feature vector. The decreased vector was classified using a classifier based on a back-propagation neural network. The recognition process requires many steps before success may be achieved. Last but not least, they compared the system's efficiency across a range of training database sizes. The examination of performance shows that productivity was higher when the feature extraction method was successful. The method was able to succeed over 92% of the time despite adverse conditions [24].

Here established that fingerprints, irises, and faces offer some of the best biometric authentication since they can reliably identify and evaluate a person at each stage of the identification process. Biometric identification and authentication often have to deal with less-than-ideal conditions such as fuzzy images, off-angles, reflections, and expression changes. These zones, imposed by unit modal biometrics, can be found using multimodal biometrics. This has led to the creation of a novel, very effective face-detection technology that can be used in a wide range of biometric systems to detect different kinds of face access attempts. The suggested system's primary features and goals are to improve picture quality and to achieve a very low degree of complexity for the security of biometric recognition frameworks. Preprocessing made use of the score level method, a Median filter with intelligent edge recognition, and a Hough transform with an anisotropic Gaussian filter. To get the features out, they used a Gabor filter. The classification is carried out via the efficient Adaptive Neuro-Fuzzy Inference System. The efficiency and effectiveness of the strategy proposed have been confirmed [25].

3. BIOMETRIC FEATURES USING SOFT COMPUTING TECHNIQUES

In this section given the throughout explanation of the proposed methodology. The four stages of the proposed methodology discussed here included data collecting, pre-processing, feature extraction, and a simulated matching model using ANN, PSO-NN, and ANFIS. At this point, a database has been created. Certain essential characteristics are duplicated from all viewpoints via image processing. For visual recognition, a variety of soft computing models are used, including ANN, PSO-NN, and ANFIS. The model's parameters had to be adjusted to get this outcome. Identifying persons from a variety of perspectives has become more beneficial for applications such as surveillance, user interfaces for machines, and even video games. With inspiration from real neurons, this work provides a feature extraction and artificial neural network-based fuzzy inference system for learning and recognizing several facial photos of the same person. A Neural Network is crucial when need to extract the structure from preexisting and predetermined data but finding an algorithmic solution is difficult. Due to its greater practicality and dependability than single-view face identification, the circumstance necessitates multi-view face recognition shown in Figure 3.

