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Optimal Neural Network Based Face Recognition System for Various Pose and Occluded Images

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Abstract

Facial recognition is a kind of pattern recognition where a human's face is stored in a database for future endeavors to decide or perceive a man's character when the face is seen by a user. One of the approaches to do this is by contrasting chosen facial components from the picture and a facial database. In these days, it seems to be famous prevalence as a business distinguishing proof and promoting instrument. In this examination, we have planned to propose a successful technique for face recognition. At first, the info picture is chosen from the information database; here we are thinking about different stance and impediment pictures. The proposed technique has two principle stages specifically, feature extraction and face recognition. In the first stage, the facial features are separated from the info face image. Here SIFT features, Active appearance model, and holo-entropy is utilized to discover the specialization of the face image. Further, the extracted features are passed to the second stage; here face recognition is finished with the assistance of Modified Artificial Neural Network (MANN). Here the conventional neural system is changed by using firefly calculation for correct placement of neuron weights. On the basis of the chosen features, MANN perceives the face images. The execution of the proposed procedure is assessed by using False Matching Rate (FMR), False Non-Matching Rate (FNMR) and Genuine Acceptance Rate (GAR), accuracy, sensitivity, and specificity. The implementation of the proposed system is done by using MATLAB.

Keywords: Face recognition, SIFT, Active appearance model, holo-entropy, Artificial Neural Network, False Matching Rate, False Non-Matching Rate, Genuine Acceptance Rate.

INTRODUCTION

Even though there are several biometric technologies Face Recognition (FR) has a few points of interest over other biometric advances: it is normal, nonintrusive, simple to utilize, and can catch faces both secretly and at a separation [1]. FR has been a long-standing issue in PC vision. The assignment of FR is to distinguish or check a human face from its records (2D and 3D modalities). FR has various certifiable applications including access control and video reconnaissance. Among different facial modalities, the extensive research has been made with 2D FR [2]. It has as on date pulled in critical consideration of explores because of the openness of reasonable computerized cameras and PCs, and its applications in biometrics and reconnaissance [3]. Explorers of emotional stature have endeavored extraordinary endeavors to create machines that can recognize facial expressions through extricating and investigating facial features like the procedure by which people recognize facial expressions through perceptual examination of facial components [4]. The first research on FR was directed in the 1950s and 1960s and reported in the brain science and building literature, individually. In spite of critical improvements and a considerable advancement in this area, programmed FR is still a troublesome undertaking in view of the extensive variety of disturbances in human appearances created by light, eyeglasses, head positions and outward appearances [5].

But irrespective of the face varieties in posture, brightening, and outward appearances, humans have the capacity to perceive faces and recognize identity initially. This normal capacity does not exist in machines; in this manner, the outlined intelligent and expert frameworks can recreate the recognition falsely [6]. The execution of FR frameworks broadly depends on the choice of the Facial Feature Extractor, preprocessor, Feature reducer and classifier which are of urgent significance while assembling any FR framework. A few fundamental methods exist for completing the extraction of facial features and among them Gabor Filters have separated itself as being a standout amongst the systems to do the consistent extraction of facial features in an effective way [7]. Within the most recent two decades, different face recognition algorithms have been contrived and face recognition frameworks are thought to be fundamentally subject to discriminative feature extraction, about which numerous methodologies have been proposed, for example, Eigenface, Fisherfaces, ISOMAP, locally linear embedding (LLE), Locality preserving projections (LPP) and Laplacian Eigenmaps [8]. Isomap, locally LLE, and Laplacian eigenmaps (LE) lead non-straight dimensionality reduction, with the presumption that the high dimensional information lies on a low dimensional complex installed inside the encompassing space. LPP strategy is a direct straight estimate of Laplacian eigenmaps and shares a significant number of the information representation properties of nonlinear systems, for example, Isomap, LLE, and LE [9]. Then after preprocessing numerous direct methodologies have been proposed for dimensionality lessening, for example, principal component analysis (PCA) and linear discriminant analysis (LDA) which has been broadly utilized as a part of representation and classification. But, PCA does not encode discriminant data which is critical for a recognition undertaking, and LDA expects to protect universal structures of tests [10].

For classification, a Sparse Representation Based Classification (SRC) strategy was proposed for face recognition. In SRC, a test model is represented as asparselinear combination of all the training samples and this test is assigned to the class with the smallest reconstruction residual. Sparse representation is additionally utilized for dimensionality diminishment of faces [11]. Further classifiers like Convolutional Neural Networks (CNNs) and Deep Learning methods have been connected to vast scale verification and recognition frameworks also. Deep CNN has been demonstrated to perform like people as far as face recognition exactness. Such a framework adventures a lot of heterogeneous preparing information to learn discriminative low-dimensional representations of faces [12]. For example, for classification, some recent frameworks for face re-distinguishing proof applications effectively utilize versatile ensembles of 2-class (target vs. non-target) classifiers to outline and upgrade facial models in view of new reference directions, yet maintaining a strategic distance from the learning defilement [13]. Each one of those previously mentioned classification method recognizes facial expressions by using different algorithms. They have been proposed to cure troubles created by the small sample size (SSS) issue and varieties of postures, enlightenments, and outward appearances [14]. Despite the fact that various face recognition systems were created, face recognition for the one-specimen per-individual issue has got expanding consideration attributable to its extensive variety of potential applications, e.g., law authorization, reconnaissance recognizable proof, criminological ID and get to control, and so on [15].

