An Effective Face Recognition System Based on Transfer Learning

Abdessalam Hattab[1,*,†], Ali Behloul[1,†]

[1]LaSTIC Laboratory, Department of Computer Science, Batna-2 University, Batna, Algeria

Abstract

Face recognition is a widely studied field in biometrics that has achieved notable success in controlled environments. However, challenges arise when faced with uncontrolled conditions such as facial expressions, occlusions, and illumination variation. This paper proposed an effective face recognition system that addresses these challenges based on fine-tuned Xception Model. The system utilized a newly proposed deep CNN model inspired by the pre-trained Xception model. We employ the Transfer Learning technique to effectively train our proposed Deep CNN model and mitigate overfitting. Our proposed system successfully addresses the challenges associated with unconstrained conditions and training Deep Learning models using limited datasets. Experimental results demonstrate the superiority of our face recognition system over state-of-the-art methods in uncontrolled environments. Impressively, the system achieved a perfect accuracy rate of 100% on the ORL database using a two-fold cross-validation protocol. On the AR database, the system achieved a significant accuracy rate of 95.17% by training only on the fully visible faces and testing on occluded faces. Additionally, the system achieved an accuracy rate of 99.93% on an AR dataset containing illumination variation using a two-fold cross-validation protocol.

Keywords

Face recognition, Convolutional Neural Networks, Transfer Learning, Pre-trained Xception model

1. Introduction

Advancements in technology have led to the widespread adoption of automatic face recognition in several applications, which have become increasingly popular for personal identification purposes and have gained popularity due to their non-intrusive and user-friendly nature. Handcraft face recognition methods, like LBP [1], PCA [2], and LDA [3], have shown commendable performance in constrained environments. However, their performance significantly degraded in unconstrained scenarios involving occlusion and variations in illumination, pose, and expression[4]. To tackle this issue, Deep Learning (DL) approaches, particularly Convolutional Neural Networks (CNNs), have obtained high accuracy rates in image recognition, including biometric applications [5], [6]. This paper introduces a novel and effective face recognition system relying on a new Deep CNN architecture inspired by the Xception model [7]. Transfer learning was employed in our study to address the challenge of limited data that can negatively impact the training performance of our proposed deep CNN model. By leveraging the power of transfer learning, we used a part of the pre-trained Xception model as a foundation for our face recognition system. The knowledge and learned representations from the pre-training on the ImageNet dataset [8] were transferred and fine-tuned on our specific face recognition task. The proposed system is designed to tackle the challenges associated with recognizing faces in uncontrolled environments, where factors like lighting, pose variations, and occlusion can significantly impact the accuracy of face recognition systems. Moreover, the system aims to address the limitations posed by small datasets, which often hinder the training of deep learning models. The primary objective of this study is to thoroughly evaluate the performance of our proposed face recognition system and compare it against existing state-of-the-art systems. The remaining sections of this paper are arranged as follows: Section 2 presents an overview of the related works. The proposed system is introduced in Section 3. Detailed experimental results, along with a comparison to previous approaches, are provided in Section 4. Finally, Section 5 concluded the paper.

2. Related Work

Over the past few years, there has been a proliferation of studies focused on face recognition. This section provides an overview of some of these research endeavors. Wang et al. [9] presented a hybrid system designed for facial recognition. The authors initially employed Local Binary Patterns (LBP) to generate LBP images, which were then utilized as input for a Deep Convolutional Neural Network (CNN). The proposed approach demonstrated a commendable accuracy rate in the task of face recognition. In their study, Ouyang et al. [10]

6th International Hybrid Conference On Informatics And Applied Mathematics, December 6-7, 2023 Guelma, Algeria

