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Age Invariant Face Recognition Model Based on Convolution Neural Network (CNN)

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ABSTRACT

Building an intelligent system similar to the human perception system in face recognition is still an active area of research, despite the advancements in technologies and face recognition research carried out when age changes. Deep learning algorithms have outperformed conventional methods in with regard to accuracy and effectiveness of recognition a variety of difficulties, including position, expression, lighting, and aging. But aging is one of the problems that affects the face the most, as it plays a significant role which directly affects facial features, so we notice some people who are very difficult to distinguish and may not be known at all because of the strong change in their features. As a result, we researched deep learning techniques generally and the convolutional neural network (CNN) specifically. This strategy is employed by a number of significant stages: The first side, includes preparing the dataset related to the subject of the study, Isolate the data between training, validation and testing. As for the second part of the work, data preprocessing, such a data augmentation, Normalization, Face detection, and resizing. After then, begin a features extraction operation by the convolution neural network (CNN) that is suggested. After all that, the classification stage begins, which was done by using the (SoftMax) function, because we have approximately (570) classes. In the testing phase, we perform the task of checking the two images entered whether they belong to the same person or not. In this paper, adopted the (Age) and (FG-Net) datasets, Finally, the verification accuracy rate for the proposed system reached 98.7 % on the (Age) dataset, and reached 99.4 % on the (FG-Net) dataset.

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1. Introduction

The human face is the most visible and visible part of the human body, so it is considered the most familiar and recognized biometric in our visual system. A biometric system uses one or more of the biometric to person identify uniquely, including their face, voice, iris, ears, DNA, and fingerprints. Many studies have been conducted and automated algorithms have been used to recognize faces, discover faces, and study some problems that affect facial features such as face pose, illumination, facial expression, and the most important of this challenge is aging. Facial

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aging is one of the most important factors that directly affect the change of some distinguishing features of the face. Therefore, Most of Age invariant face recognition (AIFR) systems focused either on local feature extraction or are completely dependent on the facial region, while there are many systems that mix the two methods. In this chapter we study one of this method in order to better understand to face recognition by age invariant. The main objective of this analysis is to identify a model that has the advantage through a set of measures in distinguishing people whose appearance has changed due to aging compared to other methods. We will summarize a set of research presented in this field: A group of researchers in [1] focused on a combination of features taken from shape and texture to identify faces that do not change with age. They relied on the phase-match feature for the shape and LBP variance for the texture feature. We know that when a person's age changes many features will change, and the tissue can undergo a change, so this method is not good at matching and identifying. The researchers in [2] presented an approach about facial appearance that changes in a coherent manner and thus matching can be performed by analyzing the coherence of the drift of trait vectors with age. They proposed a simple scale to measure the deviation between pairs of images. That is, if there are two images of the same subject, the drift will be small and coherent, and if they are from different subjects, the drift will be severe and incoherent. As for the researchers in [3] proposed a new method for face representation and matching for the age invariant face recognition problem is a maximum entropy feature descriptor (MEFD) that encodes the microstructure of facial images into a set of discrete codes. The code entropy is maximized in order to extract discriminative and expressive information from densely sampling encoded face images. An identity factor analysis method was developed to estimate the probability that two given faces have the same underlying identity. The method was tested on the FGNET dataset and accuracy was 76.2 %. A group of researchers in [4] proposed a method for recognizing age-unchanging faces known as Coupled Autoencoder Networks (CAN), which is based on CNN technology. This method extracts fixed features with age, which is done through the use of two autoencoders and then linked to two neural networks. This method assumed that facial features are divided into three parts: age features, identity features, and noise. Identity features are stable with age and are used by this model for facial verification during aging. This method was applied to the dataset (FGNET), and the best result achieved is 86.5 %. In (2018) a group of researchers [5] presented the idea of focusing on the very dense area of the face, which is the area around the eye. This area gives discriminatory information about the face to extract local features that are different for each subject. This local feature becomes strong for aging, lighting, and expression changes. Given that the entire face has a very complex structure that can change over time in terms of color, structure and texture. Therefore, this process requires full-face models of the age constants. The researchers in [6] suggest presented a new method to verify ages through aging, called Hidden Factor Analysis (HFA). This method assumed that the verification process depends on two factors: a factor that does not change with age is the identity factor, and the second factor is factor that changes with aging, and they developed an algorithm for learning to extract these factors based on Histograms Oriented Gradients (HOG). The best result of the system achieved when applied model on (FG-NET) dataset is 69 %. Irene Kotsia and others in 2017 [7], used one of the convolutional neural networks (CNN) models, where used the (VGG face) model for the purpose of verifying faces when the person's age changes. The model was applied to age groups in the (Age) database. The overall accuracy rate resulting from this model is 88.6 %.

Features extracted by CNN technology are more robust to changes occurring on a person. Therefore, in this paper, we focus our work on one of the important techniques in the field of machine learning is the field of deep learning. Specifically, the convolutional neural network (CNN) technology because, it occupied a wide area and multiple uses in deep learning algorithms because outcomes of this method have the characterized in reliable, accuracy, and time for compared with others conventional methods. The remainder of the paper is arranged as follows: The problem is stated in section 2, the theoretical background is provided in part 3, the proposed approach is shown in section 4, the experimental results are presented in section 5, and the study is concluded in section 6.

2. Problem statement

As a person ages, most of his facial feature's change. Therefore, the face recognition system affected by some difficulties that make the system unable to verify the face very efficiently. Determining process, a face depends on the modeling of some wrinkles in the face as well as the structural deformation of the bones in the person's face. Therefore, the aging process remains the main cause of significant deformation in the appearance and anatomy of human faces. For, we can say that aging is one of the most pressing challenges to human identification and criminal investigation systems. One of the main challenges that confronted our work are find the appropriate database that contains the appropriate age gradations for the person, As well as the difference in the position of the images taken, lighting and noise [8][9]. Since the field of deep learning has recently achieved success in overcoming many of these problems and challenges, especially the Convolutional Neural Network (CNN) in a variety of disciplines, although it needs a huge data set in order to process and train the neural network. But it still stands out in the process of extracting preferred features from the face that are used when distinguishing a group of people and these features have a substantial effect on the rating rate. choosing the optimal classification approach is critical, as extracting the feature from images will improve the accuracy of the authentication system.