LITERATURE SURVEY

Even though concentrated on for a considerable length of time, successful face recognition stays hard to achieve because of impediments and posture and enlightenment varieties. Posture change is a specific challenge in face recognition. Gao, *et al.* [16] proposed successful nearby descriptors for frontal face recognition. At the point when those descriptors were specifically connected to cross-pose face recognition, the execution essentially diminished. To enhance the descriptor execution for cross-pose face recognition, they proposed a face recognition algorithm in light of various virtual views and alignment error. To begin with, twists between poses were found out utilizing the Lucas–Kanade algorithm. In light of those twists, numerous virtual profile perspectives were produced from a solitary frontal face, which empowered non-frontal countenances to be coordinated utilizing the scale-invariant feature transform (SIFT) algorithm. Besides, twists demonstrated the correspondence between patches of two appearances. A two-stage alignment error was proposed to acquire precise twists, which contained posture arrangement and individual arrangement. Connections between's patches were considered to compute the arrangement mistake of two countenances. At long last, a hybrid similarity between two countenances was figured; that consolidated the quantity of coordinated key points from SIFT and the alignment error. The testresults demonstrated that their proposed technique accomplished preferable recognition precision over existing algorithms, notwithstanding when the posture distinction point was more prominent than 30°.

The discriminant examination is an essential method for face recognition since it can extricate discriminative elements to characterize distinctive people. Most existing discriminant examination techniques neglect to work for single-sample face recognition (SSFR) in light of the fact that there is just a solitary preparing test for each individual to such an extent that the inside class variety of this individual can't be evaluated in such situation. Hu Junlin, *et al.* [17] exhibited another discriminative transfer learning (DTL) approach for SSFR, where the discriminant investigation was performed on a multiple sample non-specific preparing set and afterward moved into the single-example display set. In particular, their DTL took in a component projection to minimize the intra-class variety and amplified the between class variety of tests in the preparation set and minimized the contrast between the non-specific preparing set and the exhibition set, at the same time. To make the DTL be vigorous to anomalies and commotion, they utilized a sparsity regularizer to regularize the DTL and further proposed a novel discriminative transfer learning with sparsity regularization (DTLSR) technique.

In order to boost the effectiveness of linear regression classification (LRC) Linear discriminant regression classification (LDRC) was presented recently. LDRC plans to discover a subspace for LRC where LRC can accomplish an enlarged discrimination for classification. However, as a discriminant analysis algorithm, LDRC considers an equal importance of each training sample and ignores the different contributions of these samples to learn the discriminative feature subspace for classification. Propelled by the way that some preparation tests are more effective in taking in the low-dimensional component space than different examples, Huang, et al. [18] introduced an adaptive linear discriminant regression classification (ALDRC) algorithm by taking unique thought of various commitments of the preparation tests. In particular, ALDRC made utilization of various weights to portray the diverse commitments of the preparation tests and used such weighting data to ascertain the amongst class and the inside class reproduction mistakes, and afterward ALDRC tried to locate an optimal projection grid that could expand the proportion of the between-class reconstruction error over the inside class reconstruction error. Robust Linear Collaborative Discriminant Regression Classification (RLCDRC) scheme for superior FR, we proposed in [23] which have improved performance than LCDRC. This method significantly maximizes the Reconstruction Error (RE) between the classes and also it minimizes the RE within the class. For comparison, the proposed scheme is verified on three standard database sets. Though, the proposed methodology not only out-performs LCDRC and also it proves with the superior outcome of FR.

Hongwei Ge, *et al.* [19] presented another and proficient enhanced maximum scatter difference (MSD) design in that paper. The principle shortcoming of the MSD model was that the class mean vector was developed by meant of class test normal when the inside class and between-class disperse frameworks were shaped. For a couple of given specimens with non-perfect conditions (e.g., varieties of expression, posture and loud environment), the evaluation result was extremely frail by utilizing the class test normal. That was on the grounds that there would be a few anomalies in those specimens. Consequently, the recognition execution of maximum scatters difference measure would decrease essentially. To tackle the issue, in the conventional MSD display, they used inside class maximum–minimum– median average vector to build inside class scramble grid (Sw) and between-class dissipate framework (Sb) rather than inside class mean vector. The experimental results of it demonstrated that a change of the MSD model was conceivable with the proposed system in ORL and Yale face database recognition issues.

Human face recognition has been examined throughout the previous three decades. Face recognition with thermal pictures now draws in critical consideration since they can be utilized as a part of low/none lit up the environment. However, thermal face recognition execution is still inadequate for practical applications. One principle reason is that most existing work influence just single feature to describe a face in a thermal picture. To take care of the issue, Yangjie Wei, *et al.* [20] demonstrated multi-feature fusion, a procedure that joined various features in thermal face portrayal and recognition. In that work, they composed a systematical approach to join four elements, including Local binary pattern, Gabor jet descriptor, Weber local descriptor and Down-sampling feature. The experimental results of it demonstrate that their approach outperforms techniques that influenced just a solitary feature and is robust to noise, impediment, expression, low determination and distinctive l1-minimization strategies.