*Corresponding author.
†These authors contributed equally.
a.hattab@univ-batna2.dz (A. Hattab); a.behloul@univ-batna2.dz (A. Behloul)
0000-0003-1796-9267 (A. Hattab); 0000-0002-8664-7301 (A. Behloul)

employed the Improved Kernel Linear Discriminant Analysis (IKLDA) technique along with Probabilistic Neural Networks (PNNs) for face recognition. The proposed approach showed promising results, particularly when dealing with datasets that contained only a small number of samples. Using a widely-used multi-sample dataset, Min et al. [11] trained a Deep Convolutional Neural Network (CNN) model. Subsequently, the authors utilized this pre-trained model for face recognition on various datasets. To enhance the accuracy rate, they employed the K Class Feature Transfer (KCFT) technique, which enriched the intra-class variation. In their research, Kamencay et al. [12] introduced a novel face recognition system that utilized Convolutional Neural Networks (CNNs) for feature extraction. The proposed system was evaluated using the ORL database and demonstrated an impressive accuracy rate of 98.3Ȯusliman et al. [13] introduced a set of Rotation-Invariant features based on directional coding for texture classification. These features have been used in the face recognition field and exhibited exceptional accuracy when tested on diverse face image databases. Sapijaszko et al. [14] conducted a study where they built a face recognition system that employed a preprocessing algorithm to enhance the quality of facial images. The system extracted features from the improved images based on Discrete Cosine Transform and Discrete Wavelet Transform algorithms. In the classification stage, they employed a multilayer sigmoid neural network. In their research, Hattab and Behloul [15] employed the SIFT technique to identify important regions within facial images. Subsequently, the authors utilized Adaptive Local Ternary Pattern (ALTP) to extract features from the identified regions. For the classification stage, they employed the K-Nearest Neighbors (KNN) algorithm. The proposed method demonstrated a notably high accuracy rate compared to traditional handcrafted methods. In another study, Hattab and Behloul [16] extract facial features from face images based on the pre-trained models AlexNet-v2 [17] and VGG16 [18]. They then employed Linear Support Vector Classifier (LinearSVC) for classification purposes. The proposed method achieved a high accuracy rate when evaluated on the ORL database. However, it should be noted that the models used in this approach contained a large number of parameters, reaching into the tens of millions. Mehdipour Ghazi and Kemal Ekenel [19] conducted a comprehensive analysis of the Visual Geometry Group (VGG) Face Network, a Convolutional Neural Network (CNN) architecture widely used for face recognition. The VGG Face Network utilized a massive dataset consisting of 2.6 million facial images for training. In [20], a sparse regularized Non-negative Matrix Reconstruction (NMR) method is presented, wherein the traditional L2-norm constraint on the NMR framework's representation is replaced by an L1-norm constraint. This modification aims to enhance sparsity in the representation. However, despite its advantages, the image reconstruction methods based on this approach suffer from several well-known drawbacks. These drawbacks include the requirement of an overcomplete dictionary, a significant increase in the number of gallery images, which introduces complexity issues, and limitations in terms of generalization capability. These limitations pose challenges in practical implementation and affect the overall effectiveness and scalability of the proposed method. Liao and Gu [21] introduced a novel method for face recognition called Dictionary Learning and Subspace Learning (DLSL) . This approach effectively addresses the challenges posed by corrupted data, such as noise, occlusion, and significant pose variations. DLSL incorporates a subspace learning algorithm that utilized both sparse and low-rank constraints. Through extensive experiments conducted on several face databases, the results demonstrate that DLSL outperforms many state-of-the-art algorithms. This highlights the superior performance of DLSL in achieving improved accuracy and robustness in face recognition tasks. In their study, Zeghina et al. [22] utilized the Harris Detector to identify significant regions within facial images. These regions were then extracted and fed into a proposed Convolutional Neural Network (CNN) for face recognition. The system's performance was evaluated using multiple datasets, and it achieved satisfactory results, particularly in handling occluded face images. Ayyavoo and Suseela [23] introduced a robust method that combined the use of 2D Discrete Wavelet Transform (DWT) and Contrast Limited Adaptive Histogram Equalization (CLAHE). The proposed approach involved several steps. Firstly, the image was decomposed into high-frequency and low-frequency components using 2D DWT. Next, CLAHE was applied specifically to the low-frequency components, enhancing their contrast. Finally, the features were extracted using Gabor Magnitude (GM) analysis. This method aimed to mitigate the impact of illumination effects and improve the accuracy and robustness of face recognition systems. Yuan et al. [24] introduced a collaborative representation technique that captures the relationships between data points. By integrating Fisher Discriminant Analysis (FDA) and LDA, the authors were able to effectively represent the data in a reduced-dimensional space. This novel representation yielded promising outcomes, particularly when applied to a limited training dataset. Notably, it achieved a satisfactory level of accuracy in face recognition on the AR database, which includes variations in illumination. Due to its sensitivity to noise, the traditional Linear Discriminant Analysis (LDA) did not perform well in classifying images captured under unconstrained environments. In response to this limitation, To address the challenges posed by illumination variations in face recognition, Wen et al. [25] introduced a novel approach for feature extraction called Robust Sparse Linear Discriminant Analysis (RSLDA). This method was specifically designed to address the challenges posed by noise. The researchers evaluated RSLDA on the AR database, which includes illumination variations, as well as five other databases. The experiments conducted demonstrated the effectiveness of the proposed RSLDA method. Wen et al. [26] introduced a highly effective linear regression method known as Adaptive Locality Preserving Regression (ALPR). This method proposed a single-view dimension reduction technique that obtained an excellent classification accuracy rate. The efficacy of this linear regression method has been thoroughly demonstrated across various databases. Dahmouni et al. [27] introduced a recognition method tailored for educational applications. Their proposed technique was specifically designed to address the unique requirements and challenges in educational contexts. The authors evaluated their method using the AR database, which comprises images captured under varying illumination conditions. The results of the evaluation demonstrated the effectiveness of the proposed method, achieving an acceptable level of performance. In their research, Hu et al. [28] presented a novel approach for extracting latent low-dimensional features. They introduced a strategy that utilized the non-squared L2 norm to enhance the local intraclass relationships within the data. To validate the effectiveness of their proposed low-dimensional representation, the authors conducted experiments using multiple databases. Hattab and Behloul [29] presented a face recognition method that is robust to illumination variations. The proposed method utilized four blocks of the pre-trained VGG16 architecture, followed by an Average Polling layer, to extract features from the facial images. Subsequently, Principal Component Analysis (PCA) was applied to reduce the dimensionality of the extracted features. In the classification task, Linear Support Vector Classifier (LinearSVC) was employed. The effectiveness of the proposed approach was evaluated using the Extended Yale B and AR databases, both of which contain images captured under varying illumination conditions.