3. The proposed system of Age Invariant Face Recognition (AIFR)

To perform the process of identifying and recognize the person in an efficient manner, the process of studying the model and applying the basic processes that achieve the highest required accuracy, efficiency and speed must be carried out. These operations include collecting an appropriate number of images for each person in order for the network to be properly trained, and then we start a process of pre-processing the images and preparing them for the network, so that the network begins to extract the important features from the images for the purpose of classification, as depicted in Figure. 1

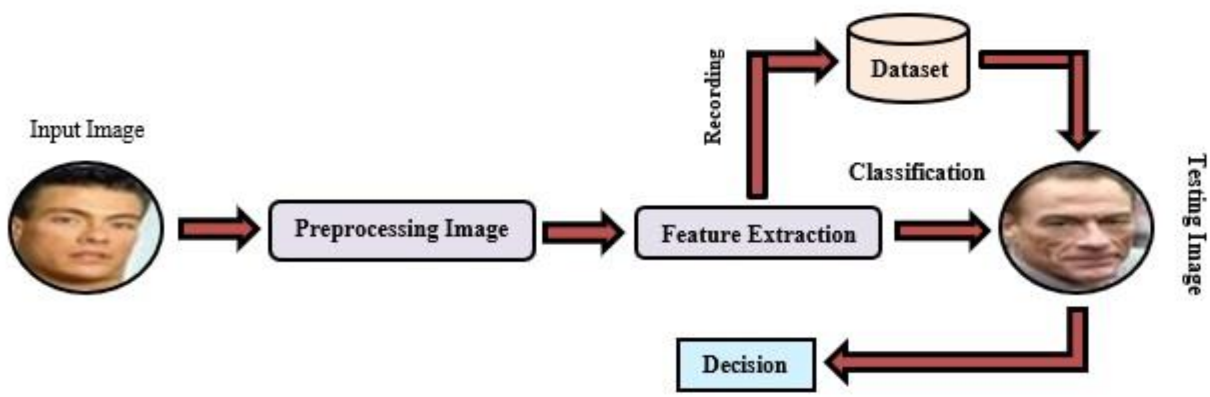

Figure. 1 The fundamental structure of a face recognition system.

4. The Methodology for AIFR

This section describes the methodology used to recognize age-invariant faces. Where, the first process begins, which is the pre-processing of the data as in the figure 2 below. After then, the process of extracting important features from the face begins with a convolutional neural network (CNN), This network is designed to identify a person with some differences in aging. Then the resulting features are fed to the activation function classifier (SoftMax) for the purpose of classification. Thus, we perform the task of checking the two images entered whether they belong to the same person or not. In this paper, adopted the (Age) and (FG-Net) datasets, Finally, the verification accuracy rate for the proposed system reached 98.75 %. for all age groups on (Age dataset) and 99.4 % on (FG-Net dataset).

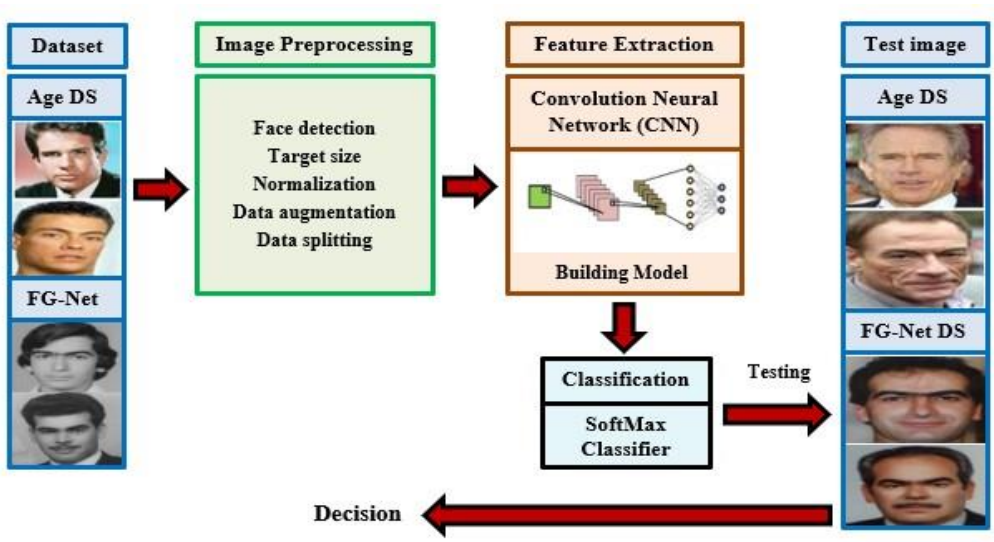

Figure. 2 Age Invariant Face Recognition Methodology [10]

4.1. Image preprocessing.

The (Age) and (FG-Net) dataset contain images that vary in illumination, position, and size. All of these challenges enter into the problem of getting to know persons, in addition to the problem of aging and the change of a person's appearance over time. Therefore, a set of treatment methods were used to get rid of most of these challenges such as defining the area of the image to be worked on, here, a face detection and cropping from the provided image were included in our work. The RGB image should then be converted to a grayscale image. Images are afterwards reduced to 160 by 160 pixels to meet the size of the model used, also data Augmentation is additionally utilized for preprocessing and increase the efficiency of the network in identifying people. Additionally, the image that was entered into the system had normalization, which included a number of activities like lowering the amount of the data used and restricting its values to the range of (0–1). All of these processes were done with the goal of enhancing the model's performance. An example of the preprocessing stage is shown in Figure 3.

