A combined method based on CNN architecture for variation-resistant facial recognition

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Abstract *– Identifying individuals from a facial image is a technique that forms part of computer vision and is used in various fields such as security, digital biometrics, smartphones, and banking. However, it can prove difficult due to the complexity of facial structure and the presence of variations that can affect the results. To overcome this difficulty, in this paper, we propose a combined approach that aims to improve the accuracy and robustness of facial recognition in the presence of variations. To this end, two datasets (ORL and UMIST) are used to train our model. We then began with the image pre-processing phase, which consists in applying a histogram equalization operation to adjust the gray levels over the entire image surface to improve quality and enhance the detection of features in each image. Next, the least important features are eliminated from the images using the Principal Component Analysis (PCA) method. Finally, the pre-processed images are subjected to a neural network architecture (CNN) consisting of multiple convolution layers and fully connected layers. Our simulation results show a high performance of our approach, with accuracy rates of up to 99.50% for the ORL dataset and 100% for the UMIST dataset.*

Keywords*: Histogram equalization, PCA, CNN, facial recognition, variations*

1. INTRODUCTION

Facial recognition is a technology that allows the identification of a person by analyzing and comparing unique features of the face, such as the shape of the nose, the distance between the eyes, or the facial lines. This technology is increasingly used in various fields such as security [1, 2], Human face recognition and age estimation [3], video surveillance [4], gender identification from an image [5], biometric identification [6] or individual identification [7-9]. However, the presence of variance that can occur in several forms (lighting, orientation, pose, accessories, etc.) in an image can affect facial recognition, since facial recognition algorithms need a clear, sharp image of the face to identify unique features and compare them with a database of recorded faces [10]. This is why it is important to take variance into account when designing and evaluating facial recognition algorithms, and to ensure that they are capable of handling a wide variety of situations and image conditions to guarantee accurate and reliable identification.

Recently convolutional neural networks (CNN) have been very successful in many computer vision applications such as medicine [11, 12], agriculture [13], and environment [14, 15]. And also, among these applications, several works dealing with facial recognition are based on the use of CNNs due to their robustness in feature extraction and classification such as [16-18]. CNNs are a category of deep neural networks used mainly in the field of computer vision. Inspired by the structure and functioning of the human visual system, CNNs are mainly used for classification tasks. Their architecture consists of several layers including convolution layers which are responsible for extracting features from the image using convolution filters applied on different parts of the image, then pooling layers which are used to reduce the dimensionality of the dataset by selecting the most important features and finally fully connected layers which are responsible for the final classification. Thanks to these layers the CNNs can automatically learn the discriminating features of a facial image.

In this paper, we propose a combined approach to improve the accuracy and robustness of our facial recognition model when multiple variance shapes are present in an image. This approach first uses histogram equalization technique pre-processing to improve the quality of the images as it adjusts the distribution of gray levels in an image to improve the visibility of details and increase the contrast this is beneficial as it enhances the contours and details of the face, thus facilitating the detection and identification of the unique facial features. Then the principal component analysis (PCA) method [19] is applied to extract the most important features from the images by reducing the dimensionality of the data set. PCA also simplifies and reduces the complexity of the face data by extracting the most important and discriminating features. And at the end, the set of processed images is transmitted to a CNN architecture for training our model. Our approach has been evaluated using two image databases which are ORL [20] and UMIST [21] which represent multiple variations in pose and lighting and accessories such as glasses, scarf, and beard... The performance of our model is evaluated using an accuracy metric.

The results of our simulations show that our method performed satisfactorily, with accuracy rates of up to 99.50% for the ENT dataset and 100% for the UMIST dataset. These results are competitive with those of other research studies in the same field.