3. The Proposed System

In recent years, Deep Learning has achieved exceptional performance in image recognition tasks, particularly through the utilization of deep Convolutional Neural Networks (CNNs). In the past decade, numerous deep CNN models have been developed, such as Xception [7], inception-v3 [30], ResNet [31], AlexNet [32] and VGG16 [18]. The Xception model has showcased its robustness and effectiveness in various image recognition tasks. The performance of Xception has been exemplary, surpassing other renowned deep CNN models, as demonstrated in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) [7]. The Xception model draws inspiration from the inception-v3 [30] model, incorporating depthwise separable convolution layers instead of inception modules. It has been built with 14 residual blocks and more than 22 million parameters. The architecture of the Xception model is illustrated in Figure 1 (a).

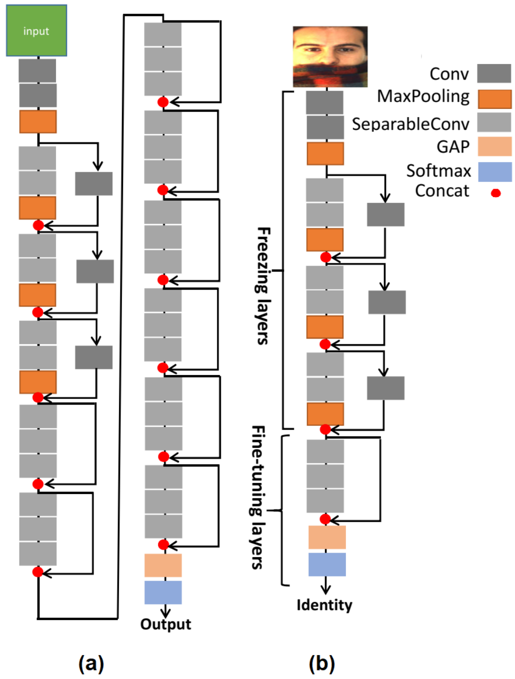


Figure 1: (a) The Xception architecture [7], (b) Our proposed model.