Meager representation of pictures utilizing orthogonal two-dimensional Krawtchouk moments (2D KCMs) for face recognition is persuaded by their capacity to catch area based higher-arrange concealed nonlinear structures from discrete directions of limitedly bolstered pictures and the invariance of relative changes of these moments to regular geometric deformation. In [21] the author conveyed the adequacy of selecting the biased arrangement of KCMs as the global and neighborhood face features instead of conventional elements got from the heuristic decision of settled request moments or projection of the moments for perceiving a character. The choice of altogether scanty 2D KCM-based elements as indicated by the proposed approach brought about profoundly proficient face recognition strategy when contrasted with alternate techniques that utilized orthogonal moments, for example, the 2D Zernike, 2D Tchebichef or 2D Gaussian-Hermite. Demos on testing databases (viz., FRGC and CK-AUC) and correlations with the entrenched projection, surface, and moment-based techniques demonstrated unrivaled recognition execution as far as mean exactness and strength of the proposed comprehensive or half and half sort discriminative KCM-based strategy, particularly when test sizes were little and the intra class faces had noteworthy varieties because of expressions.

For a considerable length of time, analysts have endeavored awesome endeavors to locate a suitable face representation for face recognition. A combination technique of Local Binary Pattern (LBP) and Gabor filters produces awesome accomplishments. LBP is great at coding fine points of interest of facial appearance and surface, while Gabor features can encode facial shape and appearance over a scope of coarser scales. Regardless of the considerable execution, this combination representation experiences low adequacy and determination difference. In this paper, Zhang, *et al.* [22] offered a novel representation procedure of face pictures which was quick and robust to determination difference. They applied dense sampling around each distinguished feature point, separate Local Difference Feature (LDF) for face representation, and then used Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) to minimize feature dimensions and lastly utilized cosine similarity assessment for recognition. They have used their proposed face representation methodology on two databases; self-collected Second Generation ID Card of China and Driver's License (SGIDCDL) database and open Facial Recognition Technology (FERET) database.

PROBLEM IDENTIFICATION

Automatically identifying or verifying a person from a digital image is called face recognition system. The common problem in existing face recognition method is given below,

- The major factors affecting the face recognition system are apose, illumination, identity, occlusion, and expression.
- Pose and illumination, the major factors that affect the performance of face recognition are occlusion and expression.
- Face recognition has acquired abundant attention in market and research communities but still remained very accosting in real time applications.
- Partial occlusions in face images pose a great problem for most face recognition algorithms.
- Most existing face recognition methods are too computational complex to meet practical application.

These are the problems of existing works and which motivate us to do this research in face recognition.

PROPOSED METHODOLOGY

Face recognition is a biometric system used to identify or verify a person from a digital image. Face recognition system is used in security. Face recognition system should be able to automatically detect a face in an image. In this research, we have intended to propose an effective method for face recognition method. Initially, the input image is selected from the input database; here we are considering various pose and occlusion images. From the input face image, the facial features are extracted. Here SIFT features, appearance features, and holo-entropy is used to find out the uniqueness of the face image. The Active appearance model (AAM) can be used to find out the appearance based features in the face image. Then face recognition is done with the help of Modified Artificial Neural Network (MANN). Here the traditional neural network is modified by means of firefly algorithm for optimizing the neuron weights. The overall semantic diagram of the proposed technique is shown in fig.1.

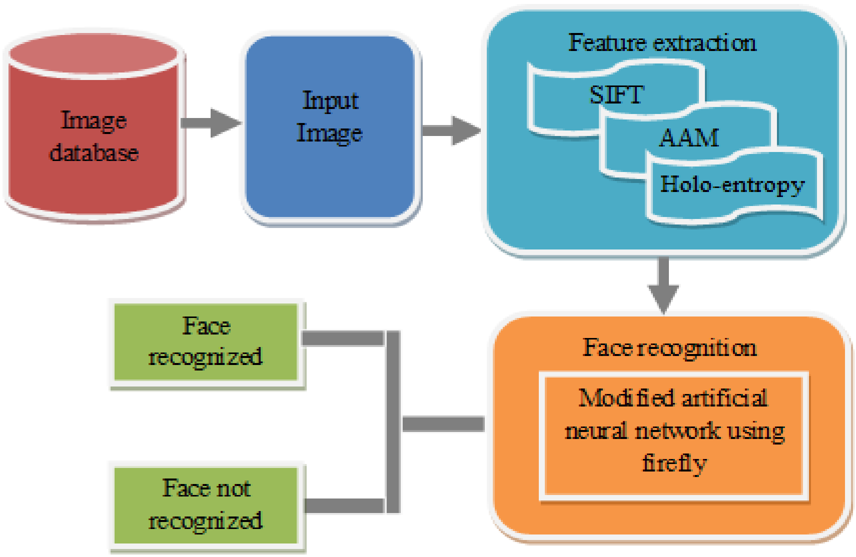

Figure 1: Scheduler diagram of the proposed algorithm for face recognition

The overall process of the proposed face recognition technique is divided into two main phases namely,

1. Feature extraction
2. Face recognition

A. Feature extraction phase

In feature extraction phase, the facial features are extracted. The proposed technique uses the SIFT, Active appearance model and Holo-entropy features from the input image. Scale Invariant Feature Transform (SIFT) is an algorithm employed in machine vision to extract specific features of images such as matching the various view of an object or scene and identifying objects. The Active Appearance Model (AAM) suits well for objects which vary in both shape and appearance. Holo entropy is a novel concept which uses entropy and correlation information to detect outliers in an input image. The detail explanation of each feature extraction technique is described below,

i. Scale Invariant Feature Transform (SIFT)