2. RELATED WORK

Facial recognition is a fast-growing research area that presents many challenges, including variation under different types such as occlusion, pose, and the presence of accessories (glasses, cap, scarf ...). To remedy this problem several relevant works have addressed this problem. The authors in [22] proposed an efficient face recognition system incorporating genetic algorithms. Their model is based on two steps: the first one consists in extracting the face features and the second one consists in matching the face models. The results of the simulations have allowed us to obtain quality results with an accuracy that reaches a value of 88.9%. In [23] the authors proposed a face recognition algorithm based on depth map transfer learning to efficiently recognize face images taken in an unrestricted environment. This method was able to record an accuracy rate that reached a value of 98.31%. On the other hand, another model based on transfer learning has been designed [24]. Its goal is to design a facial recognition model invariant to the activated age. For this a preprocessing is performed on the facial images to improve their quality, then a BES-DTL-AIFR model which is based on the Inception V3 model is also used to learn deep features and at the end, the features are passed to the optimal deep belief network model DBN. The model recorded an accuracy rate of a value of 99.14%. The authors in [25] proposed penalized competitive deep rival learning RPCL for deep face recognition in a low-resolution image. Their model achieved an accuracy value of 95.13%. Another hybrid biometric system for face recognition considering uncontrollable environmental conditions was developed in [26]. The proposed system uses two features which are discrete wavelet transform based on the Gaussian Laplace filter and Log Gabor filter. Both features were used by a multi-class support vector machine. The system was able to achieve an accuracy rate of a value of 94.68%.

3. METHODOLOGY

The figure below presents the steps of our approach. It consists of four steps which are:

- Application of histogram equalization on the set of images used
- Application of dimension reduction by the PCA method
- Labeling and data preparation
- Feature extraction and classification by CNN architecture

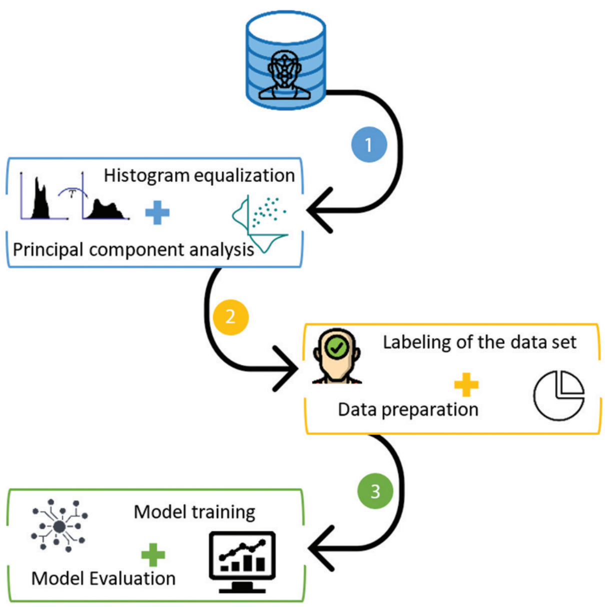


Fig. 1. Graphic representation of the different steps of our method

3.1. HISTOGRAM EQUALIZATION

The equalization of the histogram is a technique of image processing made by Gonzalez and Woods in ref which allows the uniform adjustment of the distribution of gray levels on the entire surface of an image. For this, we begin by calculating the histogram of an image (X) which is a graphical representation of the distribution of gray levels (L) in the form of a curve that indicates the number of pixels that have a particular level of gray in an image. Then the cumulative distribution function CDF of the histogram is calculated to determine the transformation to be applied to the image to equalize its histogram. We define the number NK which is the number of occurrences of the level XK it gives that the probability of occurrence of a pixel of level XK in an image is presented by the following equation

$$p_x(x_k) = p(x = x_k) = \frac{n_k}{n}, 0 \leq k < L \tag{1}$$

With: n presents the total number of pixels of an image and p_x presents the histogram normalized on [0,1].

Finally, an equalization transformation (T) is applied to the image using the CDF. It aims to replace each gray level of the image by its equivalent value in the CDF. For this we associate a new value $SK=T(Xk)$ has this transformation T on each pixel of value XK as shown in the following equation:

$$T(x_k) = (L-1)\sum_{j=0}^{k} p_x(x_j) \tag{2}$$

With $\sum_{j=0}^{k} p_x(x_j)$ showing the cumulative histogram of an image.

The resulting image will have a uniform histogram which will allow the increase of contrast and brightness of the image. Fig. 2 below shows an example of the use of this technique on an image belonging to the ORL dataset and as can be seen the cumulative histogram distributed over the entire surface so that it becomes uniform.