One notable limitation of the Xception model is its high demand for a substantial volume of training data to effectively learn all its parameters. This characteristic poses a challenge when applying the model to tasks with small datasets. In order to address this challenge, researchers have employed Transfer Learning. They trained the Xception model on a large dataset, then used the pre-trained model to classify the images of a new smaller dataset [33]. The Xception model, pre-trained on the ImageNet dataset offers promising potential for face recognition tasks due to the characteristics of the ImageNet database. With a vast collection of 1.4 million images, approximately 17% of which contain at least one face [34], the ImageNet dataset provides a rich source of diverse facial images. This extensive coverage of facial data enhances the effectiveness of the Xception model pre-trained on the ImagNet database when applied to face recognition tasks.

Through a series of experiments, we have successfully built an effective face recognition system based on the Xception model pre-trained on the Imagnet dataset. Our experiments findings suggest that a CNN model, inspired by the Xception architecture, and incorporating only five residual blocks, proves to be an exceptionally effective model for achieving accurate face recognition results, particularly on limited face datasets captured under unconstrained conditions. The paper proposes a novel CNN model that aims to achieve a balance between computational efficiency and high-performance face recognition. The proposed model comprises only five residual blocks, which are followed by Global Average Pooling (GAP) and Softmax layers. The model architecture includes 5 Convolutional layers, 9 Separable Convolutional layers, and 4 MaxPooling layers. A GAP layer is used to minimize the feature dimensions from 361*728 to 728. Overall, the model consists of less than three million parameters.

To achieve high performance while conserving computational resources, we adopt a strategic approach during the training stage. Specifically, we freeze the initial four pre-trained residual blocks, which are responsible for extracting low-level face features. This allows us to concentrate our efforts on fine-tining the fifth residual block, which plays a crucial role in capturing high-level features capable of extracting representative facial features. At the same time, we train the Softmax classifier, responsible for outputting the person's identity. The architecture of our proposed model, inspired by the Xception model, is depicted in Figure 1 (b).

4. Experiments

In this work, we proposed a face recognition system relying on the Xception model pre-trained on the ImageNet dataset. To demonstrate the effectiveness of our proposed system, we conducted comprehensive evaluations using the cross validation protocol. Our performance evaluations were conducted on the ORL and AR databases, which served as the testbeds for assessing the system's recognition capabilities. Two experiments were conducted using the AR database to assess the performance of our system. In the first experiment, an AR dataset containing persons with glasses and scarves was employed to evaluate the robustness of our method against occlusions. In the second experiment, a dataset containing images captured under illumination variation was utilized to demonstrate the system's capability to robustly recognize faces despite changes in illumination conditions. To establish a comparative analysis, we benchmarked our system's recognition rate against other recent works in the field. This allowed us to gauge the performance of our proposed system relative to existing methodologies and highlight its potential advancements. The experiments for this study were performed utilizing the resources of

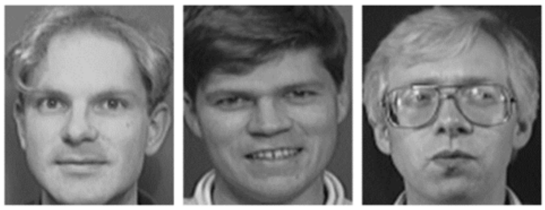


Figure 2: Samples from the ORL database.

Google Colab and leveraging the functionalities offered by the open-source Keras library. We employed the Adam optimizer with a learning rate of 0.001 to train our model for a maximum of 100 epochs, using a batch size of 32. Additionally, we incorporated early stopping measures to address the risk of overfitting by halting training in the absence of improvement in validation accuracy over 10 consecutive epochs.