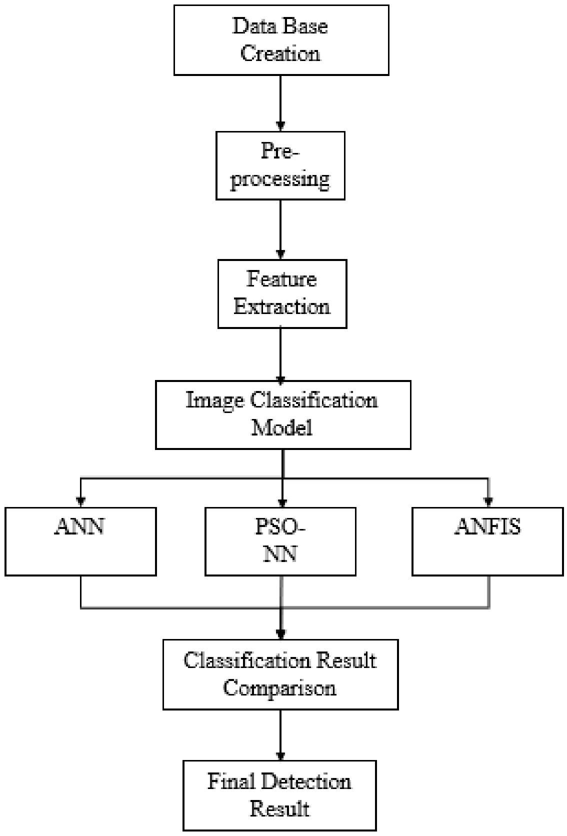

Figure 3. Proposed model for face recognition

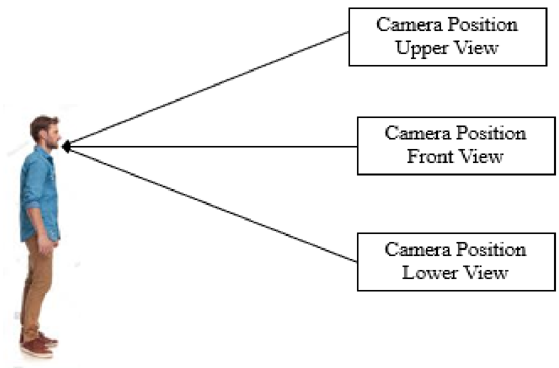

Figure 4. Position of the camera for data creation

To use a biometrics-based recognition approach, it is essential to compile a database. The ABV-IIITM, Gwalior soft computing lab is responsible for compiling the database. There were 200 persons in total, with 150 men and 50 women included in the database. The camera and subject's relative positions during data collection are shown in Figure 3. In this particular case, the database is structured to accommodate three distinct perspectives. Each page has 5 sample images to look at. Multiple views of a simple face are shown in Figure 4.

3.1 Pre-processing

The source image files are converted to grayscale to reduce file space and produce the 2-D image format. The edges of the image are then highlighted using the Sobel edge detection method. Sobel edge detection, in contrast to other techniques, generates a rough estimation of the gradient of image intensity. Sobel offers the gradient vector or the normalized gradient value for each pixel in the image. It is calculated by convolution of the horizontal and vertical picture matrix components with a tiny integer-valued filter. It makes use of 33*33-pixel matrices for this. For the experimental purpose here selected the above pixel matrices.

In this image, there are distinct lines in the paired slope mask. In these lines, the investment object is not shown. In contrast to the first image, the surrounding lines of the gradient mask are perforated. The top-to-down organizing element, which is itself replicated by the even organizing, enlarges the parallel slope mask. This image can be viewed in a larger size here. Even if there are still gaps inside the cell, the dilated slope veil depicts the diagram of the cell wall. With its infilling ability, it is employed to fill in the gaps.

3.2 Feature extraction

Facial pictures are split into numerous segments, and the centroids of each segment are intensity-weighted. You can mark various areas of the image with the bw label function. The region props functions are then used to calculate the pixel list. Used the pixel list as a guide to determine the x and y coordinates of each separated zone. From there, it is possible to determine the centroids and grayscale values of each pixel in the partitioned area. The Pythagorean triplet formula and the Euclidean distance are employed, respectively, to determine the length of the nose and the distance between the eyes.

A total of 200 persons were photographed from three different perspectives (the top, front, and bottom views). Table 1 lists the following characteristics.

Table 1. List of feature extraction

S. No.	Feature Extraction of Face		
1	Face height	Face width	Face area
2	Nose height	Nose width	Nose area
3	Mouth height	Mouth width	Mouth area
4	Left eye height	Left eye width	Left eye area
5	Right eye height	Right eye width	Right eye area

3.3 Model creation

This section explains the various models used in multi-view face recognition method.

3.3.1 Artificial neural network

Artificial neural networks can be used to address regression issues. In this case, using it to project the value for the untrained face. As a result, the model can forecast the characteristics of the person from various angles.

Here is a general explanation of how an ANN model functions.

a. Select the input and target data

b. Configure initial network architecture

c. Compose and select the data set for training, testing, and validation of the network.

d. Repeat the learning process until peak performance is reached

e. Simulate the network

Think that if the network is somewhat changed, the performance will also be slightly changed when the architecture is changed or updated. It can somewhat improve or deteriorate. If the performance is unaffected, adjustments to the network architecture are made. If there are no significant changes, keep the existing networks. An ANN's multi-layer perceptron can carry out a recognition task. Such a model consists of the input layer, the hidden layer, and the target layer.