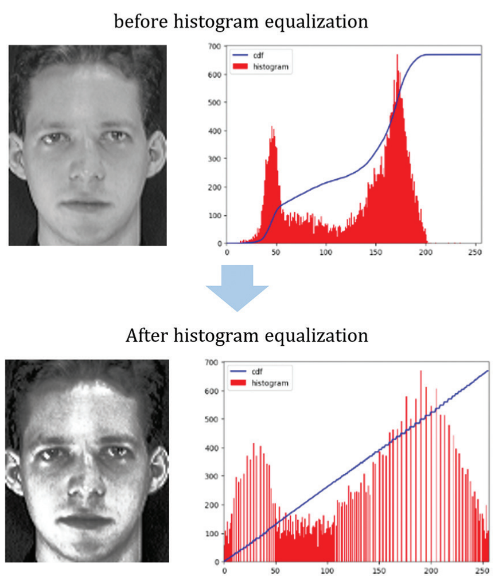


Fig. 2. Application of histogram equalization on an image belonging to the ORL database

3.2. PRINCIPAL COMPONENT ANALYSIS

Principal Component Analysis PCA [19] is a dimensionality reduction technique that decomposes a data matrix into principal components while retaining the maximum amount of information contained in the data. It aims to improve the performance of Deep Learning algorithms because it keeps just the uncorrelated variables and eliminates the correlated ones that do not contribute to a decision.

For this purpose, each image is represented by a vector Ii containing pixels, which will later be treated as a one-dimensional array were

$$\mathrm{I_i} = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix} \tag{3}$$

where $1 \leq a_{ij} \leq 255$

a represents the pixels of an image

Then the matrix will be converted to a one-dimensional array as follows:

$$\tau_i = \begin{pmatrix} a_{11} \\ \cdots \\ a_{mn} \end{pmatrix} \tag{4}$$

Where τ_i is an array that will contain many pixels.

By the soot, the average of all the images is determined by the elimination of all that is in common with the individuals, as shown by the following equation:

$$\Psi_{\mathrm{moy}} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{I_i} \tag{5}$$

Where $\sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{I_i}$ is the sum of the values for each image.

Then the matrix $\emptyset_i$ constructed by performing a subtraction between the one-dimensional array of pixels τ_i the average ψ_{moy} as shown in the equation below:

$$\emptyset_i = \tau_i - \psi_{moy} \tag{6}$$

Then another modified image matrix this time of covariance representing the interaction between the images of a single individual as shown in equation (7) Below:

$$C = \frac{1}{M}\sum_{n=1}^{M} \emptyset_n \emptyset_n^T = AA^T \tag{7}$$

where $A=(\emptyset_1, \emptyset_2, \ldots, \emptyset_M)(N^2 \times M)$

Where C is the covariance matrix, M is a set of vectors and $\emptyset_n \emptyset_n^T$ represents the tensor product of the feature vectors $\emptyset_n$ and $\emptyset_n^T$.

Subsequently, the eigenvectors U_i, are calculated from the covariance matrix C, then a sorting of these vector verticals is formed based on their eigenvalue where $||U_i||=1$ which corresponds to the importance of the direction of the data set. A selection of the first K eigenvectors that contain the most information for the projected of the dataset on the selected K eigenvectors to reduce the dimensionality of the dataset. At the end a reconstruction of the image using the K-selected eigenvectors.

As shown in Fig. 3 below, even if we apply the PCA method, we can see that the appearance of the image is preserved, but the dimensions are reduced.

Fig. 3. Application of PCA on images belonging to the ORL database

3.3. DATA PREPARATION

Once the dataset is processed a preparation is performed on it aiming to unify the size of the images (48x48) then all the images will be labeled where each image will be labeled by the class that corresponds to it, then we proceed to the formation of two subsets of data. Each of these two will be used in a learning phase the first part will be used in the training phase of our model will contain 80% of the images is will be called TRAIN, while the second subset called TEST will contain 20% of the images is will be used in the validation phase of our model.