4.1. Dataset:

We conducted evaluation experiments on two different face datasets:

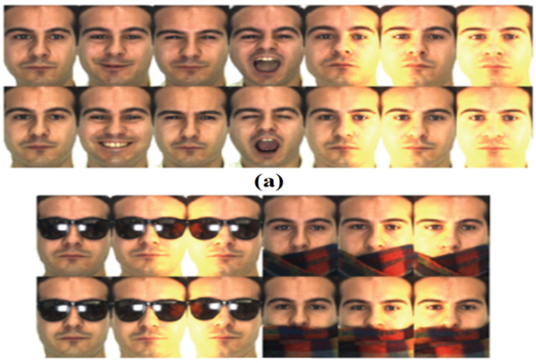
4.1.1. The ORL database:

The ORL database[1] consists of a collection of 400 face images captured from 40 individuals. Each person is represented by ten images, all of which have a resolution of 112×92 pixels. The images in this database were captured under diverse conditions, encompassing variations in illumination, facial expressions, time intervals, and the presence of eyeglasses. Samples from the ORL database are depicted in Figure 2.

4.1.2. The AR Face Database:

The AR database [35] consists of more than 4,000 face images capturing 126 individuals (56 women and 70 men). The images in this dataset were captured under constrained conditions, including various facial expressions, lighting conditions, and occlusions such as sunglasses and scarves. In this work, a subset of 100 subjects was selected, including 50 men and 50 women. Each subject is represented by 26 images. In the first experiment, we used the selected dataset to evaluate the robustness of our system against occlusions; only the images containing fully visible faces were included in the training subset, resulting in 14 images per subject (as shown in Figure 3 (a)). The remaining images, which portray individuals

[1]"AT&T laboratories of cambridge university ,the database of faces", Available online: http://cam-orl.co.uk/facedatabase.html, Accessed on 07/06/2023



(a)

(b)

Figure 3: Samples from the AR database, which (a) contains the fully visible face images, (b) contains individuals wearing glasses or scarves.

Table 1
The average accuracy of our system on the ORL database.

Evaluation protocol	Accuracy rate
Five-fold cross validation	100%
Two-fold cross validation	100%

wearing glasses or scarves, were reserved for a testing subset (see Figure 3 (b)). In the second experiment, we applied a two-fold cross validation protocol to evaluate the robustness of our system against illumination variation, where we used a dataset containing fully visible faces captured under different illumination variations (as shown in Figure 3 (a)).

.

4.2. Experimental results:

To validate the robustness of our proposed system under uncontrolled conditions, we performed experiments using the ORL database. Our system exhibited exceptional robustness, achieving a remarkable accuracy rate in the experiments. By employing the five-fold and two-fold Cross-Validation protocol (refer to Table 1), we achieved a perfect accuracy of 100%.

To demonstrate the robustness of our proposed system, we conducted a comparative analysis of our accuracy rates against state-of-the-art techniques commonly employed in face recognition research. The outcomes, as displayed in Table 2, clearly indicate that our system surpassed the accuracy rates achieved by recent works on the ORL database. For instance, the system developed by Hattab and Behloul [16] achieved a notable recognition accuracy of 100% on the ORL dataset. However, it is important to note that their system incorporated tens of millions of parameters, while our system utilizes fewer than three million parameters. This highlights the efficiency and effectiveness of our approach in achieving comparable or superior accuracy rates with significantly fewer parameters.

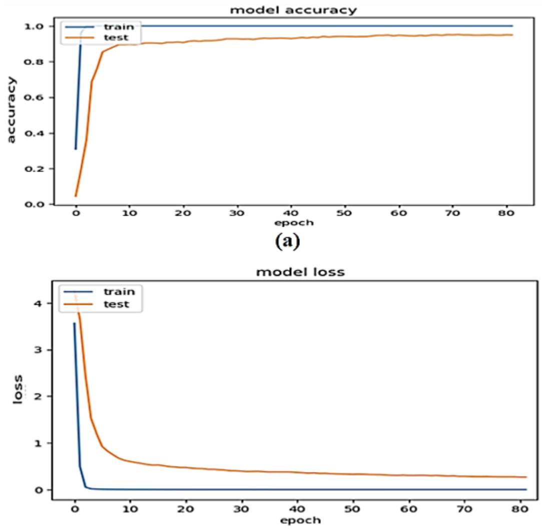


Figure 4: The accuracy (a) and loss (b) values of our proposed model on the AR database, using the occluded face for testing and the fully visible faces for training.

