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An Intelligent Human Age Prediction from Face Image Framework Based on Deep Learning Algorithms

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Age prediction is the task of extracting features from the human face image. Human aging factors can be expressed as multifactorial, gradual, time-dependent, physical, and biological damage. Attributes are extracted from a face image, and the aging factor depends on cells, tissues, and all living organisms. Human age prediction is distinct from chronological age prediction. Each human's biological identity has unique characteristics. Age prediction depends on the maturity process of organs, other tissues, and cells. Many research works have been done on age classification using various techniques from human face images. It is a difficult task to the analysis of facial appearance. Issues in the existing algorithm are inefficient and require more computation time and storage space. To address these issues, this paper proposed a Deep convolutional neural network (DCNN) with a Cuckoo search algorithm (DCNN-CS). In this proposed work, DCNN-CS produces an effective age prediction from the human face image within a minimum execution time, handling a large dataset. The accuracy rate of the convolutional neural network (CNN) got 81.32, the Deep Neural Network (DNN) got 82.34, the Long short-term memory (LSTM) got 88.12, and the proposed work SLSTM-DNN got 91.45.

KEYWORDS: Age prediction, Cuckoo search algorithm, Deep CNN, facial image.

1. Introduction

Automatic estimation of age from the facial image is done using high-level features of the image. Features are filtered from images using the framework of deep learning techniques. Detection of human age from chronological age is a major component of the identity of individuals. The detection of age is determined by organs and other tissues of the human body [8].

Identifying the human age based on the various types of tissues and billions of cells in the body is a challenging research zone. The major challenge in the estimation of age depends on chronological age (CA) and it varies from person to person. The parameters defined as age depend on nutrition, genetics, health condition, body shape, and social conditions. The biological age (BA) differs from the real age of a human being's chronological age [19].

Nowadays estimation of age-related research works has become trending because it is widely used in various real-life applications. In Japan, tobacco vending machine is not accessible to the aged below 18. Similarly, in many companies accessing some products, age-wise is categorized. In that situation estimation of age plays a vital role. For marketing the product this age-based system is very helpful to corporate companies. Computer interactions on an age basis are widely used in many areas like providing security alert signals when a child below 18 years old is left alone in the vehicle. It raises some alarm signals. At the same time, the theme park prevents the child from playing dangerous games or allows them when their age is above 18 years old [6]. Estimation of age acts as a role in the retrieval of images from a large and complex data set. Based on the input query of age in the website of Flickr.com it retrieves the related age images. It can be very useful in the identification of friends. Aging growth affects the appearance of human beings in the aspects of the color of their hair, the appearance of a human face, their way of walk, and their lifestyle. These factors are intrinsic. These factors are classified into two categories like intrinsic factors and extrinsic factors [21]. Wallraff et al. [27] describe the estimation of age based on teeth images using digital X-rays with a deep learning algorithm. Vadla et al. [24] have presented a method for the determination of age using a teeth image of a left-sided jaw digital image.

The metaheuristic algorithms work efficiently in selecting optimal solutions. We choose Cuckoo search in this prediction algorithm due to its efficiency in computing with fewer parameters. Moreover, the locally optimal solution is computed very quickly. Many research works have been done for age classification from human face images using various techniques. Issues in the existing algorithm are inefficient and require more computation time and storage space. To overcome these issues this paper proposed Deep CNN with a Cuckoo search algorithm (DCNN-CS). This proposed work DCNN-CS produces an effective prediction of age from the human face image within a minimum time of execution, handling a large dataset. The main contribution of this work is:

1. For estimating the age accurately pre-processing is implemented.
2. Detect the edge detection of face images by using Gabor Filter
3. To extract correct features from the facial image using PCA.
4. Estimation of age by using DCNN-CS.

The organization of the paper is as follows: Section 2 has a literature review discussion, Section 3 methodology of estimating the age by using DCNN-CS, Section 4 evaluates the experimented results and Section 5 concludes the paper with future directions.

2. Related Work

Automatic estimation of age is a challenging research work since it uses data sets with various characteristics of faces in various people. Identification is based on intrinsic factors of skin, hair color, teeth, etc. In recent years, for providing security in the activities of social robotics, providing video-based security systems for facial identification, detection of facial expression, and gender classification is implemented and applied in the field of computer vision and its application of pattern recognition [4]. Sakata et al. [20] proposed the estimation of age by using multi-stage CNN. It implements three tiers of operations one CNN is applied for the estimation of gender, another CNN is applied for the estimation of age group,