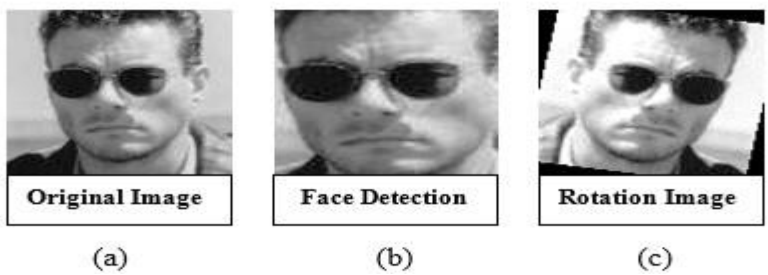

Figure. 3 Examples of preprocessing stages

4.2. Network architecture for feature extraction

After preprocessing the database and configuring the images for the second stage, the feature extraction stage begins. The Convolutional Neural Network (CNN) model was used, which is considered the latest deep learning method, and it has a set of advantages. First, CNN is able to perform feature extraction as well as classification process using a single hierarchical structure. Or by using additional classification methods from one of the machine learning methods. Second, this field can be perfectly adapted to any geometric and local modifications that occur to the image [10].

4.2.1. Building Convolution Neural Network (CNN)

Convolutional neural networks (CNNs) represent the visual cortex in the brain, CNNs are artificial neural networks Which is forward-feeding in the flow of information means in one direction only, from its input to its output. CNN architectures in general, they consist of convolutional, pooling layers, and a fully-connected layer either one or more. often stacked on top of each other to form a deep model. There is potential to add additional layers after the input layer to improve the efficiency the model that is used [11]. In our approach, we used a convolutional neural network consisting of (17) layers, of which (9) convolutional layers, (5) pooling layers, and (3) fully connected. Each of these layers has its own standards and constants that are determined and fixed during the work experience (such, number of filters, filter size, activation function) that used. Figure 4 shows a general diagram of the model used and the changes that occur in the images in each layer.

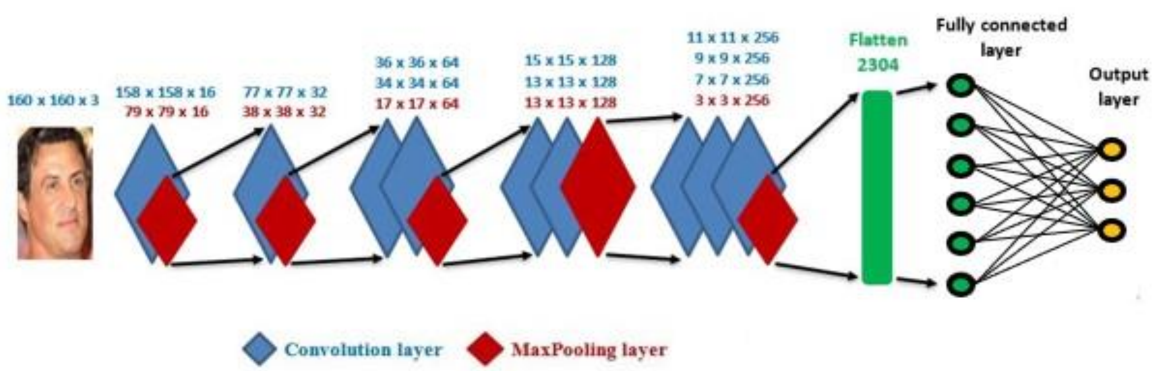

Figure. 4 Basic CNN architecture

We can summarize the proposed (CNN) Model architecture in Table1

Table 1: The suggested architecture for the (CNN) Model

The proposed Sequential (CNN) on (Age) Dataset						
Layer Kind	**Filter size**	**No. of Filter**	**Input Shape**	**Output Shape**	**Activation Function**	**No. of parameter**
INPUT	----	----	160 * 160 * 3	160 * 160 * 3	----	----
Convolution2D	3 * 3	16	160 * 160 * 3	158 * 158 * 16	Leaky_ReLU	448
MaxPooling2D	2 * 2	16	158 * 158 * 16	79 * 79 * 16	Leaky_ReLU	0
Convolution2D	3 * 3	32	79 * 79 * 16	77 * 77 * 32	Leaky_ReLU	4640
MaxPooling2D	2 * 2	32	77 * 77 * 32	38 * 38 * 32	Leaky_ReLU	0
Convolution2D	3 * 3	64	38 * 38 * 32	36 * 36 * 64	Leaky_ReLU	18496
Convolution2D	3 * 3	64	36 * 36 * 64	34 * 34 * 64	Leaky_ReLU	36928
MaxPooling2D	2 * 2	64	34 * 34 * 64	17 * 17 * 64	Leaky_ReLU	0
Convolution2D	3 * 3	128	17 * 17 * 64	15 * 15 * 128	Leaky_ReLU	73856
Convolution2D	3 * 3	128	15 * 15 * 128	13 * 13 * 128	Leaky_ReLU	147584
MaxPooling2D	1 * 1	128	13 * 13 * 128	13 * 13 * 128	Leaky_ReLU	0
Convolution2D	3 * 3	256	13 * 13 * 128	11 * 11 * 256	Leaky_ReLU	295168
Convolution2D	3 * 3	256	11 * 11 * 256	9 * 9 * 256	Leaky_ReLU	590080
Convolution2D	3 * 3	256	9 * 9 * 256	7 * 7 * 256	Leaky_ReLU	590080
MaxPooling2D	2 * 2	256	7 * 7 * 256	3 * 3 * 256	Leaky_ReLU	0
Flatten	----	----	----	2304	----	0
Dense	----	----	----	1000	ReLU	2305000
Dropout (0.3)	----	----	----	1000	----	0
Dense	----	----	----	512	ReLU	512512
Dense	----	----	----	150	SoftMax	76950
Total params:	4,651,742					
Trainable params:	4,651,742					
Non-trainable params:	0					

The proposed Sequential (CNN) **on (FG-Net) Dataset**						
The same building as the proposed structure, except:						
Dense	----	----	----	82	SoftMax	42066
Total params:	4,616,858					
Trainable params:	4,616,858					
Non-trainable params:	0					

4.2.1.1: The Convolution layer.

