An improved age invariant face recognition using data augmentation

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ABSTRACT

In spite of the significant advancement in face recognition expertise, accurately recognizing the face of the same individual across different ages still remains an open research question. Face aging causes intra-subject variations (such as geometric changes during childhood & adolescence, wrinkles and saggy skin in old age) which negatively affects the accuracy of face recognition systems. Over the years, researchers have devised different techniques to improve the accuracy of age invariant face recognition (AIFR) systems. In this paper, the face and gesture recognition network (FG-NET) aging dataset was adopted to enable the benchmarking of experimental results. The FG-NET dataset was augmented by adding four different types of noises at the preprocessing phase in order to improve the trait aging face features extraction and the training model used at the classification stages, thus addressing the problem of few available training aging for face recognition dataset. The developed model was an adaptation of a pre-trained convolution neural network architecture (Inception-ResNet-v2) which is a very robust noise. The proposed model on testing achieved a 99.94% recognition accuracy, a mean square error of 0.0158 and a mean absolute error of 0.0637. The results obtained are significant improvements in comparison with related works.

Keywords: Age invariant face recognition, Data augmentation, FG-net aging dataset, Inception-ResNet-v2, Noise image augmentation

1. INTRODUCTION

The need for automated human face recognition cannot be overemphasized as it is required for identification and authentication in various real-life applications. Examples of these applications include border control, voting systems, health care, attendance capturing, and access control. The variant nature of the face with the passage of time has been found from rigorous research to be responsible for the intra-class variations that make facial recognition systems to return a non-match for genuine users. This factor is called “aging” and it makes matching of “query face templates” with stored templates of users’ faces in databases unreliable and insecure.

It is generally accepted that the use of deep learning for face recognition application was possible due to many factors of which data augmentation [1] is a part. Face recognition is affected negatively by synthetic makeup and research has shown that synthetic makeup is one of the reasons why celebrities have trouble with face recognition systems. The lifestyle of celebrities usually involves a lot of activities that require several unique synthetic makeups. This causes serious ambiguity issues in face recognition.

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The artificial colors, contouring and uneven skin tone associated with artificial makeovers pose a challenging problem in face recognition that some researchers [2] have attempted to solve using deep convolutional neural networks with promising results. The application of convolutional neural network (CNN) to solve the facial artificial makeup challenge involved the use of augmented pictures of subjects with various types of artificial makeovers.

In some instances, the input images were split into two categories, a category with closely matched pairs of face images and the other categories were unmatched pairs. The goal was to increase the disparity in the unmatched face image pairs and the similarity in the matched face image pairs [3]. The face images of the subjects were fed into CNN networks in pairs with the aim of reducing false matches and increasing true matches across age groups. The age-invariant face recognition was achieved using distance metrics on well-ordered pairs of matched and unmatched face images. Standard databases such as the Face and Gesture Recognition Network Aging Database (FG-NET AD) [4], the MORPH database, the CAD database, the Asian Face Age Dataset (AFAD) and a lot more have been the pool from which researchers working on age-invariant face recognition systems get face images to augment. These standard aging databases provide a platform to standardize research outputs on age-invariant face recognition. The majority of the databases have a limited number of face images that are not large enough for deep learning applications and are thus augmented using a large array of standardized data augmentation processes.

Some researchers use unique face images from subjects who volunteer to have their face image used for age-invariant face recognition research [5]. The aim is usually to get face images from subjects that cover a minimum of twenty to thirty percent of a subject’s lifetime. These images are augmented and used to develop age-invariant face recognition models. A key part of the research using individual volunteer subject images is highlighting the number of participating subjects, the number of face images originally acquired, the number of augmented face images, the median age [6], the minimum and maximum age and the separation between acquired images of each subject. The data augmentation process done on face images helps researchers work on the intra-class and inter-class variations sought for age-invariant face recognition [7]. The inter-class and intra-class variations help in the modeling of appropriate datasets for the development of age-invariant face recognition systems. The augmented face images are often used as data input to several deep learning models like the convolutional neural networks to create robust age-invariant face recognition systems [8].

