DEEP CONVOLUTIONAL NEURAL NETWORK-BASED FACE RECOGNITION APPROACH

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Abstract- Facial recognition is a popular biometric identification method that analyzes face images and extracts information that may be used to identify people. It is frequently used in a variety of fields, such as surveillance, access control, attendance control, and facial recognition for potential offenders. However, it's really difficult to create an automated system that recognize faces similarly to how a human can, especially when dealing with complicated databases that present difficulties like varying posture angles reach to 180 degrees. Additionally, it can be difficult to maintain the image's high resolution without drastically reducing its size. Working on images without cropping out the face presents another difficulty because of the posing angle. In addition, the depth of a face's features can have a big impact on how accurately it is recognized. In this paper, deep learning is proposed using a convolutional neural network as a solution to address all the challenges mentioned, which is able to extract deep features and correctly recognize those features. The FEI face database was used to implement all experiments, and the acquired experimental results were presented and assessed. The testing outcomes on the FEI face database proved the efficiency of the proposed methodology, and we were able to achieve a best recognition accuracy of 98.67% and F1_score of 98.53%. The suggested strategy, which is based on CNN, performs better than current approaches.

Keywords: Face Recognition, Biometric, Deep Learning, CNN, FEI dataset.

1. INTRODUCTION

Most recently have seen a surge in interest in facial recognition since it offers a covert, a non-intrusive technique for detect, identifying, and verifying something without the subject's knowledge or permission [1]. Face recognition is used in numerous security applications, including ATM security, entrance control to significant buildings, and border crossings. security measures at airports and law enforcement [2], [3].

Because of the expanding size of face databases, the increasing accuracy and deploy ability of systems. Face biometrics technologies are expected to be most widely used by the global government sector [4]. Face recognition technology has advanced significantly since the 1990s [5]. Despite recent major advancements and broad use, there are still some drawbacks. Feature extraction's primary objective is to minimize the size of the image. by choosing the most essential features while keeping the pertinent data, and the features should be sufficiently distinct across classes to provide high classification performance [6]. But the effectiveness of face feature extraction techniques depends on robust preprocessing techniques like face detection and cropping, resizing, etc. [7].

Therefore, when we attempt to extract features from a facial image with no prior processing, we may encounter various complications and challenges. Deep Convolutional Neural Networks (DCNN), which have proven outstanding efficiency to extract deep features on several types of biometric including palmprint [8], fingerprint [9], face [10], and iris [11], are the focus of current research in face recognition algorithms.

The high ability of DCNNs to learn non-linear characteristics makes them particularly successful [12], however dealing with face recognition is still seen as a major challenge. Researchers developed a variety of techniques, each with a varied accuracy level and occasionally varying outcomes when compared to one another. Numerous facial recognition studies using popular face datasets were conducted. For instance, Zhang et al. (2015) presented a deep neural network-based method for facial recognition. in which the deep hierarchical network was constructed and trained after face image preprocessing. They used "sparse coding neural networks" and Softmax for classification. The results demonstrated that DNN is effective in extracting facial features [13]. In a different study, a new coupled mapping method based on convolutional neural network (CNN) was introduced to recognize low resolution facial images by [14]. Despite the difficulty of limited resolution, their results were encouraging.