Table 1
Survey on an estimation of age

Author	Method	Limitation/pros
Galibourg et al. (2021) [12]	Demirjian's staging approach using machine learning algorithms and also based on dental image age is classified.	Demirjian's is population-specific and machine learning helps to tackle complex data.
Amirzadi et al. (2021) [5]	Estimation of age by using inverse generalization in the Weibull method under loss function	Perform non-ID data analysis. Data are omitted by underestimation.
Vila-Blanco et al. (2020) [26]	Estimation of chronological age by using OPG images with DNN	Deep learning performs better in estimation and age prediction
Prabhu et al. (2020) [18]	Automatic Estimation of age through Machine Learning algorithm	Machine learning and automation provide better prediction
Zhavoronkova et al. (2019) [31]	Artificial intelligence-based detection of age	Advanced AI techniques are used
Taheri et al. (2019) [23]	Age assessment by using the two-level fusion and features by using score level and feature level techniques	Score and feature level fusion techniques are the much-affected quality of the image like blurring characteristics.
Mallouh et al. (2019) [16]	By using CNNs-based pre-trained transfer learning models for age classification from unconstrained images of the face	Maximum accuracy is highly possible using CNN.
Ouafi et al. (2019) [17]	Age estimation by using Two stages of facial demographic feature attributes	The quality of attributes is not ensured
Zhang et al. (2019) [30]	LSTM network with Attention to age assessment	It consumes more time and memory. But accuracy is good.
Rahman et al. (2019) [19]	Estimation of biological age by using the Centroid neighborhood approach.	The centroid approach cannot provide accuracy in terms of selecting image features.

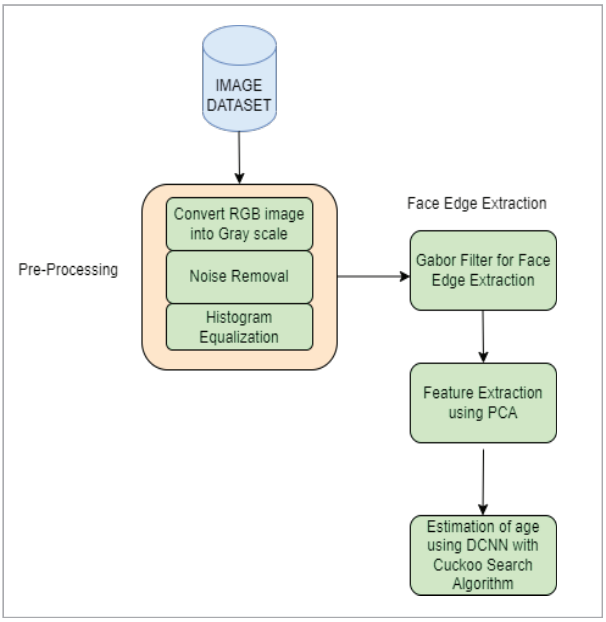
and a final layer of CNN is used for the regression of age. It uses the gait database. Vila et al. [25] describe the estimation of gender based on dental by using the architecture of VVG 16 and DASNet. The estimation of age uses the fusion technique of ELM with three variations of CNN namely Age-Net, Gender-Net, and Race-Net [10]. Table 1 shows the survey on an estimation of age.

3. Proposed Age Estimation Methodology

Estimating the age of the user via extracting features of the face image and classifying its age is a challenging task. The framework of the proposed work is shown in Figure 1.

Figure 1 describes the proposed work for estimating the age of the user which includes the collection of datasets, pre-processing, face edge detection, feature extraction, and estimation of age using a deep convolution neural network with an optimized algorithm of Cuckoo search (DCNN-CS).

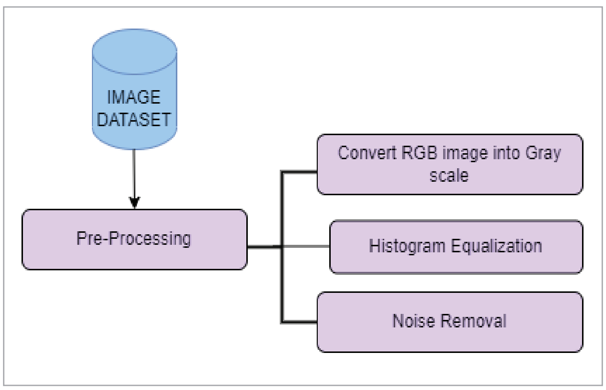
Figure 1
Proposed Framework



3.1. Pre-Processing

To get a more accurate result of age estimation from the face image, pre-processing is needed. The steps used in the pre-processing are shown in Figure 2.

Figure 2
Pre-processing



The steps involved in the pre-processing include converting the color image into greyscale, histogram equalization, and noise removal.

3.1.1. Converting RGB Image into Grey Scale

Data collected in the dataset are RGB images. To reduce the computational complexity of the algorithm and to minimize the execution time as well as storage capacity, converting RGB images into grayscale is essential.

3.1.2. Histogram Equalization

To improve the contrast of the image histogram equalization is implemented. It uniformly distributes the pixel value of the image.

3.1.3. Noise Removal

To eradicate the noises present in the image are removed using a median filter. The entire image is scanned using 3 × 3 format, and the center pixel value is calculated, then the value of a pixel in the image is replaced by its center pixel value.

$$Y[i,j] = median\{x\,[k,l],(k,l) \in Z\}, \quad (1)$$

where Z represents a neighborhood pixel value defined by the user and centered around location $[i,j]$ in the image.