In some applications, data augmentation is used to separate subject-specific facial features that are stable from variations in other facial features caused by aging [9]. This leads to the generation of age-invariant face recognition systems that are robust to variations in facial features caused by aging. Data augmentation has been used to adapt face images for applications on mobile devices and cloud environments that operate in real-time [10]. The face images for such niche applications are, usually augmented to be compatible with mobile device applications. Data augmentation is done in various ways. Famous among them are rotation, the addition of noise, landmark perturbation and synthesis techniques [11]. Face images are augmented to dramatically increase their numbers, size and suitability for deep learning applications. Face images that are not augmented usually cause overfitting, pose variance, misalignment and illumination variations. The issue of illumination variations in face images is also addressed using data augmentation techniques like face lighting as seen in [12] to create robust face recognition systems. Sometimes data augmentation is done to avoid the need for paired face images and the true age of face image samples [13].

In this work improving the accuracy of an age invariant face recognition (AIFR) system using data augmentation technique on a classical pre-trained convolution neural network is the focus of this study. It AIFR system was achieved by augmenting the FG-Net dataset at the preprocessing phase with different types of noise that incidentally improved the accuracy of the system. This was largely because the pertained CNN adapted for training the proposed AIFR model was robust to noise.

2. PROPOSED RESEARCH METHOD FOR THE IMPROVED AGING INVARINT FACE RECOGNITION USING DATA AUGMENTATION

This section describes the proposed research method for the improved age invariant face recognition using data augmentation. This network was designed to improve the recognition of the intra-class subject (same person) at different ages using data augmentation. The general procedure comprised of the same traditional steps: image acquisition, pre-processing, feature extraction, classification and system evaluation. In this work, the image pre-processing steps taken using data augmentation technique improved the performance of the system greatly. Four basic pre-processing steps were utilized. Feature extraction is the process of capturing the preferred trait descriptors but using the CNN instead of a handcrafted method. In this model, a pre-trained CNN architecture (Inception-ResNetv-2) was adopted. Classification is necessary
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2.1. Data acquisition

The face and gesture recognition network ageing database (FG-NET AD) contains 1002 images from 82 different subjects with age ranging from newborns to 69 years. However, ages up to 40 years are the most populated in the database. With the exception of recent images that were acquired digitally, other
images in the database are the scanned photographs of subjects found in personal collections. Consequently, the quality of images in the database depends on the skill of the photographer, the imaging equipment used, the photographic paper used and the overall photograph condition. The images exhibit considerable variability in resolution, image sharpness, illumination, background, viewpoint and facial expression, which makes it highly challenging data for age-invariant face recognition. Furthermore, occlusions in the form of spectacles, facial hair and hats are also present in a number of images [14-19]. The FG-NET database also contains an average of between 10-15 face images of each subject at different ages [15]. The total number of subjects by gender are 34 males and 48 females. While the total number of images by gender is 395 males and 607 females. The database of the FG-NET AD was too small for deep learning experiments. Thus, the need for data augmentation.

2.2. Training and testing the proposed AIFR model

In this section, we shall consider: training the deep learning model using the transfer learning technique, using the trained deep learning model for adaptive face recognition in FG-NET and data augmentation.

2.2.1. Training the deep learning model using transfer learning technique

Training learning was used to train the Inception-ResNet-v2 network on the pre-processed FG-NET database for age-invariant face recognition. The training process was systematic and it is summarized thus:

a. Load the pre-processed FG-NET database into MATLAB using ImageDatastore object.
b. Split the database into a training set (80% images) and validation (testing) set (20% images).
c. Resize all images in the train and test sets to 299x299 to make them compatible with the Inception-ResNet-v2 network.
d. Load Inception-ResNet-v2 network in MATLAB.
e. Specify training options for transfer learning.
f. Re-train Inception-ResNet-v2 network on the train set of pre-processed FG-NET.
g. Test the trained network on the validation set.
h. Compute the network accuracy.

2.2.2. Using the trained deep learning model for adaptive face recognition in FG-NET

The trained deep learning model was used for testing the images from the FG-NET dataset by following the steps below:

a. Read an image from the FG-NET database in MATLAB.
b. Convert the image into an RGB format if it is a grayscale image.
c. Detect and crop the face of the subject in the image using the Viola-Jones Face Detector.
d. Resize the image to 299x299 to make it compatible with Inception-ResNet-v2.
e. Load the re-trained Inception-ResNet-v2 network from Section 2.2.1.
f. Pass the image from step (d) to the re-trained network for class prediction.
g. Observe the prediction result and compare it to the ground truth.