The SIFT represents a computer vision technique which effectively extorts the distinct features from an image. It was initially employed for the object identification. The features extorted by the SIFT are invariant to image scale, rotation, and fluctuating perspectives. The innovative technique may be considered as a texture descriptor fabricated by the following four significant stages:

1. Scale-space extrema detection
2. Key point localization
3. Orientation assignment
4. Key point description

Scale-space extrema detection

The initial phase of evaluation searches over all scales and image locations. It is effectively carried out by means of a difference-of-Gaussian function to locate the probable interest points which are invariant to scale and orientation.

$$L(a,b,\sigma) = G(a,b,\sigma) * I(a,b) \tag{1}$$

Where * is the convolution operator $G(a,b,\sigma)$ is a variable-scale Gaussian and $I(a,b)$ is the input image.

$$G(a,b,\sigma) = \frac{1}{2\pi\sigma^2} e^{-(a^2+b^2)/2\sigma^2} \tag{2}$$

At each candidate location, a comprehensive model is sufficient to evaluate the location and scale. It is carried out by a Taylor expansion of the scale-space function, $D(a,b,\sigma)$, relocated in such a way that the origin is at the sample point.

$$\begin{aligned} D(a,b,\sigma) &= (G(a,b,k\sigma) - G(a,b,\sigma)) * I(a,b) \\ &= L(a,b,k\sigma) - L(a,b,\sigma) \end{aligned} \tag{3}$$

Key point localization

Key points are selected based on measures of their stability. The location of extremum E is given by,

$$E = \frac{\partial^2 D^{-1}}{\partial a^2} \frac{\partial D}{\partial a} \tag{4}$$

If the function value at E is below a threshold value then this point is excluded. This removes extrema with low contrast. To eliminate extrema based on poor localization it is noted that in these cases there is a large principle curvature across the edge but a small curvature in the perpendicular direction in the difference of Gaussian function.

Orientation Assignment

A single or multiple orientations are allocated to each key point location in accordance with the local image gradient directions. The scale of the key point is employed to shortlist the Gaussian smoothed image L, with the neighboring scale, in order that all the evaluations are carried out in a scale-invariant manner.

Use the key points scale to select the Gaussian smoothed image L, from above

Compute gradient magnitude G_m,

$$D_m(a,b) = \sqrt{L(a+1,b) - L(a-1,b))^2 + (L(a,b+1) - L(a,b-1))^2} \tag{5}$$

Compute orientation θ,

$$\theta(a,b) = \tan^{-1}(L(a,b+1) - L(a,b-1))/(L(a+1,b) - L(a-1,b)) \tag{6}$$

Form an orientation histogram from gradient orientations of sample points. Locate the highest peak in the histogram. Use this peak and any other local peak within 80% of the height of this peak to create a key point with that orientation. Some points will be assigned multiple orientations.

Key point Descriptor

The local image gradients are measured at the selected scale in the region around each key point. They are converted into an illustration which permits noteworthy levels of local shape deformation and modification in the lighting. The local gradient data from the neighboring smoothed image $L(a,b,\sigma)$ is also employed to generate the keypoint descriptor.

ii. Active Appearance Model (AAM)

The Active Appearance Model (AAM) is a successful method for matching statistical models of appearance to new images. This approach has been applied in numerous different applications. AAMs establish compact parameterizations of object variability, as learned from a training set by estimating a set of latent variables. The modeled object properties are usually shape and pixel intensities. The algorithm optimizes by considering the difference between the estimate of target image appearance and the estimate of current appearance. The least squares technique is used to increase the computation speed during thematching process. Given a set of training images with key points that form the shape descriptors of the image, it is possible to generate a model for the variations in shape using statistics.

iii. Holo entropy features

Let D be the dataset containing n number of objects $\{d_1, d_2, d_3, \ldots d_n\}$ and $m*1$ categorical attribute vector $V = [v_1, v_2 \ldots v_m^T]$. Here v_i as a random variable and V as a random vector. Let $H_D(.), I_D(.)\, and\, C_D(.)$ represents the entropy, mutual information, and correlation calculated on the dataset D. using the chain rule, entropy of V is given by,

$$H_D(V) = H_D(v_1) + H_D(v_2 \mid v_1) + \ldots . H_D(v_m \mid v_{m-1}, v_1) \qquad (7)$$

The entropy gives a measure of uncertainty with respect to a random variable. The holo-entropy HLχ(Y) given in Equation (8) is defined as "the sum of the entropy and the total correlation of the random vector V, and can be expressed by the sum of the entropies of all attributes".

$$\begin{aligned} HL_D(V) &= H_D(V) + C_D(V) \\ &= \sum_{i=1}^{m} H_D(v_i) \end{aligned} \qquad (8)$$

By means of the above-mentioned procedure, the features from the face image are effectively extorted. Subsequently, the face images are recognized by employing the innovative MANN approach, which is elaborately discussed in the following section.