In order to validate the robustness of our proposed system against occlusions, we conducted an additional experiment using the AR database. The training set consisted only the fully visible faces, while the testing set comprised faces intentionally occluded by glasses or scarves. This experimental setup allowed us to assess the system's performance under challenging conditions where occlusions are present. The accuracy and loss function values of our system on the AR database are visualized in Figure 4. In Figure 4 (a), it can be observed that our model achieved a commendable accuracy of 95.17%. This demonstrated the effectiveness of our system in accurately recognizing faces even in the presence of occlusions. Furthermore, Figure 4 (b) provides evidence of the rapid convergence of the loss function. This further supports the robustness of our system. Table 3 proves our system's effectiveness against occlusion compared to state-of-the-art methods on the AR database.

.

By applying the two-fold Cross Validation protocol, we ensured a comprehensive evaluation of our system's performance. The outstanding performance of our proposed system in handling illumination variations is evident from the results presented in Table 4. Our system achieved an impressive accuracy rate of 99.93% on the AR dataset, surpassing the performance of the state-of-the-

Table 2
The accuracy of our system compared to recent works on the ORL database.

Method	Evaluation protocol	Accuracy
Wang et al [9]	Train: 67%, Test: 33%	96.6%
Ouyang et al. [10]	Train: 80%, Test: 20%	97.22%
Min et al. [11]	Train: 10%, Test: 90%	97.77%
Kamencay et al [12]	Train: 80%, Test: 20%	98.30%
Ouslimani et al [13]	Train: 80%, Test: 20%	98.61%
Sapijaszko and Mikhael [14]	Train: 80%, Test: 20%	98.8%
Hattab and Behloul [15]	5-fold cross validation	99.75%
Hattab and Behloul [16]	5-fold cross validation	100%
The proposed System	**5-fold cross validation**	**100%**
	2-fold cross validation	**100%**

Table 3
The accuracy of our system compared to some recent works on the AR database, using the occluded face for testing and the fully visible faces for training.

Method	Accuracy
Mehdipour Ghazi and Kemal Ekenel [19]	59.09%
Chen et al. [20]	86.35%
Liao and Gu [21]	89.11%
Zeghina et al. [22]	94.72%
The proposed system	**95.17 %**

art methods evaluated on the same dataset that contain fully visible faces captured under illumination variation. Table 4 provides a comparative analysis of the accuracy rates obtained by state-of-the-art methods, clearly indicating that our proposed system outperforms other approaches in terms of recognizing faces under varying illumination conditions.

5. Conclusion

This research paper presents an effective face recognition system relying on five residual blocks from the pretrained Xception model, along with Global Average Pooling and Softmax layers. In our proposed system, we freeze the first four residual blocks while retraining the remaining layers. The model employed by our system is specifically designed to address the difficulties associated with training Deep Learning models using limited datasets. By utilizing transfer learning, we overcome the challenges of small datasets and enhance the system's ability to learn discriminative features for accurate face recognition. Our system demonstrated impressive performance under unconstrained conditions, particularly in scenarios involving illumination variations and occlusions.

Our system achieved remarkable accuracy rates across various datasets and scenarios, outperforming state-of-the-art methods. On the ORL database, we achieved a perfect accuracy of 100% by applying a two-fold cross-validation protocol. The accuracy rate of 95.17% on the AR database, utilizing occluded images in the testing set, further demonstrated the system's robustness under the occlusions curse. Additionally, our system attained an accuracy rate of 99.93% on the AR dataset, employing a two-fold cross-validation protocol with fully visible faces captured under varying illumination conditions.

Our future research endeavors will concentrate on the following main objectives. Firstly, we will focus on integrating an anti-spoofing algorithm into our system to enhance its security and prevent face-spoofing attacks effectively. Secondly, our research will extend beyond face recognition alone, as we aim to explore the realm of face-iris multimodal biometric recognition.