2.2.3. Data augmentation (the concept of image noise addition)

Gaussian, Poisson, Salt & Pepper, and Speckle noises were chosen to be added to the images from the FG-Net dataset [20]. Some amounts of these noises were added in each of the images in order to artificially inflate the datasets using label preservation transformation. Image noise addition and label preservation transformation are data augmentation techniques [21-30].

a. Image Gaussian noise addition

Gaussian noise modeling involves the addition of different random RGB values to each pixel in the image. The random values are mined from an arbitrary variable with mean (μ) value of zero and a variance 1.4 from normal density function. The mean and variance are selected to introduce a reasonable amount of noise. The mathematical model is as shown in (1) [31-33].

\[ P(Z) = \frac{1}{\sqrt{2\pi\delta}} e^{-\frac{(x-\mu)^2}{2\delta^2}} \]  

(1)

where P(Z) = Gaussian distribution noise in image, \( \mu \) = Mean, \( \delta \) = Standard deviation.

b. Image Poisson noise addition

Poisson noise is modeled by a Poisson procedure. Poisson noise is generated when a random variable is created for each pixel. The random variable has a Poisson distribution as shown in (2) [31-35]. An arbitrary sample is mined from every arbitrary variable.
\[ P(k) = \frac{e^{-\lambda} \lambda^k}{k!} \]  
(2)

where, \( P \) = Probability distribution,
\( K \) = The number of Photons measured by a given sensor element,
\( \lambda \) = Mean; that is equivalent to the value of the pixel.

c. Salt and pepper noise addition

Salt and Pepper noise can originate from transmission errors while carrying out analog-digital conversions. The salt and pepper noise was modeled by altering the value of each pixel of the image with a probability of 0.02. The pixel was altered either to black, (0, 0, 0) or white, (255, 255, 255) in RGB values, both cases with a probability of 0.01 and 0.15 respectively. The Salt and Pepper mathematical model is as shown in (3) [24, 31, 36-39].

\[ P(s) = \begin{cases} 
P_a & \text{for } s = a \\
P_b & \text{for } s = b \\
0 & \text{otherwise}
\end{cases} \]  
(3)

Where, \( P_a, P_b = \) Probability Density Function (PDF) of \( a \) and \( b \).

\( P(s) = \) Distribution of salt & pepper noise in image,
\( a, b = \) array image size

d. Speckle noise image addition

Speckle noise is a rough multiplicative noise. Speckle noise is generated by multiplying each pixel of the image by an arbitrary value. Arbitrary values are mined from an arbitrary variable with a mean 0.9 and a variance of 0.1 by a normal density function. The Speckle noise mathematical model is as shown in (4) [24, 31-34, 40].

\[ g(x, y) = f(x, y) * \mu(x, y) + \xi(x, y) \]  
(4)

where, \( g(x, y) = \) observed image,
\( f(x, y) = \) multiplicative component
\( \xi(x, y) = \) additive component of the speckle noise.

2.3. Network architecture for feature extraction and classification

The architecture adapted for this experiment is the Inception-ResNet-v2, which is a convolutional neural network that is trained on more than a million images from the ImageNet database and is used in ImageNet large-scale visual recognition challenge. The network is 164 layers deep. It can classify images into 1000 object categories and has an image input size of 299x299. In this research work, a pre-trained Inception-ResNet-v2 network was used. The convolutional neural network has already learned to extract powerful and informative features from natural images. It was used as a starting point to learn representative features from the FG-NET database using transfer learning for age invariant face recognition. The architecture was robust to noises used in the data augmentation stage [20, 31, 33, 41]. The architecture of the convolutional neural network is described in Table 1.