B. *Face Recognition*

Some facial recognition calculations distinguish facial components by separating historic points, or elements, from a picture of the subject's face. For instance, a calculation may examine the relative position, size, and/or state of the eyes, nose, cheekbones, and jaw. These elements are then used to find different pictures with coordinating elements. In face recognition phase, the extracted features are the input. Based on the input features the proposed technique recognizes the face images. For recognition, the suggested technique uses the Modified artificial bee colony algorithm. It is clearly described in below section,

i. Modified Artificial neural network

In our proposed technique use the modified artificial neural network for face recognition. Here the traditional neural networks are modified by means of firefly algorithm. Firefly algorithm is employed to optimize the weights in theneural network. The main objective of the MANN is recognizing the face image into recognized or not recognized. For training purpose back propagation algorithm is used in our suggested technique. In artificial neural network consists of a series of nodes (neurons) which have multiple connections with other nodes. Each connection has a weight associated with it which can be varied in strength, in analogy with neurobiology synapses. The principal with it which a neural network operates is relatively simple. Each neuron in the input layer holds a value so that the input layer holds the input vector. Each of these neurons connects to every neuron in the next layer of neurons. ANN structure consists of the input layer, an output layer, and hidden layers between these two layers. The number of these layers is dependent on the problem we are trying to solve, that is basically on the user. The proposed artificial neural network use 'transig' as the network parameter. Ten hidden neurons are used in the suggested MANN technique. The overall structure of artificial neural network is shown in below,

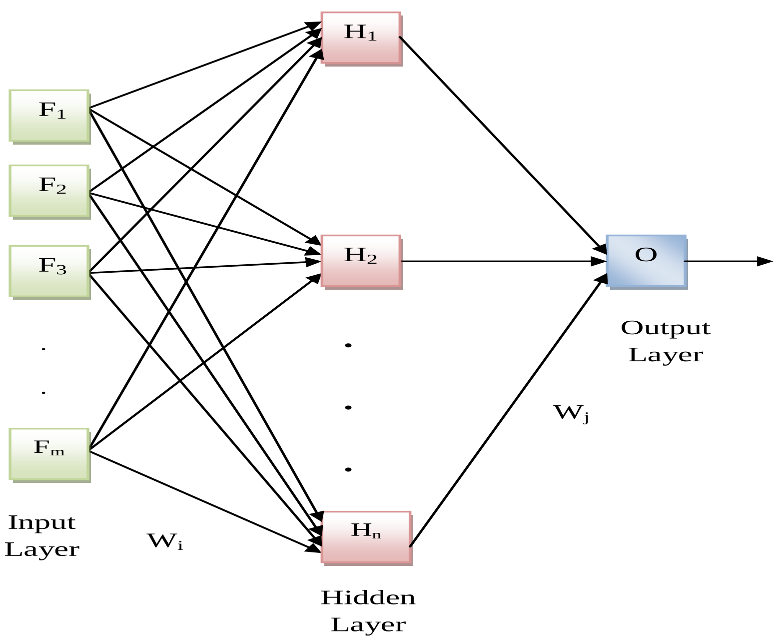

Figure 2: The structure of ANN

Step by step procedure of MANN

Step 1: Fix loads for every neurons except the neurons in the input layer.

Step 2: Develop the neural network with the input feature value as the input units, H_u Hidden units and O as the output unit.

Step 3: The computation of the proposed bias function for the input layer is,

$$I = \alpha + \sum_{n=0}^{H_U - 1} w_{(n)} F_1(n) + w_{(n)} F_2(n) + w_{(n)} F_3(n) + ...w_{(n)} F_m(n) \quad (9)$$

In our proposed modified artificial neural network, the weights are optimized with the help of firefly algorithm. The step by step procedure of firefly algorithm is illustrated in below section,

Weight Updation using Firefly algorithm

In the innovate technique, we deploy the firefly algorithm to update the weights in theneural network. Here, initially, each weight is arbitrarily arrived at within a definite search space. In proposed firefly algorithm, each solution is representing as the weight value for the neural network. Further, each solution is characterized as weightsw_i where $w_i = \{w_1, w_2, ...w_n\}$.

At first, the fitness value of each solution is estimated. The solutions with minimum error values are shortlisted as the current best weights.

$$fitness = \min \sum_{i=1}^{n} MSE \quad (10)$$

We estimate the fitness values of the each solution. The fitness value of each i^th^ solution is analyzed and contrasted with the j^th^ neighboring solution. If the fitness value of the neighboring solution is found higher, we select the neighbor solution as the best one otherwise the initial solution as the best one. Next, the updation process is carried out after the selection of best solution we update the worst solution by using equation (11).

$$w_i^{new} = w_i + A_t(w_j - w_i) + \alpha(\delta - 1/2) \quad (11)$$

Where, α and δ depict the uniformly disseminated values in the range of 0 to 1.

$$A_t = A_{t0}\, e^{-\beta D_{ij}^2} \quad (12)$$

A_{t0} - refers to the preset attractiveness,

β - represents the light absorption coefficient

D_{ij} - denotes the distance between the ith solution and jth neighboring solution

Hence, the modernized attractiveness values encourage the random weight to inch towards the current best fitness value. The best weight is updated in the first fireflies by substituting the existing old weight. Thereafter, all the fireflies are updated by performing these processes by means of estimating the fitness function. If the accuracy of the new weight in the chosen fireflies is superior to the old, it is substituted by the new weight (fireflies). Or else, the earlier weight is preserved as the best weight. The overall process to optimize the weight employing the firefly algorithm is shown as follows:

a. Create an initial population of fireflies arbitrarily.

b. Estimate the fitness of each firefly in the population.

c. Generate a new population by substituting the updation equation (11) till the new population is complete.

d. Employ the newly created population for the additional process.

e. If the test stipulation is fulfilled, stop and return the best threshold in the current population.

f. Replicate step 3 till the target is achieved.

g. At last, the optimal weight is achieved.