Additionally, many researchers have proposed various approaches using hybrid methodologies, for instance, in [15], a deep learning CNN has been used in conjunction with traditional techniques (PCA and a combined Bayesian algorithm) to acquire facial characteristics. Following that, the size of the created features was decreased using PCA. A combined Bayesian procedure was further used for facial recognition. The findings of the final test can verify that the hybrid strategy is an effective according to recognition accuracy. Deep Convolutional Neural Network and "Vector of Locally Aggregated Descriptor (VLAD)" feature encoding were used by Zheng, et al. to create a face recognition system [16]. The CASIA Web Face dataset was used to train the CNN, whereas it was tested using the IJB-A and JANUS CS2 datasets. In addition, Chandran et al. recognized children's faces using CNN and "Multi-Class Support Vector Machine (SVM)" [17]. The established architecture is based on VGG-Face, which is regarded as one type of CNN. Softmax is replaced by the SVM Multiclass. There are 43 people and 846 child faces are present in the database. The test results demonstrate that accuracy was 99.41%. Yang et al. proposed the SR-CNN face matching algorithm [18]. Convolutional neural networks, rotation-invariant texture features, and "scale-invariant feature transform (SIFT)" are all combined in this study (CNN). Using the LFW dataset, the accuracy rate was 98.98%. A strong 4-layer convolutional neural network (CNN) architecture is developed by [19] to address the problem of facial recognition. This architecture is capable of handling occluded facial images, positions, facial expressions, and changing in lighting. Results from tests on an AR database yield 99.5% accuracy in recognition, whereas an accuracy of 85.13% is reached on the FERET database. In another investigation, the researchers in [20] employed transfer learning with the AlexNet and ResNet-50 models and the performance of pre-trained CNN with multi-class support vector machine (SVM) classifier to conduct classification. The results of the experiments showed that the accuracy for the various datasets ranged from 94% to 100%. Furthermore, the work [21] presents a model of face feature detection using local descriptors, describes an update to the PCNC for the recognition of plane rotated and micro displaced face images, and provides positive results from its application to three databases. The study [22] proposes a facial image identification system that employs Deep Learning algorithms to identify faces, extract features from them, and recognize them. The FEI dataset is used to show the utility of the proposed method. The findings indicate that this method can improve accuracy while decreasing time complexity. However, it's crucial to remember that the majority of DNN-based facial recognition algorithms are frequently constructed on a huge dataset, and a large dataset might result in a model with higher accuracy where deep learning ensures results with huge data. Therefore, if those effective methods are used with a limited dataset, performance may suffer. Furthermore, if they worked without the preprocessing stage, they might be impacted. In light of the preceding findings and ideas, a new schema of DNN-based model

(DCNN) for human facial recognition is constructed in this paper. We can outline the study's major contributions:
1. Creating a DCNN model from a small set of face images without any preprocessing or augmentation.
2. The proposed technique achieves facial recognition ability while dealing with the challenge of position changes.
3. The proposed technique preserves the image's high resolution without requiring it to be significantly reduced in size.
4. Several tests are carried out on the FEI face database, with the results compared to recent improved techniques.

2. PROBLEM STATEMENT

Due to numerous causes, face recognition presents various difficulties such as lighting conditions, aging and pose variation. The management of faces with a significant degree of pose variation is one of these difficulties. Face recognition technology has improved dramatically in recent years, but it still an open issue for research. In addition, there are a variety of difficulties that could affect the face recognition scenario, such as dealing with a less images in the selected database, preserving the high resolution of the image without significantly reducing its size, and working on face images without cropping out it due to the variation in posing. Another factor that can significantly affect how well a feature can be extracted. The CNN deep learning technique is recommended in this paper as a solution to all the aforementioned problems.

3. THEORETICAL BACKGROUND

The primary principle of ANN is to simulate how the human brain processes information. [23] [24]. Deep Learning or Deep Neural Networks are phrases used to refer to ANNs (Artificial Neural Networks) with several layers. Convolutional neural networks are among the most frequently used deep neural networks (CNN). When it comes to machine learning issues, CNN does remarkably well. There are numerous layers in CNN, including a fully-connected layer (FC), a pooling layer, and a convolutional layer. The first layer of CNN is convolution, which has a group of filters. They're called filters because they operate like traditional image processing filters. The convolutional neural network, on the other hand, initializes these filters to making them highly appropriate for the current task. After the input layer, other layers could be added to improve the technique where each layer can be given a different set of filters. Consequently, we may draw out a number of features from the image. It also has many adjustment options, including stride, padding, and an activation function [25]. Equation (1) [26] can be used to explain the computations for this layer.