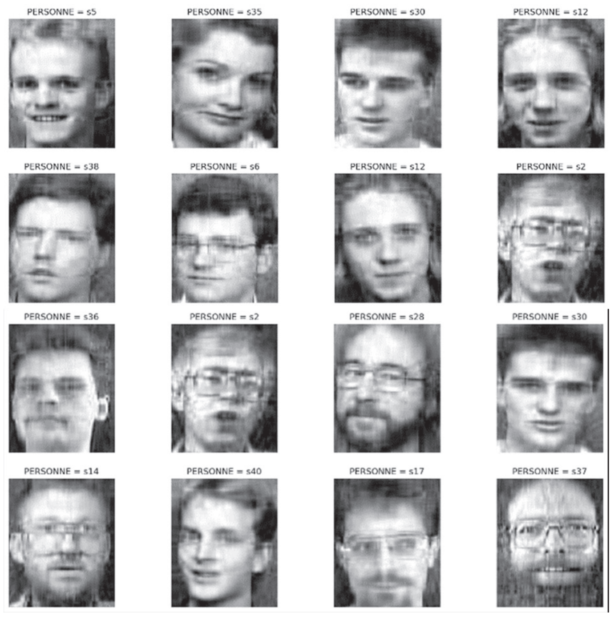


Fig. 4. Labeling of the ORL data set

3.4. CONVOLUTIONAL NEURAL NETWORK ARCHITECTURE CNN

The final phase aims at building an architecture of convolutional neural networks (CNN) which are a class of deep neural networks mainly used in the field of computer vision. Their structure and operation are inspired by the human visual system. They are used for classification tasks as they are designed for automatic extraction of image features. Their complex architecture consists of several layers in our case we used convolution layers that are responsible for the extraction of features from an image by applying convolution filters on different parts of the image. Also, the POOLING layer's role is to reduce the dimensionality of the dataset by selecting the most important features, so a FLATTEN layer has a very important role in our architecture because it allows us to convert the output of the last convolution layer into a 1D vector so that they can be used as input data by the layer of fully connected neurons DENSE to perform classification based on the extracted features. The DENSE layer consists of neurons that are connected to all the neurons of the previous layers which will allow us to learn complex relations between the features extracted by the previous convolution layers by applying linear and non-linear operations to transform the input vector into an output that can be interpreted as a prediction with the help of an activation function. In our case, we used the Rectified Linear Unit (RELU) activation function which is one of the most popular activation functions used in CNN. Its role is to introduce nonlinearity into the neural network because the convolution layers perform linear operations, which means that the output of the layer is a linear combination of the inputs. Adding a nonlinear function will allow the neural networks to learn more complex nonlinear representations of the input data. This is done using the following equation:

$$f(x) = \max(0, x) \begin{cases} if\ x > 0\ ,\ \ f(x) = x, \\ if\ x < 0,\ \ f(x) = 0 \end{cases} \tag{8}$$

x represents the output of the layer.

One of the advantages of using this activation function is that it allows us to deal with complex input data because it avoids the disappearance of gradients and also it helps in a good regularization of our model. Also, we used the SOFTMAX optimization algorithm in the output layer to perform a multi-class classification to classify the data into several categories. Its main role is to normalize the scores of each output class into a probability distribution that represents the probability of each class being the correct prediction using the following equation:

$$\sigma(z)_j = \frac{e^{zj}}{\sum_{k\grave{a}1}^{k} e^{zj}} \text{ where } j \in \{1, \ldots\ldots, k\} \tag{9}$$

Z is a vector of real numbers that represents a score for a particular class j and k is the class number.

Fig. 5 below summarizes our adopted architecture. It is composed of three convolution layers, three pooling layers, and a flattened layer. All these layers will be responsible for the extraction of features from the images. Then a fully connected layer is used to perform a classification.

Our model was compiled using a categorical_crossentropy loss function which is widely used in machine learning and in particular to solve multi-class classification problems. Its role is to measure the divergence between the probability distribution predicted by a model and the actual distribution of classes by computing the output probability of a model and the labels that correspond to the classes. This operation is performed using the following equation:

$$j(\theta) = -\sum_i y_i \times \log(\hat{y}_i) \quad (10)$$

Where $j(\theta)$ presents the total loss calculated from the predictions of the model, y_i represents the true value of class i(0 or 1) and $\hat{y}_i$ represents the probability predicted for class i by a model.