Thus, the optimal weight is adapted by means of the firefly and thereafter the captioned weights are furnished to the neural network for recognizing the face image.

Step 4: The activation function for the output layer is estimated as,

$$Active\ (I) = \frac{1}{1 + e^{-I}} \quad (13)$$

Step 5: Recognize the learning error as offered beneath,

$$O = \frac{1}{2} \sum_{n=0}^{H_U - 1} (D_n - A_n)^2 \quad (14)$$

Where,

D_n - Desired outputs.

A_n - Actual outputs.

In the modified artificial neural network, the error should be in minimum value then only the artificial neural network is well-trained for performing the testing phase. The suggested technique assigns the weight value which satisfies the minimum criteria. Then we fix the threshold value and the result of the neural network (O) is compared with the threshold value.

$$result = \begin{cases} recognized, O < \omega, \\ not\ \ recognized, O \geq \omega \end{cases} \tag{15}$$

If the output of modified artificial neural network is belowthe threshold value means then the face image is recognized otherwise the face image is not recognized. The performance of the proposed technique is analyzed in section.5.

RESULTS AND DISCUSSIONS

Here we discuss the outcome got from the proposed system. For executing the proposed strategy, we have utilized MATLAB. The proposed strategy is done in windows machine having Intel Core i5 processor with rate 1.6 GHz and 4 GB RAM.

A. Database depiction

The proposed framework is tried different things with the generally connected datasets, in particular, ORL data, Senthil database and occlusion. The point by point clarification of database depiction is taken after here;

(i) Olivetti Research Lab (ORL) Database: The ORL database was gathered somewhere around 1992 and 1994. It contains slight varieties in enlightenment, outward appearance (open/shut eyes, grinning/not grinning) and facial points of interest (glasses/no glasses). Every one of the pictures was taken against a dim homogeneous foundation with the subjects in an upright, frontal position (with resilience for some side development). A sneak peak picture of the Database of Faces is accessible. The documents are in PGM arrange, and can helpfully be seen on UNIX (TM) frameworks utilizing the "xv" program. The measure of every picture is 92x112 pixels, with 256 dark levels for every pixel. The pictures are sorted out in 40 registries (one for every subject), which have names of the structure sX, where X demonstrates the subject number (somewhere around 1 and 40). In each of these indexes, there are ten distinct pictures of that subject, which have names of the structure Y.pgm, where Y is the picture number for that subject (somewhere around 1 and 10). The database can be recovered from http://www.cl.cam.ac.uk/Research/ DTG/attarchive:pub/information/att_faces.tar.Z as a 4.5Mbytecompacttardocumentorfromhttp://www.cl.cam.ac.uk/ Research/DTG/attarchive:pub/information/att_faces.zip as a ZIP record of comparable size.

(ii) Senthil Database: This database consists of 80 grayscale face pictures of 5 individuals (all are men), including frontal perspectives of countenances with various outward appearances, impediments and shines conditions. Every individual has 16 distinct pictures. The face part of the picture is physically edited to 140x188 pixels and afterward it is standardized. The Facial pictures are resized to 99X99 to have the 297 elements. Facial pictures are accessible in both grayscale and shading pictures.

(iii) Occlusion: Facial impediments, due to shades, cap/top, scarf, and whiskers, can altogether reduce the improvement of face acknowledgment frameworks in uncontrolled situations, for example, visual conditions. The upper face impediment leads to a noteworthy drop in execution. The right acknowledgment rate diminishes from 92.7% to 37.3%. In any case, the execution diminishes on account of little lower face impediment. The execution increment on account of lower face impediment can be clarified by the neighborhood representation method, in which an adjustment in a nearby area influences just the components that are separated from the comparing piece while the elements that are extricated from alternate squares stay unchanged, though in an encompassing appearance-based face acknowledgment methodology, for example, Eigenfaces or Fisherfaces, it can influence the whole element orientation.

B. Evaluation metrics

The assessment of proposed medicinal information order strategy is done utilizing the accompanying measurements as recommended by underneath conditions,

Sensitivity: The sensitivity of the element extrication and the component division is controlled by taking the proportion of a number of true positives to the total of true positive and false negative. This sensitivity can be represented as.

$$Sensitivity = \frac{TP}{TP + FN} \tag{16}$$

Specificity: The specificity of the element extrication and the component division can be estimated by taking the proportion of a number of true negatives to the combined true negative and the false positive. The specificity can be represented as.

$$Specificity = \frac{TN}{TN + FP} \tag{17}$$

Accuracy: The accuracy of element extrication and the component division can be evaluated by taking the proportion of true values available in the population. The accuracy can be represented by the following equation as.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{18}$$

Where,

$TP \rightarrow$ True positive

$TN \rightarrow$ True negative

$FP \rightarrow$ False positive

$FN \rightarrow$ False negative

False Match Rate (FMR): It is defined as the expected probability that dual non-mate models will be wrongly realized as mirror images.