3.2. Face Edge Extraction

A Gabor filter is a linear filter used for edge extraction. It is a two-dimensional form of Gaussian kernel function which modulates the sinusoidal plane wave in the spatial domain. The representation of two-dimensional Gabor filter based on sinusoidal signal modulated by Gaussian functions as $\varphi(x, y; \sigma, \lambda\theta_m)$ is:

$$\varphi(x,y;\sigma,\lambda\theta_m) = g(x,y,\sigma)exp\left(\frac{2\pi x\theta m_i}{\lambda}\right) \quad (2)$$

It can be formulated as filter-based

$$sigmasga(x,y,\sigma) = exp\left(-\frac{x^2\theta k+y^2 y\theta m}{2\sigma^2}\right) \quad (3)$$

is a Gaussian function where,

$$x\theta_m = x\cos(\theta_m) + y\sin(\theta_m) \quad (4)$$

$$y\theta_m = x\sin(\theta_m) + y\sin(\theta_m). \quad (5)$$

By using the Equations (4)-(5), is the standard deviation of the Gaussian function is represented as σ with the dimension of x, y. The wavelength and orientation of the image is represented by λ, θ_m. The parameter value y is taken as 0.2 value. In this proposed work, Gabor filter with 5 orientations and 4 scales are applied. Therefore, the angle value θ_m is applied by 25,45,60,120,180 with their wavelength values are 40, 70, 110, 150. After applying the Gabor Transform to the face image which detects the edges of the image.

3.3. Feature Extraction Using PCA

It extracts the relevant features of the image after edge extraction in the dataset is performed, which is based on multivariate statistical analysis in correlation matrix. Main motivation behind using PCA is, it consider top feature for dimensionality reduction. It uses only very few components as possible in reduction operation. By using dimensionality reduction in Principal component analysis, it extracts the relevant features of the image.

In the prediction of age from the face image, define the impact factor of matrix Z by:

$$Z = \left(z_1, z_2, \dots z_p\right)' \tag{6}$$

$$Z = \begin{bmatrix} z_{1,1} & z_{1,2} & \cdots & z_{1,n} \\ z_{2,1} & z_{2,2} & \cdots & z_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ z_{p,1} & z_{p,2} & \cdots & z_{p,n} \end{bmatrix} = \{z_{i,j}\} \tag{7}$$

Here, $z_{i,j}$ is the value of factor ($i = 1, 2, \dots, p, j = 1, 2, \dots, n$), p is the dimension of Z.

Step 1: To standardize the dataset of face image,

$$z^*_{i,j} = \frac{z_{i,j} - \bar{z}_j}{\sigma_j} \tag{8}$$

$$\bar{Z}_j = \frac{\sum_{i=1}^{p} z_{i,j}}{P} \tag{9}$$

$y^*_{i,j}$ is the normalized value of $z_{i,j}$ and $\bar{Z}_j$ and σ_j are mean and standard deviation.

Step 2: Compute the correlation coefficient matrix of Z^* and its impact factor Y is defined as:

$$K = \frac{1}{P}(Z^*)^T Z^* = \begin{bmatrix} y_{1,1} & y_{1,2} & \cdots & y_{1,m} \\ y_{2,1} & y_{2,2} & \cdots & y_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ y_{p,1} & y_{p,2} & \cdots & y_{p,m} \end{bmatrix} \tag{10}$$

Step 3: Compute eigen values for K with its factor value. By using the characteristic equation of $|Y - \lambda F| = 0$, m is the value of characteristics λ_j of K. Sort the eigenvalues from biggest to smallest value that is $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \dots \geq \lambda_p$. Compute the eigenvector and it can be expressed as:

$$EIV_j = \left[eiv_{1,j}, eiv_{2,j}, \dots, eiv_{p,j}\right], j = 1,2, \dots, n \tag{11}$$

Step 4: Compute the contribution rate of variance α_j and contribution rate of cumulative variance of principal component analysis which is expressed as:

$$\alpha_j = \frac{\lambda_i}{\sum_{i=1}^{n} \lambda_i} \qquad \alpha(j) = \sum_{i=1}^{n} \alpha_i \tag{12}$$

The dimensionality reduction of PCA along with its 1original feature values is as follows:

$$Q = \left[z_{i,1}, z_{i,2}, \dots, z_{i,n}\right] \begin{bmatrix} eiv_{1,1} & eiv_{1,2} & \cdots & eiv_{1,n} \\ eiv_{2,1} & eiv_{2,2} & \cdots & eiv_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ eiv_{b,1} & eiv_{b,2} & \cdots & eiv_{b,n} \end{bmatrix} \tag{13}$$

3.4. Estimation of Age from Face Image Using DCNN with Cuckoo Search Algorithm

3.4.1. Deep Convolution Neural Network (DCNN)

The robust estimation of age from the human facial dataset images using deep CNN is based on the concept of transfer learning. For the accurate estimation of age from the human facial images requires high level features. Therefore, deep CNN (DCNN) model is implemented. Figure 3 shows that architecture of transfer leaning in CNN.