References

[1] T. Ojala, M. Pietikäinen, D. Harwood, A comparative study of texture measures with classification based on featured distributions, Pattern recognition 29 (1996) 51–59.

[2] M. Turk, A. Pentland, Eigenfaces for recognition, Journal of cognitive neuroscience 3 (1991) 71–86.

[3] P. N. Belhumeur, J. P. Hespanha, D. J. Kriegman, Eigenfaces vs. fisherfaces: Recognition using class specific linear projection, IEEE Transactions on pattern analysis and machine intelligence 19 (1997) 711–720.

[4] S. G. Kong, J. Heo, B. R. Abidi, J. Paik, M. A. Abidi, Recent advances in visual and infrared face recognition—a review, Computer vision and image understanding 97 (2005) 103–135.

[5] A. HATTAB, A. BEHLOUL, A Robust Iris Recognition Approach Based on Transfer Learning, International Journal of Computing and Digital Systems 13 (2023) 1065–1080. doi:10.12785/ijcds/130186.

Table 4
The accuracy rate of our proposed system compared to some recent works on the AR database, using only the images containing fully visible faces.

Method	Evaluation protocol	Accuracy
Ayyavoo and Suseela [23]	Train/Test: 5/9 images	98.78%
Yuan et al. [24]	Train/Test: 5/9 images	99.18%
Wen et al. [25]	Train/Test: 7/7 images	93.01%
Wen et al. [26]	Train/Test: 7/7 images	98.47%
Dahmouni et al. [27]	Train/Test: 7/7 images	98.45%
Hu et al. [28]	Train/Test: 7/7 images	98.81%
Hattab and Behloul [36]	2 fold cross validation	99.79%
The proposed System	**2-fold cross validation**	**99.93%**

[6] A. Hattab, A. Behloul, Face-Iris multimodal biometric recognition system based on deep learning, Multimedia Tools and Applications (2023). doi:10.1007/s11042-023-17337-y.

[7] F. Chollet, Xception: Deep learning with depthwise separable convolutions, in: Proceedings of the IEEE conference on computer vision and pattern recognition, 2017, pp. 1251–1258.

[8] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, L. Fei-Fei, Imagenet: A large-scale hierarchical image database, in: 2009 IEEE conference on computer vision and pattern recognition, Ieee, 2009, pp. 248–255.

[9] M. Wang, Z. Wang, J. Li, Deep convolutional neural network applies to face recognition in small and medium databases, in: 2017 4th International Conference on Systems and Informatics (ICSAI), IEEE, 2017, pp. 1368–1372.

[10] A. Ouyang, Y. Liu, S. Pei, X. Peng, M. He, Q. Wang, A hybrid improved kernel LDA and PNN algorithm for efficient face recognition, Neurocomputing 393 (2020) 214–222.

[11] R. Min, S. Xu, Z. Cui, Single-sample face recognition based on feature expansion, IEEE Access 7 (2019) 45219–45229. doi:10.1109/access.2019.2909039.

[12] P. Kamencay, M. Benčo, T. Miždoš, R. Radil, A new method for face recognition using convolutional neural network, Advances in Electrical and Electronic Engineering 15 (2017) 663–672.

[13] F. Ouslimani, A. Ouslimani, Z. Ameur, Rotation-invariant features based on directional coding for texture classification, Neural Computing and Applications 31 (2019) 6393–6400.

[14] G. M. Sapijaszko, W. B. Mikhael, Facial Recognition System Using Mixed Transform and Multilayer Sigmoid Neural Network Classifier, Circuits, Systems, and Signal Processing 39 (2020) 6142–6161.

[15] abdessalam Hattab, ali Behloul, A Robust Face Recognition Method Based on ALTP and SIFT, in: Advances in Communication Technology, Computing and Engineering, RGN Publications, 2021, pp. 155–169.

[16] A. Hattab, A. Behloul, New Approaches for Automatic Face Recognition Based on Deep Learning Models and Local Handcrafted ALTP, ICST Transactions on Scalable Information Systems 9 (2021) 171547. doi:10.4108/eai.20-10-2021.171547.