Each convolution layer links to one or more feature maps from a preceding layer. This layer a 2-D weight matrix and uses a convolution filter Between its 2-D inputs and convolution mask, the convolution is computed in each plane [12]. The total number of convolutional layers used in our work is (9). Where, A grayscale (160 * 160) face image is accepted by the first input layer and sent to the first convolutional layer, which contains 16 filters of (3 * 3) pixels in size. Then the output of this layer is sent to the next layer of the gyrus after its dimensions are reduced by the Pooling layer, to come after the second fibrosis layer, which contains (32) filters and also a size (3 * 3) and so the process continues until the last layer before entering the fully connected layers. These layers are the result of the feature extraction process. The following formula is used to calculate the convolution layer's feature map [13]:

$$Yk = f\,(Wk * x) \tag{1}$$

where (x) represents the input image, and (Wk) relates to a convolutional filter for the feature map. Convolution layer operation is displayed in Figure 5.

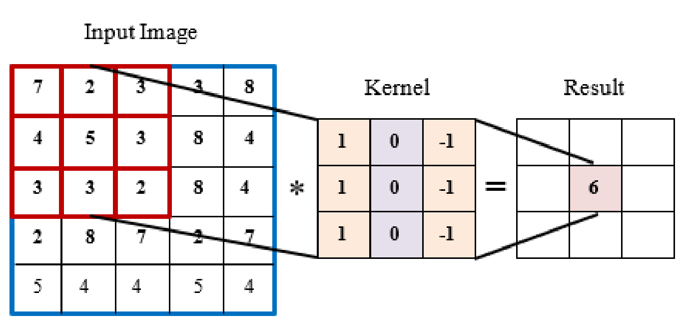

Figure 5 Operation of the convolution layer

4.2.1.2: The Pooling layer.

The dimensions of each feature map are reduced while preserving the most important information. There are three forms of grouping: First, the largest element is selected from among the elements of the chosen group. Second, the average value is chosen by adding the chosen values and dividing by their number. Third, the total value is chosen by summing all the selected elements. We used the maximum clustering step (2 * 2) to halve the feature map size. We also used an assembly step (1 * 1) in one of the model steps, this stage makes the representation of the inputs smaller and more practical by reducing the spatial dimension. Then the activation function is applied to the result to generate the output. The syntax of the pooling layer's feature map is [13]:

$$Yk_{ij} = \max(p,q) \in ij \quad xkpq, (2.2) \tag{2}$$

The element at position is represented by (xkpq), and the pooling region I j represented (p, q). Pooling layer operation is depicted in figure 6.

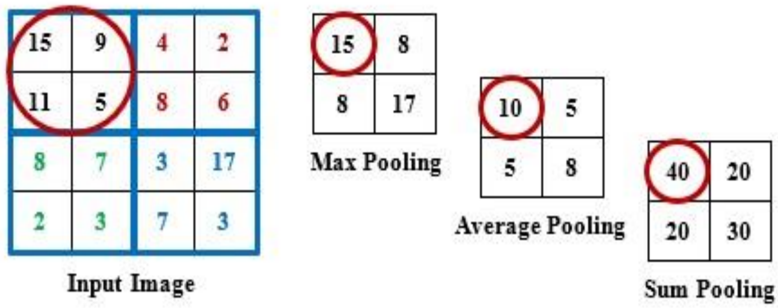

Figure. 6 Pooling layer operation

4.2.1.3: Fully Connected layer

After the process of extracting the important features from the face images, which will be ready for the classification process, the (3) fully connected layers begin to play their role in the classification process, and we used the dropout variable with a value of (0.3) for the purpose of reducing the complexity and reducing the output by stopping some nodes and running The other part of it, as well as we used the SoftMax activation function for the purpose of the final classification of the network. These fully connected layers capture the symmetrical features that do not change in the face when a person's age changes for different parts of the face such as the shape and position of the eyes and mouth. As shown in the figure. 7

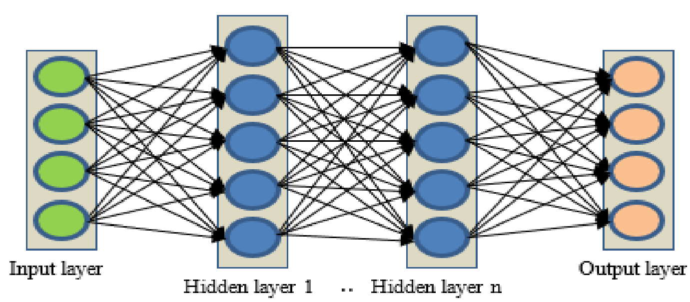

Figure. 7 fully connected layer

- ***Rectified linear units (ReLU) and (leaky ReLU)***

This layer's objective is to increase the impact and speed of training. a function (ReLU), changing all negative numbers in the output to zeros. while (leaky ReLU) activation function, which is similar to working with the concept of (ReLU) as well but different from (ReLU) when the value of the input is negative, the activation function (Leaky ReLU) multiplies the value by a small integer instead of zeroing as ReLU does and usually the value is (0.01) so that the negative part gains a value, although small, is an active attempt to solve the ReLU problem [14].

4.2.2. Classification using SoftMax method

Most of the time the sigmoid classifier is used when the classifiers are binary. But, when there are multi classification tasks, traditional SoftMax classifier has excellent performance. It can normalize all kinds of features according to the number of classifications. Therefore, we are in our work after extracting the important features from our work (Age) and (FG-Net) dataset by the sequential Convolution Neural Network (CNN) technology and because we have (570) people in the (Age) dataset as well as (82) people in the (FG-Net) dataset Therefore, the (SoftMax) classification technology was used, the obtained accuracy reached (98.7) in the (Age) dataset, and it reached (99.4 %) in (FG-Net) dataset.