Figure 3
Transfer Learning

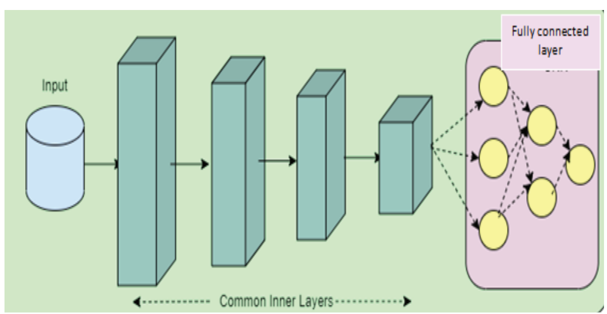


Figure 3 shows the transfer learning that transfers the input features of the facial image, and it is pre-trained with the model of DCNN. Features of facial images are extracted via transfer inner layers. Traditional CNN model contains a convolution layer, a pooling layer, an activation layer, and a fully connected layer. The mathematical representation of applying the input features in the CNN model can be expressed as the following:

$$v = u \times \mathcal{F} \rightarrow v[i] = \sum_{j=-\alpha}^{+\alpha} u[i-j]\,\mathcal{F}[j]. \quad (14)$$

The input feature data is in the form of in 3 × 3 convolutional kernel. Therefore, it contains 9 features in matrix format with 9 neurons. The output is in 3 × 3 matrix is called as feature map. The mathematical representation of convolution layer is expressed as follows:

$$conv_{ij} = \sigma\big((CV * u)_{ij} + c\big). \quad (15)$$

Here, $*$ denotes a convolutional operation. Then it can be expressed as the following:

$$CV * u = \sum_m \sum_n CV_{mn} a_{(i-m)(j-n)}. \quad (16)$$

In this proposed work, deep CNN uses the version of ResNets. It is also called the residual block. Figure 4 shows that ResNets in deep CNN.

Figure 4
ResNets in Deep CNN

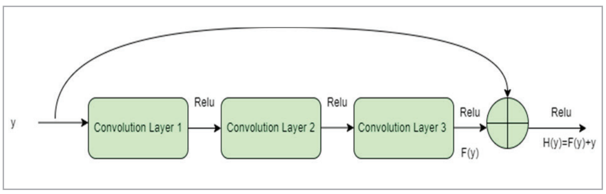
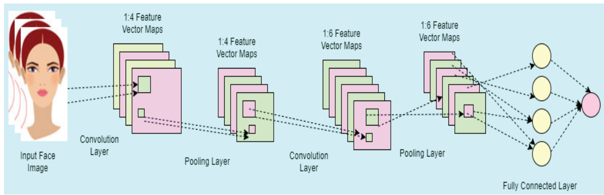


Figure 4 uses deep residual network (ResNet) with many residual blocks. Each residual block contains three convolution layers, namely, (Convolution layers 1, 2 and 3) with a summator. The connection between the layers and the summator are sequential connection format and shortcut connection format. The sequential connection includes the three consecutive convolutions with input value of y and produce $F(y)$. Similarly for the shortcut connection, format input value of y and produce $H(y) = F(y) + y$. To get a more accurate estimation of age, one needs to set the value of $F(y) = 0$, which makes the network weight $H(y) = y$ disappear and represents the identity of mapping function, which removes the three convolution layers and decrease its depth and accurately estimates the age. Figure 5 shows the framework of DCNN.

Figure 5
Framework of DCNN



From the observation in Figure 5, DCNN includes many layers, like convolution, pooling and fully connected layer. It extracts the features of face image and detects its age.

Convolution Layer

This layer extracts the features from the face image and creates a feature map. The convolution layer 1 extract the face edge and it is trained the model with its high-level features of the image. The convolution layer's kernel extracts the features via input plane and each neuron of the input layer provides the feature map. The weights that are used in the neurons of the neural network represent the feature map stack. The neurons that are present in this layer are referred to as stack depth of DCNN. Each neuron shares the same bias value with its weights to form a stack. The various parameters used in the convolution layer are the size of the input, feature map, size of kernel, and stack depth. The computed output is expressed as the following:

$$FM_P = \frac{I_P - K_P}{S_P} \quad (17)$$

$$FM_Q = \frac{I_Q - K_Q}{S_Q}. \quad (18)$$

Here, FM_P, FM_Q are feature map size, I_P, I_Q are input size, K_X, K_Y aresize of kernel, S_P, S_Q row a column of the stride. In the neurons of convolution layer, the non-linear activation function is used with weights and its bias value. The activation function of sigmoid is used in the output of pooling layer.

Pooling Layer

Pooling layer, or subsampling layer, is considered as a mediator of convolutional layers. In these types of pooling layers, the various operations like max and average pooling in the DCNN. To prevent from overfitting in the pooling layer [1] one needs to reduce its dimensionality. Moreover, pooling layer implements various operations like translation, scaling, and rotation.

This DCNN extracts the high-level features of the human facial image. The outputs of convolutional layer are transmitted into the input of the next layer. The pooling layer minimizes the dimensionality of data. Final output of the prediction of age is derived from the fully connected layer. To increase the accuracy of prediction of age and to optimize the updated weight value in the CNN model, Cuckoo Search Algorithm (CS) for the detection of age from facial image dataset is used.