| Block | Type          | Repeat | Depth | Filter / Stride | Output size | Branch 1 | Branch 2 | Branch 3 |
|-------|---------------|--------|-------|-----------------|-------------|----------|----------|----------|
| 1     | Convolution   | 3x3/2  |       | 149x149x32      | (32)        |          |          |          |
| 1     | Convolution   | 3x3/3  |       | 147x147x32      | (32)        |          |          |          |
| 1     | Convolution   | 3x3/1  |       | 147x147x64      | (64)        |          |          |          |
| 1     | Max Pooling   | 3x3/2  |       | 73x73x160       | (96)        |          |          |          |
| 1     | Convolution   | 3x3/3  |       | 71x71x192       | (64, 96)    | (64,64,64,96) |          |          |
| 1     | Convolution   | 3x3/2  |       | 35x35x384       | (192)       |          |          |          |
| 1     | Max Pooling   | 3x3/3  |       | 35x35x384       | (32)        | (32,32,2) | (32,48,64/2) |          |
| 2     | Inception-A   | 5      | 3     | 35x35x256       | (32)        | (32,32,2) | (32,48,64/2) |          |
| 3     | Reduction-A   | 1      | 3     | 17x17x256       | (384)       | (256,256,384) |          |          |
| 4     | Inception-B   | 10     | 3     | 17X17X896       | (192)       | (128,160,192) |          |          |
| 5     | Reduction-B   | 1      | 3     | 8x8x1792 (256,384/2) (256,288/2) (256,288,320/2) |          |          |          |          |
| 6     | Inception-C   | 5      | 3     | 8x8x1792 (192) | (192)       | (192,224,256) |          |          |
| 7     | Average Pooling| 8x8    |       | 1792            |             |          |          |          |
| 8     | Dropout       | Keep   | 0.8   | 1792            |             |          |          |          |
| 9     | Softmax       |        |       | 82              |             |          |          |          |

Table 1. A detail architecture of the convolution neural network (modified Inception-ResNet-v2) used for feature extraction and classification

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3. RESULTS AND DISCUSSION

In this section, the evaluation methodology and results of the research are given and a comprehensive discussion is made.

3.1. Evaluation methodology

The performance evaluation metrics adopted in this work include testing accuracy, mean absolute error (MAE), mean square error (MSE), and loss function. These metrics are the most widely used for classification evaluation in the biometric and forensic analysis [2, 42-48].

a. Mean squared error

The MSE is a measure of the quality of a predictor, it is always non-negative, and values closer to zero are better. Where, $n$ in this case, is the number of iterations, $Y\omega$ is the training loss and $Y\phi$ is the testing loss. Therefore, MSE is computed as shown in (5) [49].

\[
MSE = \frac{1}{n} \sum_{i=1}^{n} (Y\omega - Y\phi)^2
\]

(5)

The mean squared error is the mean $\left( \frac{1}{n} \sum_{i=1}^{n} \right)$ of the squares of the errors $(Y\omega - Y\phi)^2$

b. Mean absolute error

The MAE is a measure of the dissimilarity between two variables. In this case between $Y\omega$ which is the training loss and $Y\phi$ which is the testing loss. $n$ is the number of iterations. Therefore, MAE is computed as shown in (6) [50].

\[
MAE = \frac{\sum_{i=1}^{n} |Y\phi - Y\omega|}{n}
\]

(6)

The MAE is an average of the absolute errors$|Y\phi - Y\omega|$.

c. Loss function

Categorical cross-entropy and center loss were used as the loss functions for the improvement of the research model design. A loss function tells how good a classifier. Categorical cross-entropy is a loss function used to calculate the dissimilarity between two likely distributions. This dissimilarity is calculated for each point in the training and testing database. The mathematical expression used to evaluate the probability of dissimilarity is as shown in (7) [51, 52].

\[
L_{cross}(y\hat{y}) = - \sum_{i=1}^{N} \sum_{t=1}^{C} y_i^t \cdot \log(y_i^t)
\]

(7)

For an instant, $(x, y)$ can be defined as, where: $x =$ input value, $y =$ true value, $\hat{y} =$ predicted value by the system, $N =$ sum of iteration and $C =$ sum of class labels.