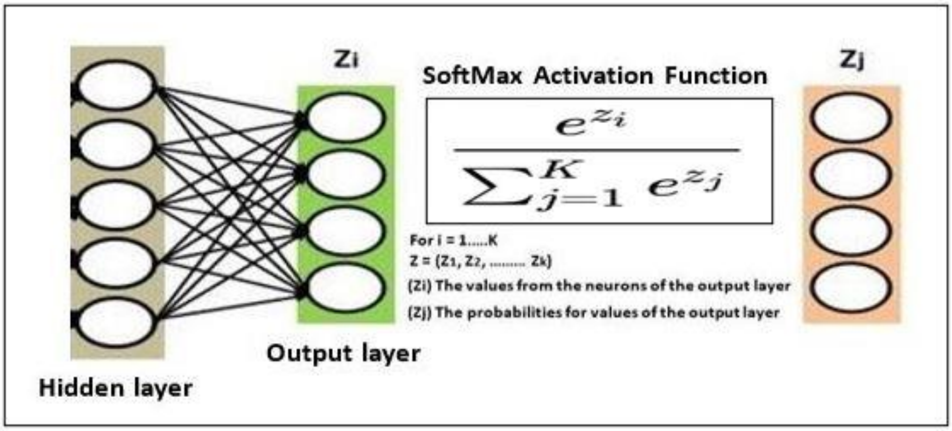

Figure. 8 SoftMax Activation Function [18]

5. Experimental results

In this paper, Google Colab pro, which offers Python3, served as the environment. The hardware of the machine was an HP model with an Intel (R) Core (TM) i5- 7200U CPU running at 2.50GHz and 8GB of RAM. (Age) and (FG-Net) dataset is utilized in the experiments and different evaluation metrics are used to evaluate the proposed model such as an accuracy, recall, precision and f1-score.

5.1. Datasets:

In our work we used two datasets related to aging, namely, (Age) and (FG-Net) dataset.

5.1.1: Age Dataset

This dataset includes 16,516 images from 570 different subjects that were taken in real world and it include various positions, expressions, noise, and occlusions. The age range of the data in this dataset is also 1 to 101. The average age range for each person and the average quantity of face images are 29 and 50.3 years, respectively [7]. Figure 9 shows some examples from the dataset.

Figure. 9 Samples of faces images from the Age dataset

5.1.2: FG-Net Dataset

his dataset includes 1002 images from 82 different subjects that were taken in real world and it include various positions, expressions, noise, and occlusions. The age range of the data in this dataset 1 to 69. the average number of face images are 12-13 each person [15][16]. Figure 10 shows some examples from the dataset.

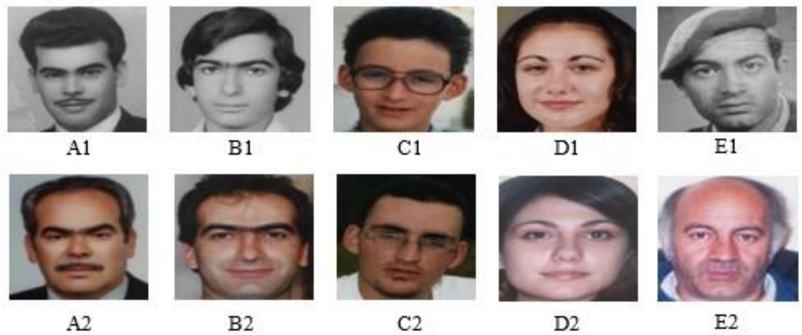

Figure.10 Samples of faces images from the FG-Net

5.2. Evaluation metrics.

There is a set of metrics that are used to measure the performance and evaluation of the proposed method. These scales are accuracy, Precision, recall, and F1 score [17].

5.2.1: Accuracy.

Accuracy can be defined in simplest terms as the ratio of the number of correctly predicted faces to all the faces entered. It can be calculated in the following way:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

5.2.2: Recall.

Recall can be defined in simplest terms is the ratio of appropriately positive faces to all positive faces in the data. It can be calculated in the following way:

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

5.2.3: Precision.

The precision is determined by dividing the number of accurately ranked positive faces by the total number of labeled faces deemed positive. It can be calculated in the following way:

$$precision = \frac{TP}{TP + FP} \tag{5}$$

5.2.4: F1_Score.

The F1 score relates the above factors, seeks a balance between recall and precision, and is used to assess the strength of a test because of its ability to correctly classify cases. It can be calculated in the following way:

$$F1score = \frac{2 * precision * recall}{precision + recall} \tag{6}$$

5.3. Experimental on Datasets:

After conducting a pre-processing operations for the data, the data was trained on a group of models, and each time details were used that differed from the previous time in terms of the number of layers used, as well as the number of filters used in each layer, in addition to The activation function that plays an effective role in motivating the model to improve the results of the model, and in the end it was the best model that achieved promising results as shown in Part (4.2.1), which is illustrated in Figure (4) in terms of the inputs and outputs of each layer, while the table (1) .shows the details of the model that It was adopted in this paper on the two data sets that were used in this work.

5.3.1: Age Dataset

The dataset (Age) contains 16516 images from 570 categories, Because the size of (Google Drive) is limited to (15) gigabytes as a main memory of grief, and the size of the database is very large (570) classes, so the work was divided into four stages according to the table 2 below, so that the same model was applied in all its stages to all the divided categories and thus we found the values The average that represents the average of the final results of the dataset. The images were divided into three categories: The first category, related to the process of training and extracting key features. The second category relates to the process of making sure that training is on the right track, and this process is between training and the final testing of the model. The third category of photos is of the final model testing process. Table 3 and Figure 11, 12 and 13 respectively present the performance results of the proposed model.

Table 2: Includes details of the model used at each stage

Stages	No. of Person	No. of original image	No. of training images	No. of testing images	Image size	No. of layers	No. of filters	Activation function
Stage 1	150	5897	75222	4110	160*160	17	1200	Leaky_ReLU
Stage 2	150	4239	73910	4041	160*160	17	1200	Leaky_ReLU
Stage 3	150	3430	67536	3692	160*160	17	1200	Leaky_ReLU
Stage 4	120	2950	45772	2487	160*160	17	1200	Leaky_ReLU

Table 3. The performance results of the proposed technique on Age Dataset

Approach used	Stages	No. of Person	No. of original image	Accuracy	Precision	Recall	F1 score	Loss function
Sequential CNN	Stage 1	150	5897	99.8	100	100	100	0.01
	Stage 2	150	4239	96.1	96	96	96	0.17
	Stage 3	150	3430	99.6	100	100	100	0.02
	Stage 4	120	2950	99.6	100	100	100	0.02
In Result		**570**	**16516**	**98.7**	**99.0**	**99.0**	**99.0**	**0.05**