3.4.2. Cuckoo Search Algorithm

In nature, some female Cuckoos randomly select the host bird's nest and lay their eggs. There, they remove the host bird's eggs for increasing the probability of growth of their own eggs. Let us suppose that the host bird finds the alien egg in its nest and then it is destroyed, so the Cuckoo eggs or the whole nest vanish. The main interest towards implementing Cuckoo search [28] is that in age prediction, more parameters are required to be analysed, and Cuckoo search can compute the age with fewer parameters. It also produces best local optimal solution. Rules which are followed in Cuckoo search algorithm is given below:

Rule 1: Cuckoo randomly chooses the nest of another bird and lays one egg at a time.

Rule 2: To generate next generation of Cuckoo by choosing the best quality of egg in the best nest.

Rule 3: There are fixed host nests, and host bird numbers identifying the Cuckoo's egg and its probability is expressed as $prob_c \in [0, 1]$.

To generate the new solution C_{newi}^{t+1} at a time t and its Levy flight distribution is the following:

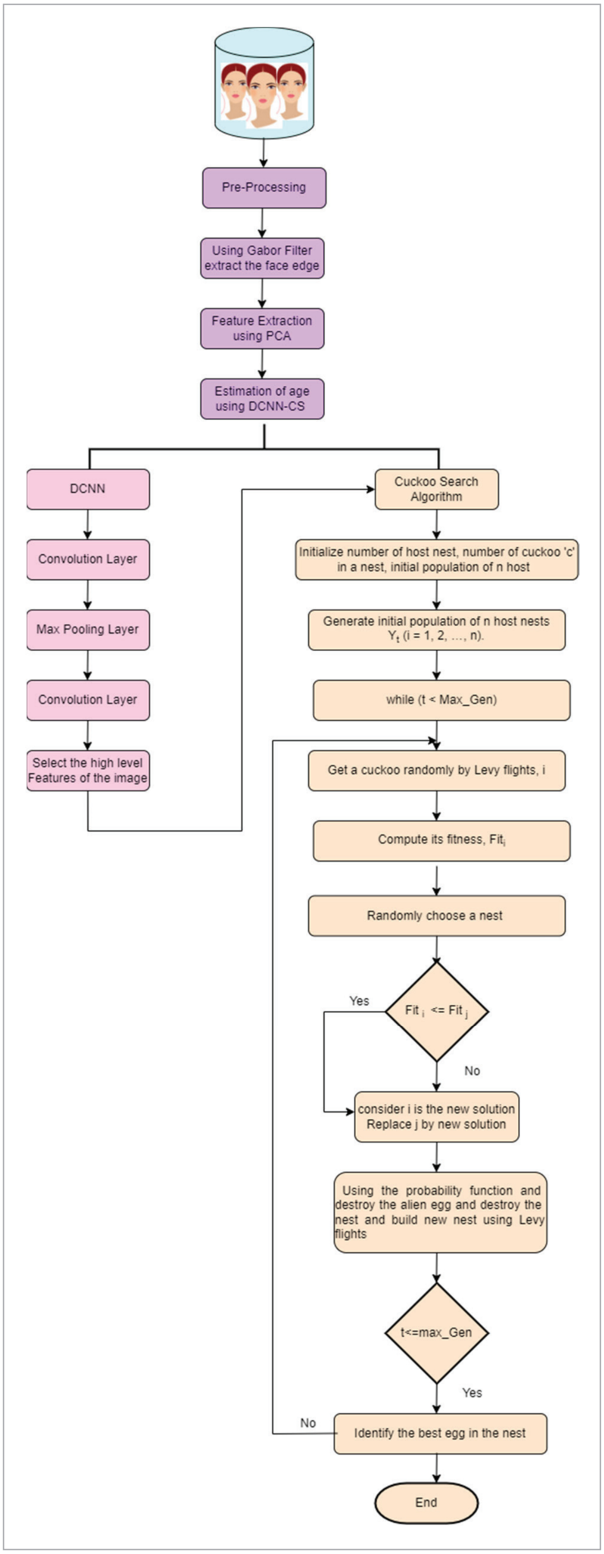
$$C_{newi}^{t+1} = c_{newi}^{t} + \alpha \otimes levy(step, \lambda). \tag{19}$$

Here $\alpha > 0$ is the scaling factor of step size, $levy(step, \lambda)$ is the step length. The probability distribution is defined by:

$$levy(step, \lambda) = \frac{\lambda\Gamma(\lambda)\sin(\pi\lambda/2)}{\pi}\frac{1}{step^{1+\lambda}}. \tag{20}$$

The implementation of the concept of Cuckoo search algorithm is given below:

Figure 6
Work Flow of proposed work



Step 1: Initializing population of n host nests, y_i, $i = 1, 2, 3, ..., n$

Step 2: $d = 1$

Step 3: **While** $d \leq stop\_criteria\ or\ Max_{gen}$ **do**

Step 4: fitness value is computed as $fitn(y_{new})$ in each nest

Step 5: Generate new solution Y_{newi}^{t+1} is generated by Levy flightusing Equation (19&20).