3.3.2 ANFIS model structure

The system obtains exceptionally accurate recognitions by combining subtractive clustering and ANFIS. Sequentially, data mining, fuzzy logic, and neural networks are all merged. To apply fuzzy logic or simply ANFIS, the data must first be clustered to provide the fuzzy membership functions required. ANFIS generates a fuzzy rule basis from a set of data, which neural network training can use to refine the rules. The suggested facial recognition model's flow is shown in Figure 5.

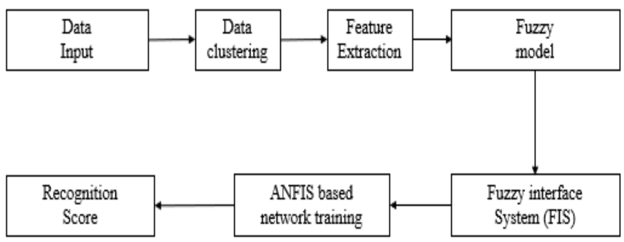

Figure 5. ANFIS model for face recognition

It offers a comprehensive look at the complete face-recognition process from several angles. In the context of the recognition process, also discussed how to create a database, extract features, and create models.

3.3.3 Training procedure and pattern set

Only those architectural models that performed well were chosen. Tabular results are presented here. The ANN face prediction model was created using the following process:

a. The face data was chosen as an input for the models' training, validation, and testing, as well as for the output variables.

b. The initial network architecture as configured, as shown in Table 2.

c. To enhance the functionality of the neural network, the number of hidden layer neurons was determined."

d. Selected performance evaluation measures, such as mean percentage accuracy, correlation coefficient, and contingency table or confusion matrix, were used to test the trained neural network.

e. Until a specific predicted performance requirement was met, step 4 was performed five times.

The following is how the training process was carried out: training data patterns were sequentially supplied to the input layer and then propagated across the network.

Table 2. Models for network architecture

Reference	Architecture Name	
Model Name	Model A	Model B
Model Structure	14-6-50	14-8-50

4. RESULT AND DISCUSSION

This section presents the simulation results for ANFIS, ANN, and PSO-NN. the findings of research into the best neural network architecture for facial recognition. The outcomes demonstrate that the neural network's architecture and data selection can significantly affect the outcomes of recognition. The three models are utilizing here are ANFIS, ANN, and PSO-NN. After choosing an initial architecture, numerous variables, and properties are adjusted to see which is best. It also shows how the two models contrast with one another. More than 400 Thapar University, Patiala, India studying participants aged 18 to 21 have been enrolled into a database. Up, down, and directly in front are all possible positions for the subject. Pentium IV hard drive holds the images. The original 403 images were narrowed down to 50 for this research. This section displays the calculations for the NN model, PSO-NN model, and ANFIS model. A wide variety of advantage points are employed in this simulation. For the neural network model-based recognition process, have constructed a variety of different models. Each with a different number of neurons in the hidden layer is reflected. The model was tested in three separate studies. Only 66.66% of the data is used for training and 33.33% is used for testing in this scenario.

All six models have been trained and tested from all three angles.

4.1 Experimental result reference Model-A (14-6-50)

Tables 3-5 contain the testing and training results for experiment 1.

Table 3. Experiment-1 testing and training result of model-A

Reference	Down View (%)	Front View (%)	Up View (%)	Combined View (%)
Training set	72.12	88.78	71.50	91.25
Testing set	65.48	81.90	65.89	85.63

Table 4. Experiment-2 testing and training result of model-A

Reference	Down View (%)	Front View (%)	Up View (%)	Combined View (%)
Training set	71.64	75.25	28.98	81.69
Testing set	65.61	68.14	21.48	78.12

Table 5. Experiment-3 testing and training result of model-A

Reference	Down View (%)	Front View (%)	Up View (%)	Combined View (%)
Training set	80.48	21.58	85.98	85.72
Testing set	75.69	15.32	75.46	81.35