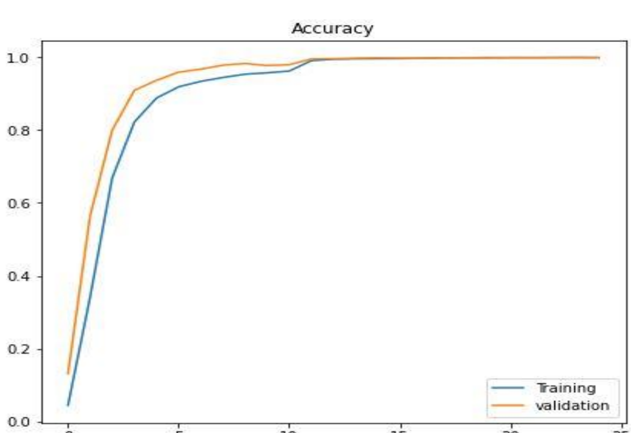

Figure. 11 The accuracy from this model

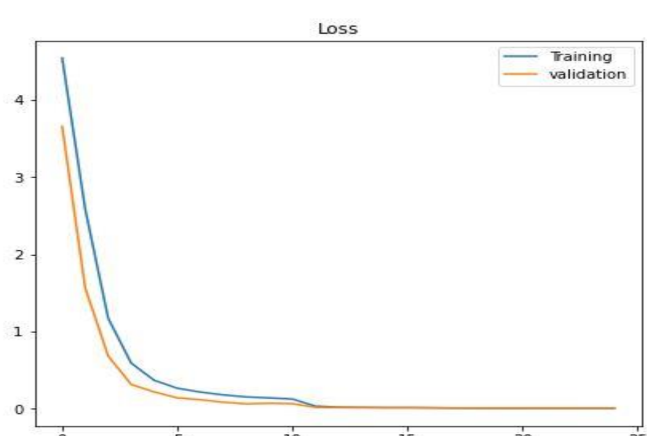

Figure. 12 The loss function from this

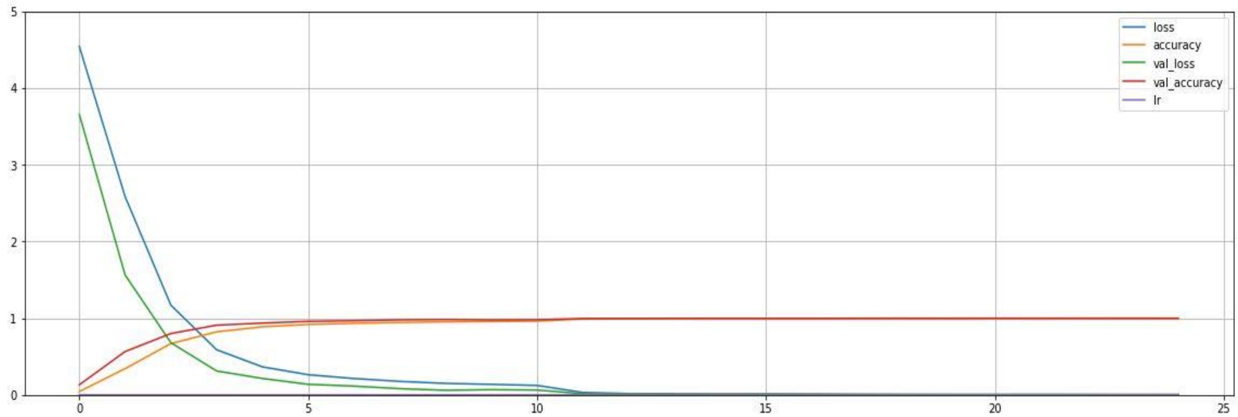

Figure. 13 The accuracy & loss function from this model

5.3.2: FG-Net Dataset

The dataset (FG-Net) contains 1002 images from 82 categories, and each class contains images of different ages. This dataset is used to test the efficiency of the sequential model used. The images were divided into three categories: The first category, related to the process of training and extracting key features. The second category relates to the validation process and sure that training is on the right track, and this process is between training and the final testing of the model. The third category of photos is of the final model testing process. Table 5 and Figure 14, 15 and 16 respectively present the performance results of the proposed model.

Table 4: Includes details of the model used

No. of Person	No. of original image	Image size	No. of layers	No. of filters	Activation function	Length of vector feature
82	1002	160*160	17	1200	Leaky_ReLU	2304

Table 5. The performance results of the proposed technique on FG-Net Dataset

Approach used	No. of Person	No. of original image	Accuracy	Precision	Recall	F1 score	Loss function
Sequential CNN	82	1002	99.4	100	100	100	0.01