Step 6: Choose the candidate solution y_{oldi}^{t}

Step 7: IF $fitn(y_{oldi}^{t}) > fitn\ (Y_{newi}^{t+1})$ **then**

Step 8: Replace y_{oldi}^{t} by new solution Y_{newi}^{t+1}

Step 9: **End IF**

Step 10: Probability ($prob_c$) of worst nest is destroyed and built a new nest one.

Step 11: **End While**

Step 12: Estimate the age from human facial image by using Euclidean distance as:

$$E = \sqrt{\sum_{j=1}^{N}\left(x_j - y_j\right)^2}. \tag{21}$$

Here, x_j, y_j are distance between two points. In the above algorithm, replacing the new generation is based on Cuckoo egg in the nest and also replacing the worst generation by new one. Figure 6 shows that flow of proposed work.

4. Results and Analysis

For the prediction of age from the human facial image, DCNN with Cuckoo search algorithm is used. Data set used in the estimation of age is UTK Face Dataset [3], and FGNet datasets [11]. They are composed of a total of 1,002 images of 82 people with age range from 0 to 69 and an age gap up to 45 years. Cross-Age Celebrity Dataset (CACD) [9] contains 163,446 images from 2,000 celebrities collected from the Internet. This large dataset contains 0 to 115 age span with more than 22,000 face images. It provides the caption for dataset like age, gender, ethnicity, date, and time. To implement this DCNN-CS, Python programming language was used. Keras is the interface for the TensorFlow library. This proposed work is evaluated by the metrics of Pearson correlation coefficients, MAE, RMSE, Standard deviation (SD), and cumulative score (CS). It is compared with existing algorithms like CNN, DCNN [19], and SVR [11].

4.1. Evaluation Metrics

To evaluate the PCOS prediction system using proposed cyst segmentation and classification system, confusion matrix is implemented. From the confusion matrix, the evaluation metrics such as accuracy, precision, recall and F1-score are computed. The additional metrics such as ROC-AUC score and cross validation accuracy also computed. The confusion matrix template is shown in Table 2 and using the variables True positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN), the metrics are computed using the following Equations (22)-(27).

Pearson Correlation Coefficient

$$\rho(x, y) = \frac{\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{N}(y_i - \bar{y})^2}} \tag{22}$$

Here, x and y are various features (attributes) and N is the number of samples.

MAE

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_{pi} - \hat{y}_{ai}\right| \tag{23}$$

It shows the error between the age and the estimated age.

RMSE

It is similar to MSE but for compute this by root of MSE.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_{pi} - \hat{y}_{ai}\right)^2} \tag{24}$$

Standard Deviation (SD)

$$SD = \sqrt{\frac{1}{N-1}}\sum_{n=1}^{N}(|t_n - y_n| - MAE)^2 \tag{25}$$

Cumulative Score (CS)

$$CS(y) = \frac{N_y}{N} \times 100\% \tag{26}$$

Here, number of samples N_y is whose MAE is within y year.

Precision

$$precision = \frac{TP}{TP+FP} X100 \tag{27}$$

Recall

$$recall = \frac{TP}{TP+FN} \quad (28)$$

F1-Score

The F1-score is a measure of accuracy based on the precision and recall values. It is calculated as:

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (29)$$

Accuracy

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} X100 \quad (30)$$

In the estimation of age from the UTK face dataset using DCNN uses rate of learning as 0.00020 with its 0.8 as momentum. The various types of CNN are GoogLeNet [9], DenseNet [13], and ResNets are implemented. The proposed work uses ResNets [22] in DCNN. Human age is determined by facial structure [14, 29] and it may be different from that detected using our human eye. One may consider a sample age between 31 to 34 year old humans who may be have similar facial structure, which in this situation makes it difficult to distinguish by human being. Table 2 shows the Classification of age grouping in accuracy and MAE regression results of UTK Face dataset, CACD and FGNet dataset using DCNN.

Table 2
Classification accuracy and MAE Regression in DCNN using UTK Face dataset

Technique	Classification accuracy			MAE Regression
	Individual	5 Years	10 Years	
GoogLeNet	0.78	0.92	0.88	9.17
DenseNet	0.86	0.91	0.89	9.34
ResNet	0.91	0.94	0.92	9.12

Table 2 presents data which simulates ResNet and has highest accuracy in classifying UTKFace dataset of 91% for individual classification, for 5 years age group classification of 94%, for 10 years age group classification of 94%. It also produces lowest MAE regression value of 9.12 for DCNN.

Table 3
Classification accuracy and MAE Regression in DCNN using CACD Face dataset

Technique	Classification accuracy			MAE Regression
	Individual	5 Years	10 Years	
GoogLeNet	0.82	0.78	0.89	9.12
DenseNet	0.89	0.84	0.91	9.68
ResNet	0.92	0.91	0.94	9.09

Table 3 presents data which simulates ResNet and has highest accuracy in classifying CACD Face dataset of 92% for individual classification, for 5 years age group classification of 91%, for 10 years age group classification of 94%. It also produces lowest MAE regression value of 9.09 for DCNN.