4.2 Experimental result reference Model-B (14-8-50)

The human face is one of the most popular and straightforward traits to employ in biometric security systems. Face recognition technology is more common and used since it does not require direct physical contact between the user and the device. Cameras scan a user's face and compare it to a database to confirm their identification. Because of the benefits and ease of use that soft computing models offer; face recognition is used in this research work. In this instance, 14 separate traits were extracted from the images of the faces. The extracted features include eye height, width, and area; mouth height; nose width; face height; face width; and mass center. The recognition method uses soft computing models including neural networks, PSO-NN, and ANFIS. By varying various parameters, such as the number of neurons in the hidden layer, and then training the network with a well-known backpropagation technique. This will able to build a range of models for the neural network structure.

The decision-making process for the best network considers accuracy as well as overall performance. The ideal model configuration consists of one input, one output, and a hidden layer with ten numbers of neurons. The model's training algorithm has an accuracy of 0.001. The best model's test results are accurate at 92.9% and its training outcomes at 97.2%. Therefore, use PSO-NN recognition for neural network construction, which is based on the best model obtained in the final step, instead of conventional BPA training. This is outperformed the most ideal BPA-trained ANN model in terms of results. The accuracy percentage for training and testing using PSO is 98.00% and 94.8%, respectively. The rules and the functions of the FIS system used by ANFIS ensure that the model's conclusions are always 100% accurate. Tables 6-8 contain the testing and training results for experiment 1.

Table 6. Experiment-1 testing and training result of model-B

Reference	Down View (%)	Front View (%)	Up View (%)	Combined View (%)
Training set	85.59	91.49	69.48	92.54
Testing set	75.75	90.76	79.82	90.86

Table 7. Experiment-2 testing and training result of model-B

Reference	Down View (%)	Front View (%)	Up View (%)	Combined View (%)
Training set	91.45	69.48	20.68	94.56
Testing set	73.29	78.56	31.79	86.47

Table 8. Experiment-3 testing and training result of model-B

Reference	Down View (%)	Front View (%)	Up View (%)	Combined View (%)
Training set	91.87	18.69	85.68	97.20
Testing set	79.25	18.29	79.63	87.67

Working on this subject of facial recognition in a small space is challenging. Systems that can identify persons at any time and in a variety of circumstances are urgently needed.

Low-resolution images and poor lighting are significant issues in this region, as are sunglasses, long hair, or other objects that partially obscure the subject's face. Since face recognition technology has advanced significantly in the last ten years, this work is now useful in a variety of contexts. Here are a few instances of face-recognition software in use. This proposed face-recognition system could be useful for identification systems, document control, and access control. Commercial uses include online account security, finding a person's identity in a database for law enforcement, and video surveillance. Considering all of the requirements, face recognition technologies appear to have the most chance of becoming widely used. Face recognition technology is used in many security systems, including computer user accounts and access control.

5. CONCLUSION

Face recognition is a simple biometric used in security systems. This feature verifies the identification of the human face. Face recognition technology is frequently utilized since it doesn't require physical contact between the user and the gadget. Camera’s image the user's face and compare it to a database to verify their login. It can be set up in minutes without pricey images. Due to the practical benefits and ease of implementation, this research will focus on facial recognition utilizing soft computing models. These 14-featured faces are for your viewing enjoyment. Right eye height, right eye width, right eye area; left eye height, left eye width, left eye area; mouth height, mouth width, nose width; face height, face width, face area, center of mass; left eye height, left eye width, left eye area; right eye height, left eye width, right eye area; Recognition uses neural networks, PSO-NN, and ANFIS. Using the traditional back propagation method, different models were generated by varying neural network architectural factors, such as the number of neurons in the hidden layer. It is chosen the most reliable network to ensure precision. The best model has one input, one output, and one hidden layer. The best model scored 92.9% accuracy during testing and 97.2% throughout training.

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