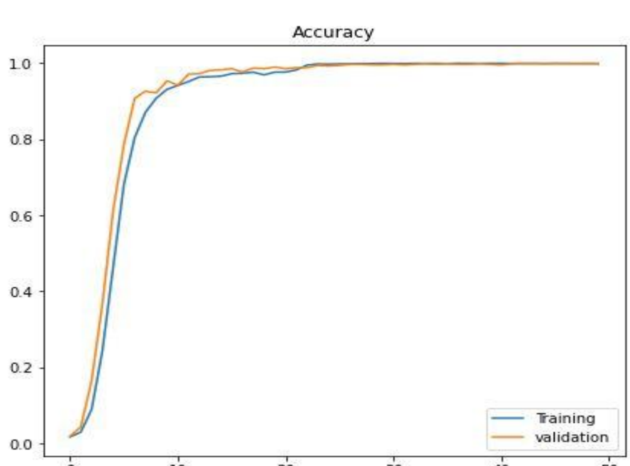

Figure. 14 The accuracy from this model

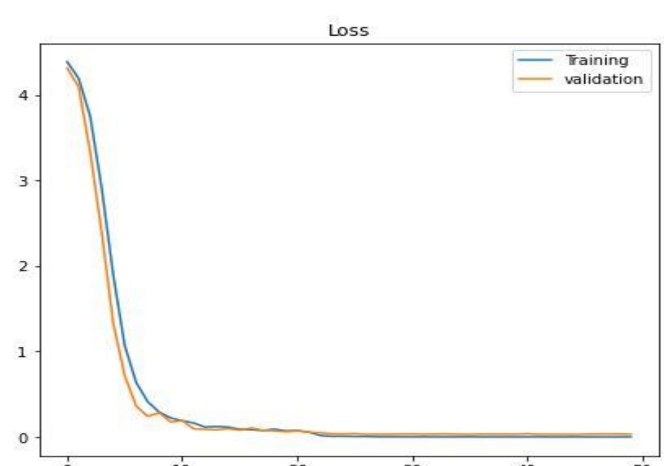

Figure. 15 The loss function from this model

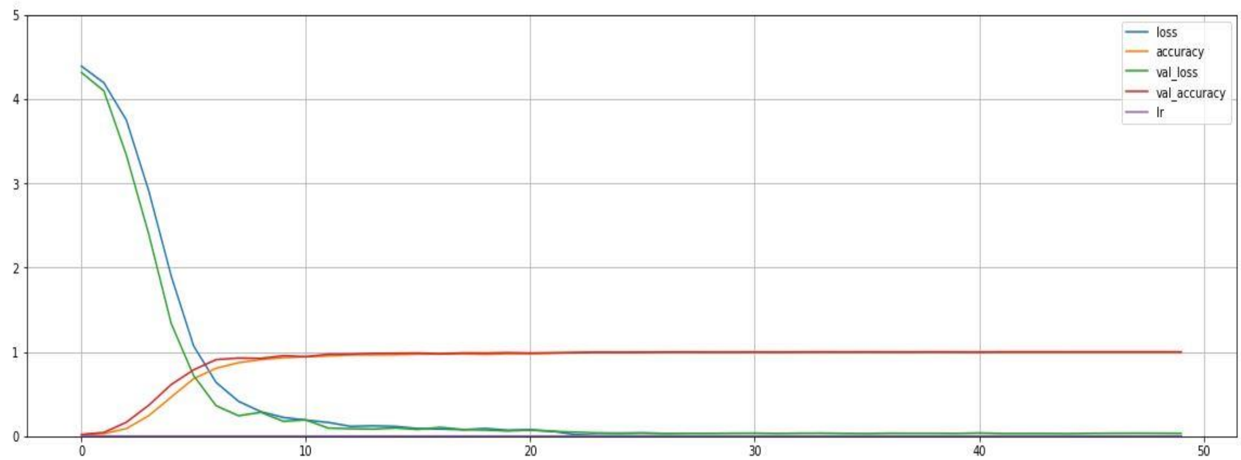

Figure. 16 The accuracy & loss function from this model

Table (6) includes the process of comparing the results obtained from the proposed model with a group of previous proposed models, in which good results were achieved in matching and identification. However, the proposed model achieved promising results, although it is a new structure that has not been trained before and has not been used in any previous study where it was trained. on the same dataset in the first part (age) in addition to the dataset (FG-Net).

Table 6: Comparison of the proposed models with a set of previous models

Author	Year	Technique used	Dataset	Accuracy
Zhifeng Li et al. [6]	2013	Hidden factor analysis (HFA)	FG-Net	69.0 %
Chenfei Xu et al. [4]	2017	Coupled Autoencoder Networks (CAN)	FG-Net	86.5 %
S. Moschoglou et al. [7]	2017	VGG face	Age	88.6 %
Hongming Shan et al. [19]	2021	Multi task learning face (MTL Face)	FG-Net Age	94.78 % 96.23 %
Xuege Hou et al. [20]	2021	multi task learning - mutual information minimization (MT – MIM)	FG-NET Age	94.21 % 96.10 %
proposed model	**2023**	**Building Convolution Neural Network (CNN)**	**FG-Net** **Age**	**99.40 %** **98.70 %**

5.4. Visualization of convolution layers via feature maps representation

In this section of the work, we will explain the filters that were used in this model, as well as the stages of extracting features and changes that occur on the image when applying filters to it in Figures 17 and 18. Figure 17 shows the filters that were used in the model before applying them to images, and Figure 18 Shows changes to images after applying filters to them. Each colored square in this map represents a specific set of filters. The purpose of this work is to show the intermediate stages that images go through during their passage between the layers from the input stage to the stage of finding features for the purpose of classification.