Table 4
Classification accuracy and MAE Regression in DCNN using FGNet dataset

Technique	Classification accuracy			MAE Regression
	Individual	5 Years	10 Years	
GoogLeNet	0.75	0.82	0.81	9.56
DenseNet	0.81	0.79	0.88	9.18
ResNet	0.89	0.90	0.91	9.11

Table 4 presents data which simulates ResNet and has highest accuracy in classifying FGNet dataset of 89% for individual classification, for 5 years age group classification of 90%, for 10 years age group classification of 91%. It also produces lowest MAE regression value of 9.11 for DCNN.

Figure 7 shows the cumulative score (CS) of various algorithms.

In the observation of Figure 7, the cumulative score various existing algorithms like CNN, DCNN, SVR with various age group of people in the UTK face data set, FGNet dataset and CACD face daataset. The various age groups are categorized as age groups from 0 to 15, age group of 16 to 50 and above 51 age group. Our proposed work produces better prediction of age group in the range of 0 to 15 and above 51. Table 3 shows that various metric measures for implementing in various algorithms.

Figure 7

Cumulative Score

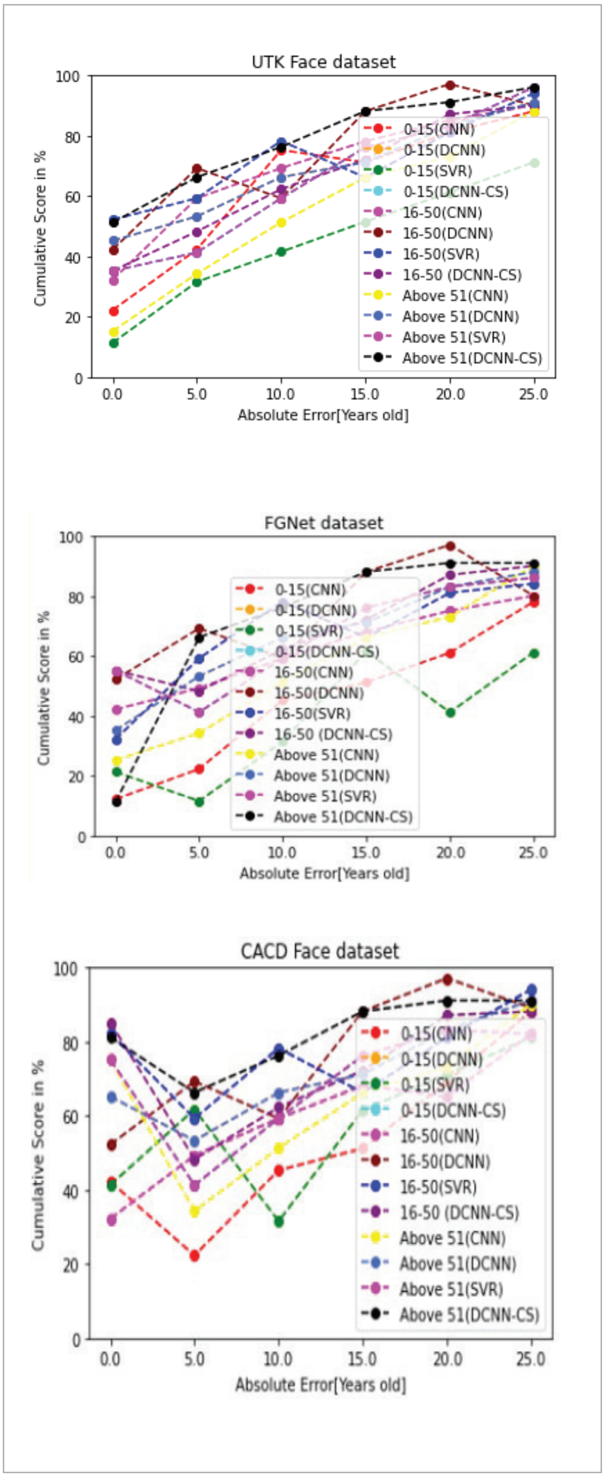


Table 5

Metric Measures of MAE, Correlation and RMSE

	CNN	DCNN	SVR	DCNN-CS
MAE	17.34	15.45	22.05	8.55
Pearson Correlation	0.23	0.18	0.19	0.12
RMSE	22.55	18.26	28.34	12.87

In the observation of Table 5, it describes that statistical metric measures are implemented in the four models like CNN, DCNN, and SVR. A comparison of MAE, RMSE and Pearson correlation coefficient in CNN got (17.34,22.55,0.23), DCNN got (15.45,18.26,0.18), SVR got (22.05, 28.34,0.18), DCNN-CS got (8.55,12.87, 0.12). In the above analysis, DCNN-CS model performs best in the evaluation of age from human facial images in the aspects of MAE, RMSE, and Pearson Correlation coefficient. Table 4 shows the metric measures of precision, recall and sensitivity of various algorithms in the estimation of age.