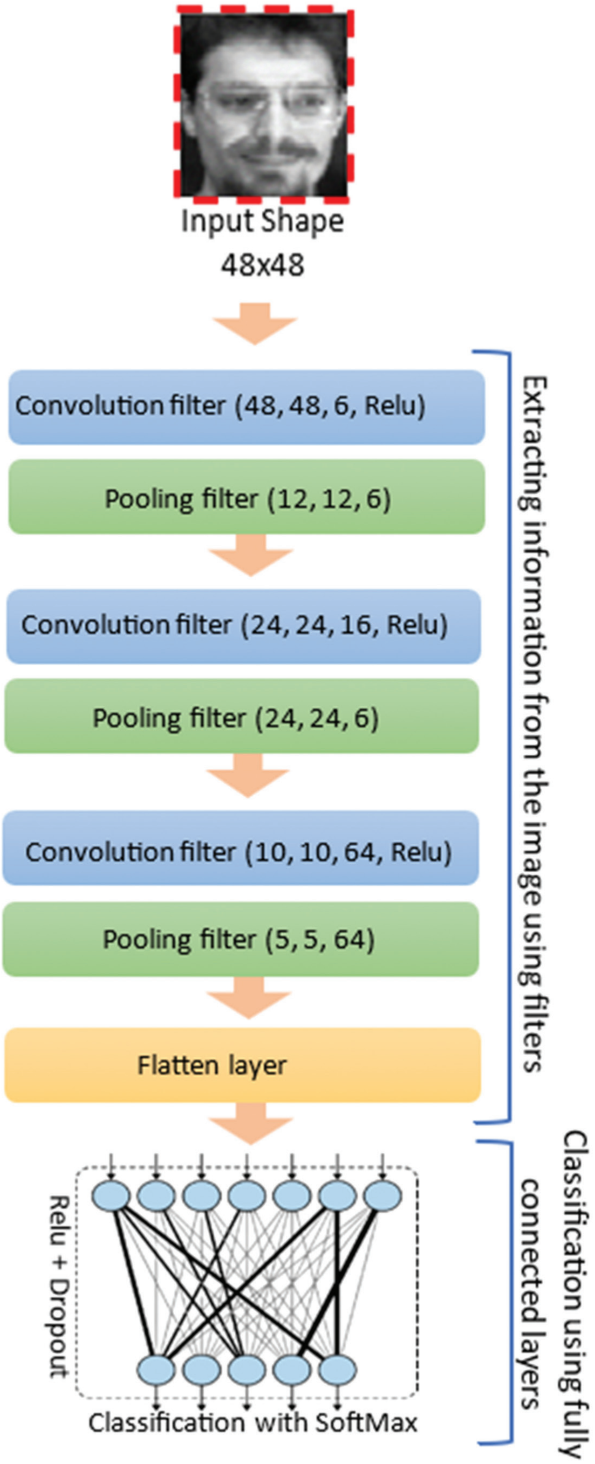


Fig. 5. CNN architecture adopted for our approach

The main objective of using this loss function is to minimize the value of the loss by adjusting the weights and biases of our model to obtain predictions that are as close as possible to the actual labels.

The classification performance evaluation of our model is performed using an accuracy metric which has as its main objective to measure the proportion of correct predictions about the set of predictions resulting from our model. This measure represented in percentage (%) is performed by comparing the predictions of our model with the real labels belonging to the data set used as shown in the following formula:

$$Accuracy = \frac{N_c}{N_t} \times 100 \quad (11)$$

Where N_c represents the correct number of predictions predicted by our model and N_t is the total number of items in the data set used.

We also note the use of the Adam optimization algorithm. Its role is to update the weights of our model by calculating the gradients of our model for a training batch of data, then updates the first-moment (M_t) and the second moment (V_t) using the following two formulas:

$$M_t = \beta_1 \times m_{(t-1)} \times (1 - \beta_1) \times g \quad (12)$$

$$V_t = \beta_2 \times v_{(t-1)} \times (1 - \beta_2) \times g^2 \quad (13)$$

Where g represents the gradients, β_1 and β_2 represents the exponential decay parameters.

Then the moment biases M_t and V_t are corrected using the following two formulas:

$$M_{t\_corr} = \frac{M_t}{(1-\beta_1^t)} \quad (14)$$

$$V_{t\_corr} = \frac{V_t}{(1-\beta_2^t)} \quad (15)$$

Namely, t is the iteration number.