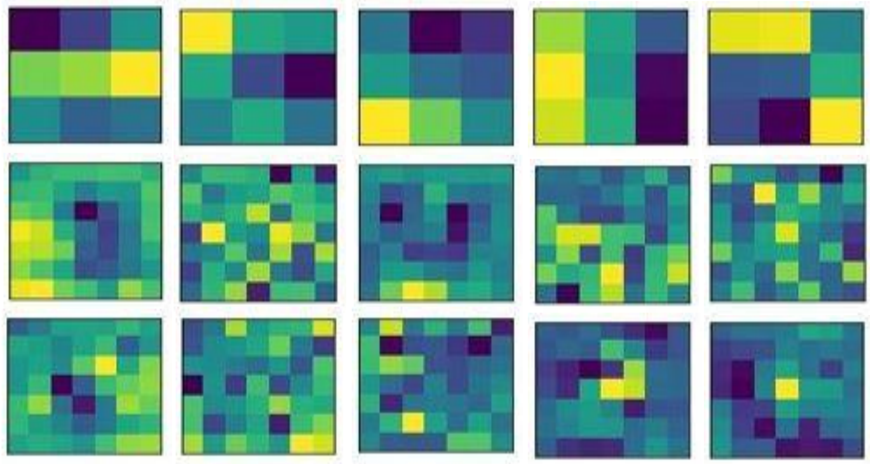

Figure 17: filters prior to applying to the images

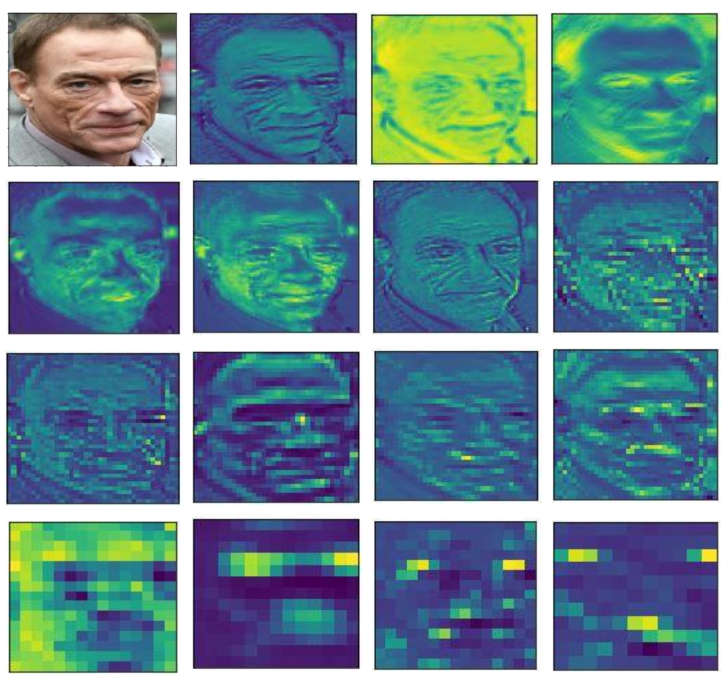

Figure. 18 set of images that follow the convolution process

6. Conclusion.

The accuracy and efficiency of human face recognition technology is greatly affected by the presence of age gaps in the images that are used in the experiment of the model, which may be 10 years or more. Also, some people have strong changes in features as they age, which occurs due to the increasing influence of aging patterns, which directly affect facial features. In addition, the alignment, orientation, and position of a person's face and the focus area in photographs greatly affect the accuracy and discrimination of a person's face. Therefore, this step is very important for measuring and calculating the efficiency of the system, so all these things must be taken into account and attempted to be addressed, if possible, in the preprocessing step of the data. Therefore, In our approach, a serial model of Convolutional Neural Networks (CNN) and classification by (SoftMax) technology is presented for the purpose of studying the recognition of age-invariant faces. Based on deep learning, the proposed model yielded promising results on the (age) and (FG-Net) datasets. Although each one contains a number of challenges and the most important is the age gaps, but it is better than other databases used in the same field.

References.

[1] A. S. O. Ali, V. Sagayan, A. M. Saeed, “Age-Invariant Face Recognition System Using Combined Shape and Texture Features,” The Institution of Engineering and Technology (IET), Vol. 4, Issue 2, pp. 98-115, 2015.

[2] S. Biswas, G. Aggarwal, N. Ramanathan, R. Chellappa, " A Non-Generative Approach for Face Recognition across Aging ", 2nd International Conference on Biometrics: Theory, Applications and Systems, Arlington, pp. 1-6, vol.15, October 2008.

[3] D. Gong, Zhifeng Li, D. Tao, J. Liu, Xuelong Li, " A maximum entropy feature descriptor for age invariant face recognition", In Proceedings of the conference on computer vision and pattern recognition, pp. 5289-5297, 2015.

[4] Chenfei Xu, Q. Liu, Mao Ye, “Age invariant face recognition and retrieval by coupled auto-encoder networks”, Neurocomputing, Vol. 222, pp. 62-71, 26 January 2017.

[5] Y. Mahajan, S. Sondur, " Aging Face Recognition Using Deep Learning ", International Journal of Engineering and Applied Sciences (IJEAS), Vol. 5, Issue 8, ISSN: 2394-3661, August (2018).

[6] D. Gong, Zhifeng Li, D. Lin, J. Liu, X. Tang, “Hidden factor analysis for age invariant face recognition ", Proceedings of the IEEE International Conference on Computer Vision (ICCV), pp. 2872-2879, 2013.

[7] S. Moschoglou, A. papaioannou, C. Sagonas, J. Deng, I. Kotsia, S. Zafeiriou. "AgeDB: the first manually collected, in-the-wild age database". IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), pp. 51-59, ISSN: 2160-7516, 2017.

[8] A. V. Nefian, “Embedded Bayesian networks for face recognition,” International Conference on Multimedia and Expo, Lausanne, Switzerland, Vol. 23, pp. 133-136, 2002.

[9] Stan Z. Li, Anil K. Jain, " Handbook of Face Recognition ", Springer Science + Business Media, pp. 1-394, 2005.

[10] A. M. Osman, S. Viriri, " Face Verification across Aging using Deep Learning with Histogram of Oriented Gradients ", International Journal of Advanced Computer Science and Applications (IJACSA), Vol. 11, Issue 10, 2020.

[11] W. Rawat, Z. Wang, " Deep Convolutional Neural Networks for Image Classification: A Comprehensive Review ", Massachusetts Institute of Technology, Vol. 29, Issue 9, pp. 2352 – 2449, 2017.

[12] M. Nimbarte, K. Bhoyar, "Age Invariant Face Recognition using Convolutional Neural Network", International Journal of Electrical and Computer Engineering (IJECE), Vol. 8, No. 4, pp. 2126-2138, August 2018.

[13] W. Rawat, and Z. Wang, " Deep Convolutional Neural Networks for Image Classification: A Comprehensive Review ", Massachusetts Institute of Technology, Vol. 29, Issue 9, pp. 2352 – 2449, September 2017.

[14] F. M. Bachay, M. H. Abdulameer, "Hybrid Deep Learning Model Based on Autoencoder and CNN for Palmprint Authentication", International Journal of Intelligent Engineering and Systems, Vol. 15, No. 3, pp. 488-499, 2022.

[15] https://yanweifu.github.io/FG_NET_data/

[16] Z. Mortezaie, and H. Hassanpour, "A SURVEY ON AGE-INVARIANT FACE RECOGNITION METHODS", Jordanian Journal of Computers and Information Technology (JJCIT), Vol. 5, Issue 2 August 2019.

[17] M Sokolova, G. Lapalme, " A systematic analysis of performance measures for classification tasks ", Information Processing and Management, Vol. 45, Issue 4, pp. 427-437, July 2009.

[18] Michael Nielsen, "Neural Networks and Deep Learning", Accelerating the world's research, 2015.

[19] Z. Huang, J. Zhang, H. Shan, "When Age-Invariant Face Recognition Meets Face Age Synthesis: A Multi-Task Learning Framework", Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pp. 7282-7291, 2021.

[20] X. Hou, Y. Li, S. Wang, "Disentangled Representation for Age-Invariant Face Recognition: A Mutual Information Minimization Perspective", Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV), Vol. 8, pp. 3692-3701, 2021.