Wen et al. proposed a loss function called center loss in addition to using the categorical cross-entropy loss. The notion is to increase the discriminative power of the totally learned features by decreasing the intra-class variations. The center loss function is as shown in (8).

\[
L_{center}(y\hat{y}) = \frac{1}{2} \sum_{i=1}^{N} \sum_{t=1}^{C} (\hat{y}_i^t - c_{y_i})^2
\]

(8)

While $c_{y_i}$ is the $y_i$th class center of the features, $N$ is the number of iterations. Wen et al. observed that equation 8 does not attain the anticipated result. Two adjustments were made by Wen et al. to resolve this issue. The first adjustment is to bring up to date the centers based on a mini-batch as a replacement for the entire dataset. The second adjustment led to the introduction of two new variables, $\alpha$, and the $\delta$-function. $\alpha$ is used to regulate the learning rates of the centers and the $\delta$-function is a Boolean that results in 1 if the situation is true and 0 if the situation is false. The (9) defines the updated function of the class center.

\[
\Delta c_j(y, \hat{y}) = \frac{\sum_{i=1}^{N} \delta(y_i = j). (c_{y_i} - \hat{y}_i)}{1 + \sum_{i=1}^{N} \delta(y_i = j)}
\]

(9)
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The new center of each class is as shown in (10)

$$c_j^{t+1} = c_j^t - \alpha \Delta c_j^t$$  \hspace{1cm} (10)

While $\alpha \in [0, 1]$, Wen et al., introduced $\lambda$ to balance the two-loss functions of the total loss function. The complete function is shown in (11).

$$\mathcal{L} = \mathcal{L}_{\text{cross}} + \lambda \mathcal{L}_{\text{center}}$$ \hspace{1cm} (11)

In the event $\lambda$ is set to 0, the total loss function is equal to the categorical cross-entropy function.

d. Accuracy

Where true positive (TP) symbolizes all experimented activities be appropriate to positive groups classified properly as positive groups. True negative (TN) are all experimented activities be appropriate to negative groups classified into negative groups. False-positive (FP) are all experimented activities be appropriate to negative groups being classified as positive groups, and false negative (FN) are all experimented activities be appropriate to positive groups being classified as negative groups.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100\%$$ \hspace{1cm} (12)

e. System specification

The training and testing of the proposed model was successfully completed on a CPU with Core i7 processor and 64GB RAM in 10 hours using Matlab version 2018b software tools.

3.2. Results

In this section, the research results are presented and explained. Table 2 shows the performance of the proposed age invariant face recognition model. The performance of the proposed AFIR system was measured using accuracy, loss, mean squared error and mean absolute error. The training/testing accuracy and loss plot of the proposed AFIR model are shown in Figure 4 and Figure 5 respectively. Furthermore, the progression plot of square errors vs. iterations and absolute errors vs. iterations of the proposed AFIR model are shown in Figure 6 and Figure 7 respectively. The MSE and MAE is as calculated by (5) and (6).

| Table 2. The performance of the proposed AIFR model |
|-----------------------------------------------------|
| Parameters                                      | Results                |
| Training accuracy                               | 100\%                  |
| Testing accuracy                                | 99.94\%                |
| Training loss                                   | 0.008\%                |
| Testing loss                                    | 0.003\%                |
| Mean squared error (MSE)                        | 0.0158                  |
| Mean absolute error (MAE)                       | 0.0637                  |

Figure 4. Training and testing accuracy plots of the proposed AFIR model

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**The new center of each class is as shown in (10)\n\[ c_j^{t+1} = c_j^t - \alpha \Delta c_j^t \] (10)**

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Figure 5. Training and testing loss (error function) plots of the proposed AFIR model

Figure 6. Progression plot of square errors vs. iterations of the proposed AFIR model

Figure 7. Progression plot of Absolute errors vs. iterations of the proposed AFIR model

Table 2. The performance comparison of AIFR using mean absolute error (MAE)

| No. | Publication | Face dataset/dataset size | Algorithm | Evaluation protocol | Performance evaluation (MAE) |
|-----|-------------|---------------------------|-----------|---------------------|------------------------------|
| 1   | Proposed    | FG-NET/1002 (using-data argumentation technique) | Classification (CNN) | 20% test, 80% train data | MAE 0.0634 |
| 2   | [53]        | FG-NET/1002               | Classification (CNN) | N/A                 | MAE 2.8            |
| 3   | [54]        | FG-NET/1002               | Classification     | Leave-one-person-out | MAE 3.31       |
| 4   | [55]        | FG-NET/1002               | Classification     | 98.8% train, 1.2% test | MAE 4.5        |
| 5   | [56]        | FG-NET/1002               | Classification     | Leave-one-person-out | MAE 4.8        |
| 6   | [57]        | FG-NET/1002               | Classification     | 20% test, 80% train  | MAE 4.5         |
The performance comparison of Age Invariant Face Recognition (AIFR) system using percentage accuracy is as shown in Table 3.