False Non-Match Rate (FNMR): It is defined as the expected probability that dual models will be wrongly identified as non-mirror images.

Genuine Acceptance Rate (GAR): The genuine acceptance rate is theratio of truly matching samples, which are matched by the system and total numbers of tests.

$$GAR = 1 - FAR \tag{19}$$

C. Performance Analysis

The below shown table.1 classifies the solutions of three datasets. Our proposed method uses MANN with firefly algorithm for face recognition. Table.1 is arranged in the underneath area, From table.1, the evaluation metrics are processed for the three numbers of datasets, through which we can achieve the efficiency of proposed medical data classification system. The accuracy values of three datasets are 0.955%, 0.9322% and 0.9175%. The sensitivity values for the three datasets are 0.985%, 0.9758% and 0.9566%. The specificity values for the three datasets are 0.542289%, 0.50684%,and 0.54862%. The FMR values for the three datasets are 0.23%, 0.2105%, and 0.2686%. The FMNR values for the three datasets are 0.15%, 0.11%, and 0.12%. The GAR values for the three datasets are 0.985%, 0.9758%, and 0.9566%.

Table 1: Performance of the proposed method using different dataset

Dataset	Accuracy	Sensitivity	Specificity	FMR	FMNR	GAR
ORL database	**0.955**	**0.985**	**0.542289**	**0.23**	**0.15**	**0.985**
Senthil database	**0.9322**	**0.9758**	**0.50684**	**0.2105**	**0.11**	**0.9758**
Occlusion	**0.9175**	**0.9566**	**0.54862**	**0.2686**	**0.12**	**0.9566**

D. Effectiveness of the classification

In this section, we explain the efficiency of the medical data classification using MANN classifier. The Active appearance model (AAM) can be used to find out the appearance based features in the face image. Then face recognition is done with the help of Modified Artificial Neural Network (MANN). To prove the efficiency of our work, we compare the proposed work to existing work. Here the proposed method made use of modified artificial neural network using firefly algorithm for optimizing the neuron weights.

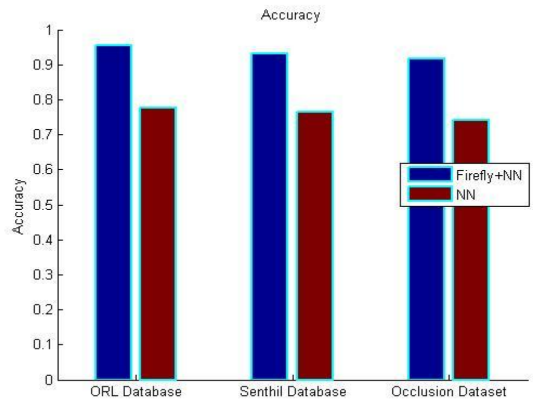

Figure 3: Accuracy comparison for three datasets

When analyzing figure 3, the proposed MANN using firefly algorithm is compared with the existing methods using the traditional neural network. Analyzing this figure 3, we are able to detect that the proposed method achieves high accuracy value than the existing methods. The proposed method has 0.955% of accuracy while the existing method has only 0.775% of accuracy for the ORL database. For Senthil database,0.932% of accuracy value is achieved using the proposed method while the existing method achieves only 0.7645% of accuracy value. The proposed method achieves 0.9175% of accuracy value while the existing method achieves 0.74% of accuracy value for the occlusion dataset. From this, it is clear that the proposed method achieves higher accuracy value for all the datasets compared to the existing methods.

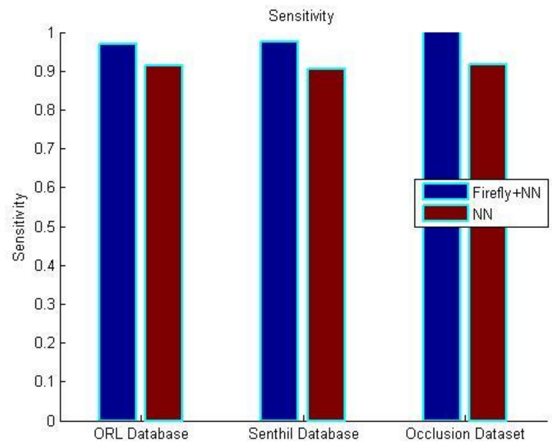

Figure 4: Sensitivity comparison for three datasets

When analyzing figure 4, it is obvious that the proposed method achieves high sensitivity value for three different datasets than the existing methods. For ORL database the value of sensitivity for the proposed method is 0.985% while using existing methods the sensitivity value is 0.9575%. For Senthil database, the sensitivity value is 0.9758% using the proposed method and using the existing method the sensitivity value is 0.9322%. For occlusion dataset the sensitivity value using the proposed method is 0.9566% while using the existing methods the sensitivity value is 0.9%. Thus from this, it is clear that the proposed method has the better sensitivity value than the existing methods.