$$Z_{u,v,c^l} = B_c^l + \sum_{i=-k_h^l}^{k_h^l} \sum_{j=-k_w^l}^{k_w^l} \sum_{c^{l-1}=1}^{c^{l-1}} W_{i+k_h^l, j, k_w^l, c}^{c^l} {}^{l-1}Z_{u+i,v+j,c^{l-1}} \quad (1)$$

where, Z_{u,v,c^l} represents the convolution layer's output, pixel coordinate represented by (u,v), a channel bias is B_c^l, the kernel weighs is symbolized in the equation by $W_{i,j,c^{l-1}}^{c^l}$

the convolution layer kernel's dimensions in terms of width and height are, respectively, denoted by k_h^l and k_w^l, the channel number is C, while the current layer is l, and the prior layer is $l-1$. The layer after convolution is pooling. The main objective of pooling is to down-sample the complexity of following layers. It is equivalent to reducing the resolution in the context of image processing. Pooling has no impact on how many filters are used. The most popular sort of pooling strategy is the max-pooling approach [27]. Only the highest value of each sub-inside is returned after dividing the image into rectangular sub-regions. Equation (2) [27] can be used to demonstrate the maximum pooling calculations.

$$q_{a^l,b^l,c} = \max_{0 \le a < p_h, 0 \le b < p_w}(O_{a^l \times ph+a, b^l \times pw+b, c}) \qquad (2)$$

where, $q_{a^l,b^l,c}$ is the pooling layer's output, the height of the pooled channel is denoted in the equation $0 \le a^l < p_h^l, p_h^l$, while the width of the pooled channel is $0 \le a^l < p_w^l$, In addition, p_w^l is the height of each pooled window is symbolized via $0 \le c < c^l = c^{l-1}$.

The final layer, known as the fully-connected layer, has neurons arranged similarly to how they are in a typical neural network. Each completely connected node in a layer is therefore directly coupled to every other fully connected node in the layer above it and the layer below it. A fully linked layer, on the other hand, has numerous characteristics that necessitate difficult computing during training. Therefore, it is possible to decrease the quantity of nodes and connections by using the dropout technique [25]. Equation (3) [26] depicts how this layer was calculated.

$$g_r = \sum_{a=1}^{m_1^{l-1}} \sum_{b=1}^{m_2^{l-1}} \sum_{c=1}^{m_3^{l-1}} W_{a,b,c,r}^l Q(c)_{a,b}, \forall 1 \le r \le m^l \Bbbk \qquad (3)$$

where, g_r is an FC layer output, m_1^{l-1} is the width of the previous channel, m_2^{l-1} is the height of the previous channel, m_3^{l-1} is the number of the previous channels, $Q(c)_{a,b}$ is a vector of pooling layer outputs, $W_{a,b,c,r}^l$ is the weights between the pooling and FC layers, and m^l, Figure 1 illustrates CNN's main organizational structure.
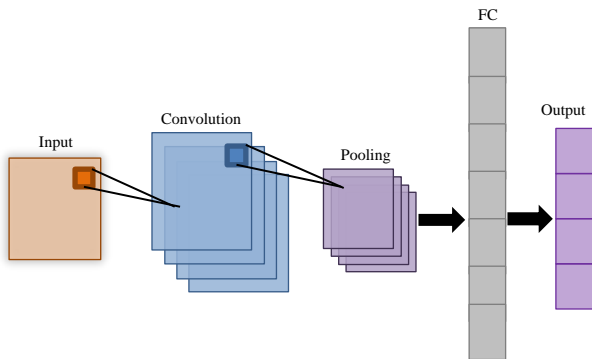