[17] A. Krizhevsky, One weird trick for parallelizing convolutional neural networks, arXiv preprint arXiv:1404.5997 (2014).

[18] K. Simonyan, A. Zisserman, Very deep convolutional networks for large-scale image recognition, 2014.

[19] M. Mehdipour Ghazi, H. Kemal Ekenel, A comprehensive analysis of deep learning based representation for face recognition, in: Proceedings of the IEEE conference on computer vision and pattern recognition workshops, 2016, pp. 34–41.

[20] Z. Chen, X.-J. Wu, J. Kittler, A sparse regularized nuclear norm based matrix regression for face recognition with contiguous occlusion, Pattern Recognition Letters 125 (2019) 494–499.

[21] M. Liao, X. Gu, Face recognition based on dictionary learning and subspace learning, Digital Signal Processing 90 (2019) 110–124.

[22] A. O. Zeghina, O. Zoubia, A. Behloul, Face Recognition Based on Harris Detector and Convolutional Neural Networks, in: International Symposium on Modelling and Implementation of Complex Systems, Springer, 2020, pp. 163–171.

[23] T. Ayyavoo, J. J. Suseela, Illumination preprocessing method for face recognition using 2D DWT and CLAHE, Iet Biometrics 7 (2018) 380–390.

[24] M.-D. Yuan, D.-Z. Feng, Y. Shi, W.-J. Liu, Dimensionality reduction by collaborative preserving fisher discriminant analysis, Neurocomputing 356 (2019) 228–243.

[25] J. Wen, X. Fang, J. Cui, L. Fei, K. Yan, Y. Chen, Y. Xu,

Robust sparse linear discriminant analysis, IEEE Transactions on Circuits and Systems for Video Technology 29 (2018) 390–403.
[26] J. Wen, Z. Zhong, Z. Zhang, L. Fei, Z. Lai, R. Chen, Adaptive locality preserving regression, IEEE Transactions on Circuits and Systems for Video Technology 30 (2018) 75–88.
[27] A. Dahmouni, N. Aharrane, K. El Moutaouakil, K. Satori, A face recognition based biometric solution in education, Pattern Recognition and Image Analysis 28 (2018) 758–770.
[28] L. Hu, W. Zhang, Z. Dai, Joint Sparse Locality-Aware Regression for Robust Discriminative Learning, IEEE Transactions on Cybernetics (2021).
[29] A. Hattab, A. Behloul, A Robust Iris Recognition Approach Based on Pre-trained Inception-v3 Model, International Journal of Computing and Digital Systems 13 (2023) 1065–1080. doi:http://dx.doi.org/10.12785/ijcds/130186.
[30] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, Z. Wojna, Rethinking the inception architecture for computer vision, 2016. doi:10.1109/cvpr.2016.308.
[31] K. He, X. Zhang, S. Ren, J. Sun, Deep residual learning for image recognition, 2016.
[32] A. Krizhevsky, I. Sutskever, G. E. Hinton, Imagenet classification with deep convolutional neural networks, 2012.
[33] K. Shaheed, A. Mao, I. Qureshi, M. Kumar, S. Hussain, I. Ullah, X. Zhang, DS-CNN: A pre-trained Xception model based on depth-wise separable convolutional neural network for finger vein recognition, Expert Systems with Applications 191 (2022) 116288.
[34] K. Yang, J. H. Yau, L. Fei-Fei, J. Deng, O. Russakovsky, A study of face obfuscation in imagenet, in: International Conference on Machine Learning, PMLR, 2022, pp. 25313–25330.
[35] A. Martinez, R. Benavente, The AR face database: CVC technical report, 24 (1998).
[36] A. Hattab, A. Behloul, An Illumination-Robust Face Recognition Approach Based on Convolutional Neural Network, in: Modelling and Implementation of Complex Systems: Proceedings of the 7th International Symposium, MISC 2022, Mostaganem, Algeria, October 30-31, 2022, Springer, 2022, pp. 135–149.