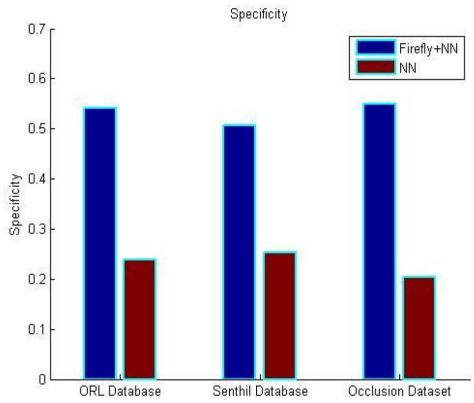

Figure 5: Specificity comparison for three datasets

On analyzing figure 5, it is clear that the proposed method achieves better specificity value than the existing methods for the three datasets. For ORL database the specificity value is 0.542289% while using the existing methods the specificity value is 0.238806%. For Senthil dataset, the value of specificity using the proposed method is 0.50684% while using the existing method the value of sensitivity is 0.2538%. For Occlusion database the value of specificity using the proposed method is 0.54862% while using the existing method the value of specificity is 0.20378%.Thus from this, it is clear that the proposed method has high specificity value for the three datasets than the existing methods.

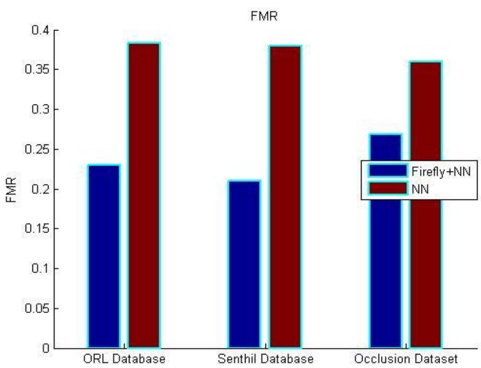

Figure 6: FMR comparison for three datasets

On analyzing figure 6, it is clear that the proposed method has better FMR than the existing method. For ORL database the value of FMR is 0.23% for the proposed method and it is 0.3825% for the existing method. For Senthil dataset, the value of FMR is 0.2105% for the proposed method and it is 0.3795% for the existing method. For Occlusion database the value of FMR is 0.2686 for the proposed method and for the existing method it is 0.3598%. Thus, from this, it is clear that the proposed method has better FMR than the existing methods for the three datasets.

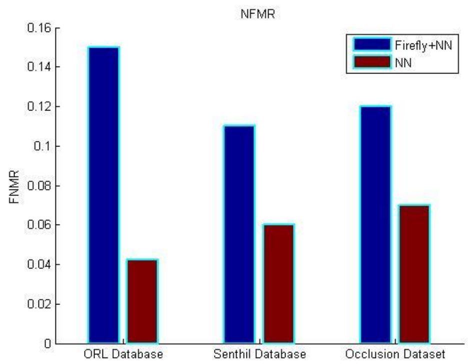

Figure 7: NFMR comparison for three datasets

On analyzing figure 7, it is clear that the proposed method has better NFMR than the existing methods. For ORL database the value of NFMR for the proposed method is 0.15% while for the existing method the value of NFMR is 0.0425%. For Senthil database, the value of NFMR is 0.11% while for the existing methods the value of NFMR is 0.06%. For Occlusion database the value of NFMR is 0.12% while for the existing methods the value of NFMR is 0.07%. Thus, from this, it is clear that the proposed method has better NFMR than the existing methods for the three datasets.

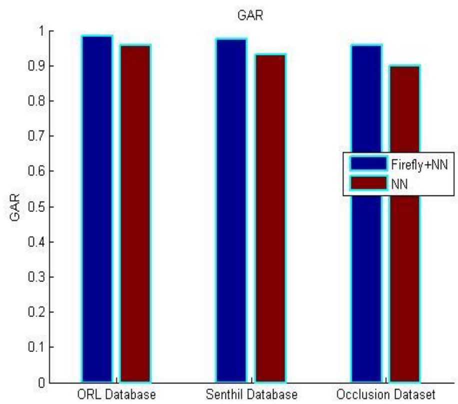

Figure 8 GAR comparison for three datasets

On analyzing figure 8, it is clear that the proposed method has better GAR that the existing methods. For ORL database the value of GAR is 0.985% using the proposed method while by using the existing method the value of GAR is 0.9575%. For Senthil database, the value of GAR is 0.9758% using the proposed method while by using the existing method the value of GAR is 0.9322%. For Occlusion dataset the value of GAR is 0.9566% using the proposed method while using the existing method the value of GAR is 0.9%. Thus, from this, it is clear that the proposed method has high GAR than the existing method for the three datasets.

CONCLUSION

An effective method for face recognition technique is proposed in this paper. The implementation of the proposed technique is done by MATLAB platform. Initially, the SIFT, AAM, and holo entropy features are extracted from the input face image. Then the extracted features are fed to the Modified artificial neural network. Based on the features the input image is recognized. The performance of the proposed technique is evaluated by False Matching Rate (FMR), False Non-Matching Rate (FNMR), Genuine Acceptance Rate (GAR), accuracy, sensitivity, and specificity. Experimental results indicate that the proposed face recognition framework have outperformed by having better accuracy of 95.5% for ORL database when compared existing NN only achieved 77.5%. And also the suggested technique achieves the minimum FMR and the maximum value of NFMR and GAR when compared to the existing NN. From the result, we understand our proposed approach of MANN classifier based recognition outperformed than existing approaches. In future, the researcher will have sufficient opportunities to perform various recognition algorithms to improve the recognition accuracy and produce newer heights of excellence in performance.

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