And finally, the Adam algorithm will update all the weights of our model using the following formula:

$$\theta_{(t+1)} = \frac{\theta_t - \alpha \times M_{t\_corr}}{\sqrt{V_{t\_corr}} + \varepsilon} \quad (16)$$

In the formula, θ represents the weights of our model, α corresponds to the learning rate and ε is a small value added to avoid division by 0 (in our case we used 10-8).

All these operations will allow our model to adjust the learning rates adaptively based on the estimates of the first and second moments, which guarantees rapid convergence and stability during the training phase of our model.

4. RESULT AND DISCUSSION

Our model was trained using two databases ORL and UMIST which each represent the presence of variations of different types, over a total of 150 epochs, where each epoch corresponds to an iteration on the TRAIN training data set. Also, the batch_Size parameter was set to 8 which means that the model is trained using mini-batches of a sample of 8 mages at a time. We also note that the TEST dataset is used for the validation of our model during the training phase. The loss function and evaluation metrics are calculated for this dataset after each epoch.

The results of our simulations shown in Table 1 below have demonstrated a remarkable performance recorded in both cases (ORL and UMIST) as shown in Table 1 below. In the case of the ORL database which represents the presence of variations in contrast, lighting, and occlusion (glasses, sling ...) our approach recorded an accuracy rate of up to 99.50% which is the best score recorded among the other techniques while a value of 0.07 was recorded by our model as the precision of the loss function which indicates that our model has succeeded in minimizing the value of the loss function. In the case of the UMIST database which represents a variation at the pose level (from profile to front view), our model was able to achieve 100% value in accuracy and a value of 0.0000093 was recorded by our model as the accuracy of the loss function.

In the case of the ORL database, as illustrated in Figure 6 below, the analysis of the graph representing the evolution of the two values Accuracy and Loss during the two training and validation phases shows that the accuracy value increases constantly and that the loss value also decreases constantly, which indicates that our model is gradually improving until it reaches optimal values (99.50% for accuracy and 0.07 for loss value) on the two data sets Train and Test. On the other hand, in the case of using the histogram equalization technique combined with the CNN, the two values (precision and loss) do not reach interesting values (92.50% as the maximum precision value and 0.31 as the minimum loss value) which makes the model resulting from this technique weak compared to our method.

Table 1. Simulation results on both databases

Database	ORL		UMIST	
Technique	**Accuracy**	**Loss**	**Accuracy**	**Loss**
CNN	93,75%	0.25	99,13%	0.15
ACP	93,75%	0.15	100%	0.00065
Equalization + CNN	92,50%	0.31	99,13%	0.081
Method	99,50%	0.07	100%	0.0000093