Figure 1. A convolutional neural network's internal structure

4. THE PROPOSED METHODOLOGY

The methodology for facial recognition we suggest is introduced in this section. Figure 2 illustrates the key steps of the suggested recognition technique.
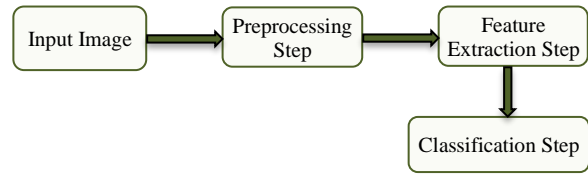

Figure 2. The key steps of the suggested recognition technique

4.1. Preprocessing Step

The first stage of the suggested methodology is preprocessing, which facilitates and gets the input images ready for the subsequent stages so they can function properly with the suggested methodology. where it entails resizing the images to 320×240 and turning them into grayscale versions of the input images.

4.2. Feature Extraction Based on CNN

This section, where features are extracted using CNN, goes into detail about the main idea of the suggested methodology, which is to extract deep features that allow the recognition process to go quickly enough.

Various layers that appear in the proposed CNN-based model, which we designed and constructed especially for facial images. There are multiple layers in the proposed model, comprising the layers for the input, "convolution", "activation function unit (ELU)", "pooling", "fully connected (FC)", "dropout", and "output layers". Input layer is first configured to accept a 320×240-pixel grayscale facial image. After that, two convolution layers are suggested for use. These layers enable the analysis of the face's grayscale features. An activation function for the rectifier linear unit (ELU) is present in each convolution layer. The pooling layer is applied after each convolution layer. By using windowing and maximum operations, the size of data in this layer can be reduced. After that, a fully linked layer is applied, we add a dropout layer after the fully connected layer to build a model that is more generalizable and less sensitive to overfit the training set of data. The optimal size of the suggested CNN architecture is determined empirically by gradually adding more filters after increasing the number of convolutions and max-pooling and finally choosing the network that performs the best. The suggested CNN architecture is summarized in Table 1. In addition, the block diagram structure of the proposed CNN model can be described by the Figure 3.

4.3. Classification Step

The final phase of the suggested methodology is the Classification step, which is carried out inside the built-in CNN and uses the Softmax function as the final layer, which are frequently used for multiple classification problems. To accommodate the number of categories, this layer has been updated.

Table 1. The proposed CNN architecture in brief

| Tyoe of Layer	Filter size	Function of Activation (AC)	number of filters	Fully connected units Layer	Shape of the input	Shape of the Output	No. of parameter
Convolution1	7×7	ELU	12	-	240, 320, 1	234, 314, 12	600
Max pooling 2D	6×6	-	-	-	234, 314, 12	39, 52, 12	0
Convolution2	7×7	ELU	12	-	39, 52, 12	33, 46, 12	7068
Max pooling 2D	4×4	-	-	-	33, 46, 12	8, 11, 12	0
Flatten	-	-	-	-	-	1056	0
Fully connected	-	ELU	-	256	-	-	270592
Rate of dropout: 0.5	-	-	-	256	-	-	0
The output Fully connected layer	-	Softmax	-	200	-	-	51400
Total number of parameters: 329,660							
The trainable parameters: 329,660							
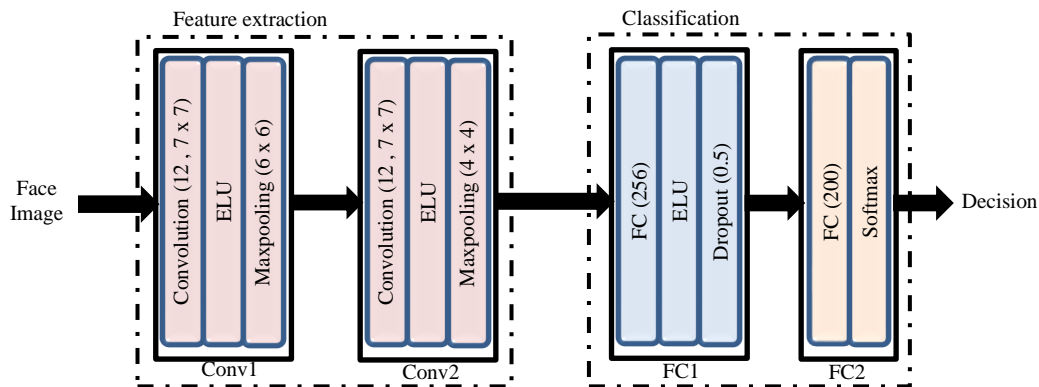
Figure 3. The proposed CNN model architecture