Table 6

Metric Measures of Precision, Recall in Smart Home system

Algorithm	Precision	Recall	F1-SCORE
CNN	53.26%	58.43%	64.71%
DCNN	74.12%	64.16%	72.24%
SVR	67.81%	64.72%	68.34%
DCNN-CS	85.13%	78.12%	83.19%

Table 6 compares the existing algorithms and the proposed DCNN-CS technique. Here CNN got F1score of64.71%, and precision of 53.26%, and recall of 58.43%. DCNN got F1-score of 72.24%, precision of 74.12%and recall of 64.16%and SVR technique obtained F1-score of68.34%, precision of 67.81%, and recall of 64.72%. The proposed technique of DCNN-CS is obtained F1-score of83.19%, precision of 85.13% and recall of 78.12%. Figure 8 shows the computation time.

Figure 8
Computation Time

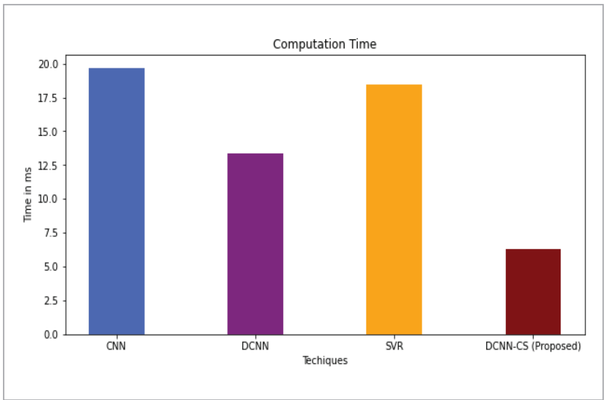


Figure 8 shows the computation time of various algorithms. CNN got 19.67 ms, DCNN got 13.34 ms, SVR got 18.47 ms, and the proposed work of DCNN-CS got 6.31 ms. Table 5 shows the Standard deviation (SD) of various algorithms.

Table 7
SD of various Algorithms

	SD [Years-old]			
Age Category	CNN	DCNN	SVR	DCNN-CS
0-15	9.81	8.96	12.56	7.24
16-50	8.55	9.33	13.11	6.87
Above 51	12.33	10.46	12.78	9.45

Table 7 shows the standard deviation of various algorithms, like CNN, DCNN, and SVR in various age categories. Our proposed work produces better performance. Figure 9 shows the proposed technique with its accuracy rate.

Figure 9 shows the accuracy rate. CNN got 81.32, DNN got 82.34, LSTM got 88.12, and the proposed work SLSTM-DNN got 91.45. In the analysis of statistical and metric measures, our proposed work produces prominent result in the aspects of minimum error rate, accuracy, and computation time. Table 8 shows the confusion matrix of UTK face data set.

The age groups 0-2, 4-6, 8-15 and 15-20, 25-35 and 40-60 are predicted with relatively high accuracy rate in the diagonal values.

Figure 8
Accuracy

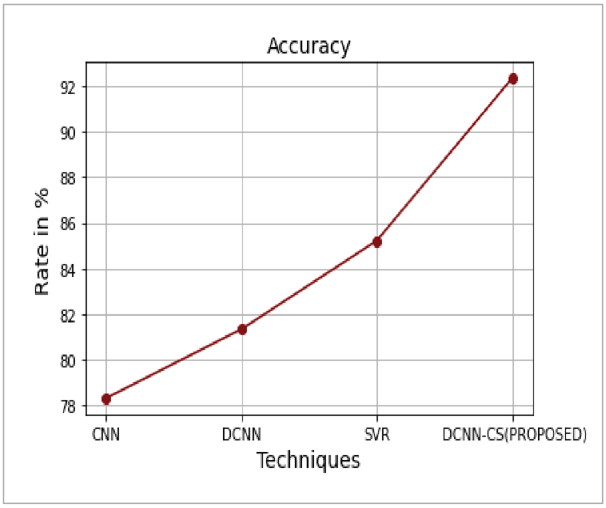


Table 9
Confusion Matrix of UTK face data set

	0-2	4-6	8-15	15-20	25-35	40-60
0-2	**0.656**	0.145	0.026	0.005	0.004	0.008
4-6	0.256	**0.574**	0.173	0.024	0.011	0.12
8-15	0.004	0.018	**0.076**	0.054	0.045	0.023
15-20	0.002	0.012	0.033	**0.256**	0.187	0.123
25-35	0.004	0.0005	0.004	0.142	**0.278**	0.176
40-60	0.003	0.006	0.023	0.045	0.132	**0.378**

6. Conclusion

An intelligent framework for the estimation of age accurately by using UTK face dataset. To get more accuracy, pre-processing is required. Before extracting the features, Face edge is detected by using Gabor filter. Estimation of age uses DCNN-CS. This proposed work is implemented in UTK Face dataset which contains a large amount of data. The two deep learning models, such as Deep Convolution Neural Networks and Transfer Learning are used for feature selection due their efficient learning model. The output of DCNN is fed as input in the optimization algorithm of Cuckoo search algorithm. These evaluated results are analyzed and compared with various traditional approaches. The proposed optimized DCNN-CS is used for the estimation of age from human face image. DCNN-CS performs better than other approaches by obtaining the accuracy rate of CNN got 81.32, DNN got 82.34, LSTM got 88.12, and the proposed work SLSTM-DNN got 91.45. The limitation of this proposed work is that it only classifies age. In the future, the proposed model will implement the estimation of gender using various deep learning algorithms.

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