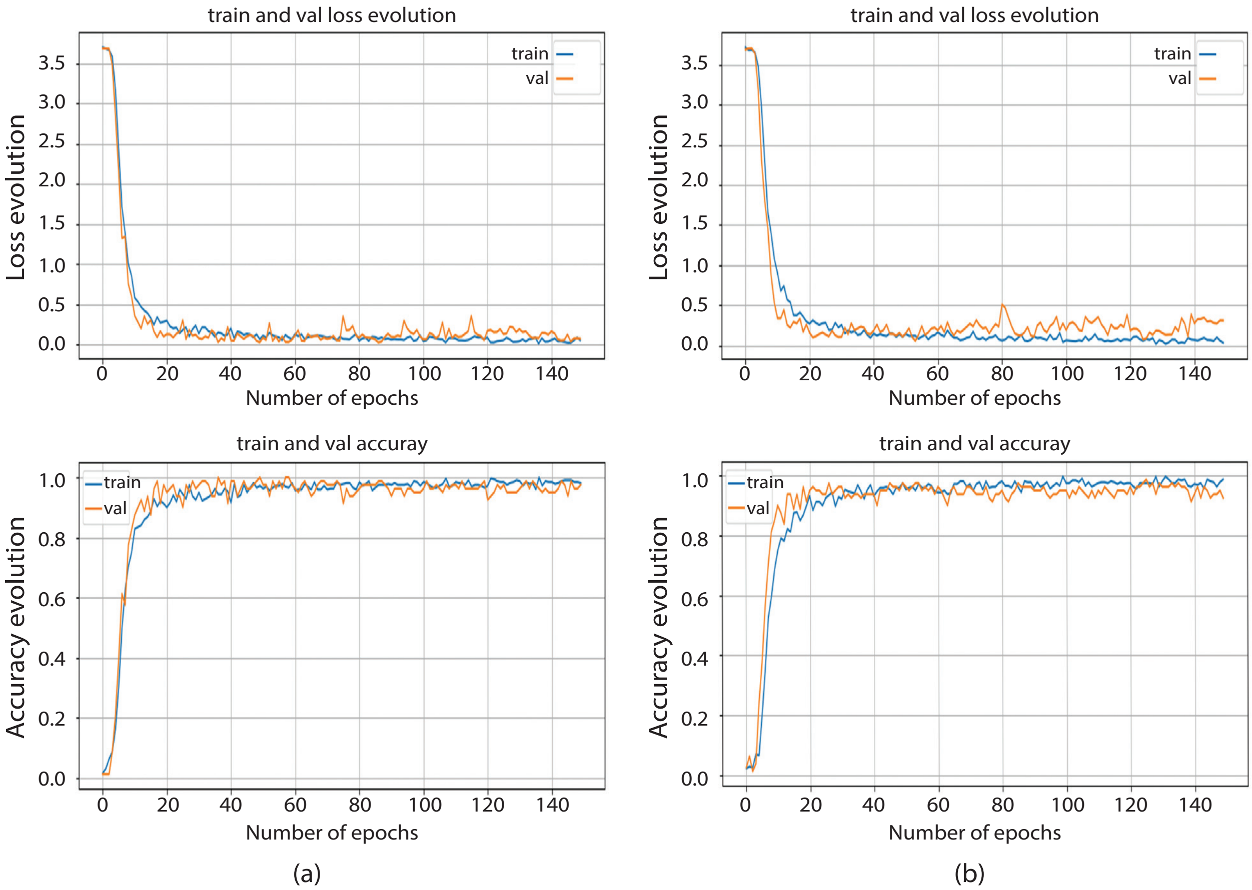
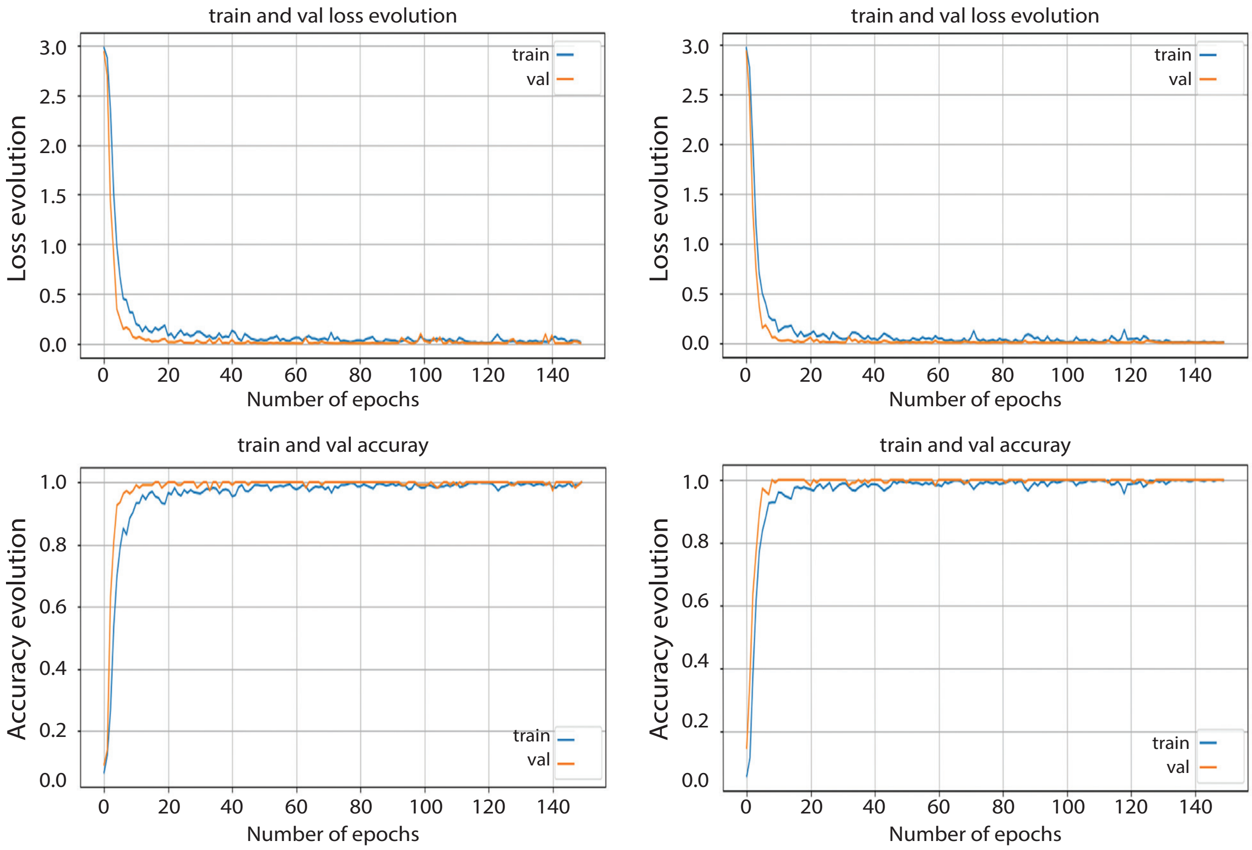