5. EXPERIMENTAL RESULTS

The proposed face verification approach is implemented using Google Colab, which offers Python3 in a free environment, using a GPU Nvidia Tesla k80 12GB processor with 13GB of RAM. The suggested technique's performance is assessed using the FEI face Database [28], and the overall proposed authentication method is assessed through accuracy and F1_score.

5.1. FEI Dataset

It refers to a Brazilian facial database with a collection of facial images that were gathered between June 2005 and march 2006 at the "FEI Artificial Intelligence Laboratory in Brazil's So Bernardo do Campo". There are 2800 photos in all, and 14 images for each of the 200 individuals. All images are colorful and were all taken with the subject standing up front and rotating the profile up to about 180 degrees against a plain white background. Each image is 640×480 pixels in size and may vary in scale by roughly 10%. There are 100 subjects total, 100 of each gender [28].

5.2. Performance of Assessing the Proposed Technique via Accuracy and F1-Score

We split the FEI dataset divided into 2200 face images for training process and 600 face images for testing process. Before inserting the images into the training model, they are converted to grayscale and reduced in size by half while preserving the image dimensions. The model is then trained on the well-liked Keras deep learning framework, with the classification function defined as the Softmax function, each convolution layer's weights

initialized using the ELU function, and training for 100 epochs. To choose the proper model parameters, numerous tests were set up and then analyzed. The most perfect accuracy rate after several training sessions were 98.67% when the kernel in the first convolution was 12 with Maxpooling 6×6 and the kernel in the second convolution was 12 with a 4-by-4 Maxpooling. The results of evaluating various network parameters are shown in Table 2. In this table, the parameters of the convolution and pooling layers are evaluated one at a time by adjusting one parameter while determining the values of the other parameters. Accuracy and F1-score are the evaluation criteria for the suggested technique.

The relationship between the proposed network's accuracy and the number of training iterations is also shown in Figure 4.
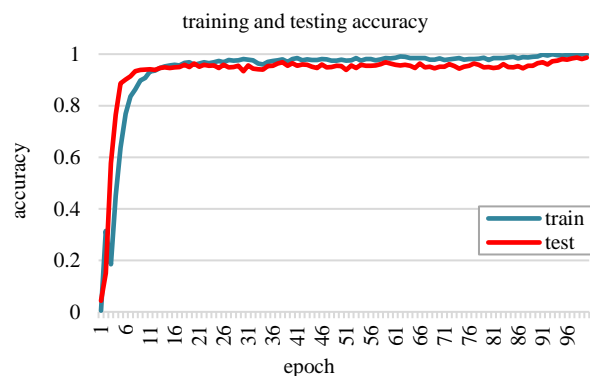

Figure 4. The accuracy of the proposed model

The commencement of the accuracy with a sharp rise can be seen in the Figure 4. By then, the indicator starts to progressively increase at epoch 15, and after epoch 80, the precision of access is largely stable. Figure 5 also showed the connection between the training phase's iteration count and the loss function of the suggested network (categorical crossentropy).

Figure 5. The loss function of the proposed model

We can see from the Figure 5 that the loss function begins with a significant decline. Epoch 15 marks the start of the indicator's subsequent steady decline, while epoch 90 marks the point at which the loss function becomes largely stable.