Table 3. The performance comparison of AIFR using percentage accuracy

| Author | Study/methodology | Results on percentage accuracy |
|--------|-------------------|--------------------------------|
| Proposed | An Improved Age Invariant Face Recognition Using Data Augmentation | The proposed model achieved a recognition accuracy of 99.94%. The investigational study of face recognition was done using FGNET data. Experimental results achieved on AG-IIM showed training and verification accuracies of 89.8% and 88.2% respectively. |
| [58] | Age-invariant face recognition system based on identity inference from appearance age | The method realized an overall verification accuracy of 93% on FG-NET AD. |
| [59] | Age-invariant face recognition system using combined shape and texture features. This technique merged texture and shape feature sets to achieve age invariant facial recognition. Feature-aging for age-invariant face recognition\(^1\); This method was used to forecast the aging of face structure in order to improve the consequence of age advancement on face recognition. | Face recognition rates (%) of the Gabor methods and Age-invariant methods with face images from different age groups show the best performance of 32.7% on testing accuracy. Recognition rates of this method equated with state-of-the-art algorithms on FGNET gave 86.5% recognition rate |
| [60] | Age invariant face recognition and retrieval system using coupled auto-encoder networks (CAN) | The scheme was capable of attaining a determined classification accuracy of 99% on FGNET database. Time-lapse run on FG-NET using numerous cataloging techniques like nearest neighbor, linear discriminant and subspace discriminant obtained results of 70.4%, 78.4%, and 80.6% respectively. |
| [61] | A geometrical approach for age-invariant face recognition | Experimentations were done on the FG-NET aging database, and a recognition accuracy of 64.47% was achieved. |
| [62] | Face recognition across time-lapse using convolutional neural networks | |
| [63] | Age invariant face recognition based on texture embedded discriminative graph model. This proposed model takes full advantage of the information of texture variations and geometry topology contained in face images. | |

3.3. Discussion

From the results presented in subsection 3.2, it is observed that the testing accuracy of the proposed model is 99.94%. This signifies that if this model is embedded into a smart surveillance camera, it could correctly identify the face of the same subject across large age variation (in this experimental setup an average of 25 years was used) with 99.94% accuracy. Other metrics used in the measurement of the model are testing error of 0.04%. The mean squared error is 0.0153, while the mean absolute error is 0.0637 with a maximum iteration setting of 5000 and epochs of 50. Details of these metrics interpretation and relevant areas presented in subsection 3.1. The proposed AIFR model performance metrics outperform the results recorded in the literature to the best of our knowledge when compared to others using a similar dataset.

One of the novelties of this research work is that different types of noise augmentation were used to improve the accuracy of the AIFR system, as against the traditional practice of noise elimination at the preprocessing phase in order to improve the output accuracy. It is observed from these results that this new technique is more efficient form AIFR systems. The results show that a generic pre-trained classical CNN architecture (Inception-ResNet-v2) can be adapted in the AIFR domain. Thus saving processing time, computing resources and acquisition of huge training data that are not readily available in this AIFR domain. From the result obtained it is observed that the experimental design at the pre-processing phase greatly impacts the quality of the feature extracted and output of the classifier. Thus in this paper, the final result of the AIFR system is greatly improved as compared to other related works.

4. CONCLUSION

In this paper, a novel methodology of improving the accuracy of age invariant face recognition using noise augmentation technique and adapting a pre-trained deep convolution neural network (DCNN) was proposed. Experimentation was performed on the FG-Net dataset. The FG-Net dataset was augmented at the preprocessing stage using four types of noises to improve the features extracted and get a better classification. The augmented data was used to build an age invariant face recognition model. The model on testing was found to be very accurate in comparison to similar research works carried out on the same dataset.
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