Fig. 6. Graph representing the evolution of precision and loss values a: in the case of our approach and b: in the case of using histogram equalization + CNN

In the case of the UMIST database as illustrated in Fig. 7 below the analysis of the graph representing the evolution of the two values Accuracy and Loss during the two phases Training and Validation we note the stability of the curves over the periods and also that the value of accuracy increases in a constant way and that the value of loss also decreases constantly until reaching a final value of accuracy of 100% and 0.0000093 as the final value of a loss on the two sets of data Train and Test. It is also noted that in the case of using the PCA technique combined with the CNN, the model also reaches a final accuracy value of 100% but the final value recorded by this model 0.00065 shows that it is not effective as the case of our method.



(a) (b)

Fig. 7. Graph representing the evolution of the precision and loss values a: in the case of our approach and b: in the case of using the PCA + CNN method

A comparison aimed at evaluating our approach with other research works using the same databases (ORL and UMIST) has been carried out as illustrated in Table 2 below. The analysis of this comparison shows that our approach is competitive with other results of various research works done in the same direction and achieves convincing results in terms of the accuracy rate of facial recognition with the presence of variations and occlusion of different types.

Table 2. Comparison of the accuracy rates of others research works with our approach

ORL		UMIST	
Method	**Accuracy**	**Method**	**Accuracy**
LBP+CNN [8]	100%	Genetic algorithm [27]	100 %
HSL [28]	96.67 %	SESRC&LDF [29]	99.13 %
GABOR [30]	100%	Fusion Local& Glob [31]	99.4 %
Modified PSO [32]	99 %	CRHM [33]	99.51%
LTP-Deep CNN [34]	98.75 %	SIFT+SVM [35]	99.44%
Method	99.50 %	Method	100%

5. CONCLUSION

Facial recognition, part of the artificial intelligence sector, is a technique that aims to identify an individual from an image. This identification can be ineffective in the presence of variation or occlusion. In this paper, we propose a new approach aimed at improving the performance of face recognition in the presence of different types of variation or occlusion. To this end, we have used two image datasets (ENT and UMIST) that present the presence of several variations and occlusions. Our method begins with a pre-processing phase performed on the images used, which consists in applying histogram equalization to increase the contrast and visibility of facial image details, thereby improving recognition accuracy. Next, the PCA method was also applied to all the images used, reducing the dimensionality of all the facial image data while retaining the most important information. The second phase consists of passing all the pre-processed images from the first phase to our own CNN architecture, which consists of several convolution layers for extracting image features and also fully connected layers for image classification. The results of our simulations demonstrated the effectiveness of our approach, recording an accuracy value of 100% when using the UMIST dataset and 99.50% when using the ENT dataset. These results make our approach competitive with others developed by other researchers. This combination can be used in biometric face recognition systems, as it has demonstrated high performance. It should also be noted that in the future, we plan to use other techniques to improve the performance of our model in face recognition in the presence of variance or occlusion, such as the use of reinforcement learning techniques to improve CNN efficiency and reduce dependence on training data, as well as exploring other deeper and more complex CNN architectures.

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