In order to show the stability of the proposed model, we adopted different kind of test based on learning rate to make sure there is no extreme gap in the results. We tested the model by increasing the learning rate by one and viewing and recording the outcomes. The acquired accuracy and F1 values were close, indicating that the suggested model has strong stability in the training and testing stages as indicated in Table 3.

Table 3. The Performance Results of Changing the Learning Rate Values

Learning rate	Accuracy	F1_score
0.0001	97.07%	97%
0.0005	97.40%	97.33%
0.001	96.17%	96.13%
0.005	96.83%	96.75%
0.01	96.67%	96.56%
0.05	97.50%	97.46%
0.1	98.67%	98.53%
0.5	97.33%	97.23%

Table 2. The outcomes of testing the proposed technique's performance

No. of filters in Conv1	Size of filter in Conv1	Maxpooling1	No. of filter in Conv2	Size of filter in Conv2	Maxpooling2	Activation function	Accuracy	F1_score
12	7×7	6×6	-	-	-	Leaky ReLU	95.17%	95.06%
12	7×7	6×6	10	7×7	4×4	LeakyReLU	96.33%	96.31%
10	7×7	6×6	10	7×7	4×4	Leaky ReLU	96.67%	96.51%
8	7×7	6×6	8	7×7	4×4	Leaky ReLU	97.50%	97.43%
12	7×7	6×6	12	7×7	6×6	Leaky ReLU	96.33%	96.40%
12	7×7	4×4	12	7×7	4×4	Leaky ReLU	97.17%	97.24%
12	7×7	6×6	12	7×7	4×4	Leaky ReLU	98%	97.77%
12	7×7	6×6	12	7×7	4×4	ReLU	96%	95.89%
12	7×7	6×6	12	7×7	4×4	ELU	98.67%	98.53%
12	7×7	6×6	12	5×5	4×4	ELU	94.17%	94.30%
12	5×5	6×6	12	5×5	4×4	ELU	94.50%	94.58%
12	3×3	6×6	12	3×3	4×4	ELU	97.17%	97.25%
12	9×9	6×6	12	9×9	4×4	ELU	96.17%	96.12%

5.4. Comparison of Proposed Model with Related Works

Despite the pose challenge and the limited number of images utilized for the database, the proposed technique's findings were encouraging, which is regarded as a key feature of the method. The findings demonstrated that the suggested method was well-organized in terms of model construction since it uses fewer layers than [22], which raises the computational complexity of the model and lengthens training. In addition, unlike [20], our model is independent of the CNN standard used version models. The distinction is that we constructed our model in accordance with the face recognition issue.

Table 4 demonstrated the approaches taken and the outcomes in comparison to the strategy that was suggested. Comparing the outcomes of our suggested technique to some recent previous works, the results were encouraging.

Table 4. Comparison of Proposed Model with other methods used FEI

Reference	Method	Accuracy
S. Almabdy and L. Elrefaei (2019) [20]	Alexnet	98.70%
	Resnet-50	98.50%
A. Curtidor, et al. (2021) [21]	RLD	93.57%
H.P. Win, et al. (2021) [22]	CNN	99.10%
The proposed model	CNN	98.67

6. CONCLUSION

To address the issue of human face recognition on problematical face images such as pose challenge, a suggested strategy based on "convolutional neural network " has been presented in this study. We used CNN to extract features from different facial posture orientations and classify them in order to complete the face recognition task. Numerous tests on the FEI database and comparisons with other widely used facial recognition techniques were utilized to demonstrate the efficiency of the proposed methodology. We have successfully maintained the image's high resolution since reducing its size to half only. Moreover, we recognized face images without cropping out the face portion and with poses reaching 180 degrees. In addition, via CNN, we extracted depth features and recognized the face with a smaller number of face images. One of the limitations we encountered is that when the layers increased in number, The model's overall complexity increased along with the computing time. The best recognition accuracy for the suggested technique is 98.67% and F1_score of 98.53%. Comparing with other technique, our technique had promising results in respect to the challenge of pose in FEI database.

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