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Face recognition using deep convolutional neural networks

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ABSTRACT

This paper presents a Deep Convolutional Neural Network (DCNN) based facial recognition model that handles illumination, expression, and position variations, among other typical challenges in the area. The model's flexibility and generalizability are enhanced using data augmentation methods for the features extracted from preprocessed face images using CNN. The model was evaluated for performance using five well-recognized datasets: ORL, Yale, Extended Yale B, JAFFE, and LFW. The proposed model attained 97% accuracy on ORL, 93% on Yale, 98% on Extended Yale B, 100% on JAFFE, and 98% on LFW, surpassing current state-of-the-art techniques. To make the model more resilient on smaller datasets such as ORL and JAFFE, data augmentation was performed. On the other hand, Extended Yale B and other more diverse datasets performed well even without augmentation. Also, preprocessing techniques, such as data balance and augmentation, have improved identification abilities, especially in real-world situations like LFW. Overall, this study underscores the power of DCNNs for face recognition and highlights how tailored data augmentation can boost performance across different datasets.

1. Introduction

Facial recognition, a rapidly evolving component of computer vision, is widely used in security, social media, biometrics, and personalized user experiences. Facial recognition management has evolved from traditional techniques, such as geometric-based methods, to modern and accurate models powered by artificial intelligence, especially deep learning. As a result, the urgency for reliable and rapid identification systems has increased [1]. However, traditional methods follow the manual design of features such as eigenfaces and Fisherfaces, which face challenges due to pose, illumination, and occlusion variations. Existing methods struggle to leverage the underlying diversity of facial data, particularly in large-scale real-world scenarios, and they fail to exhibit robustness across various groups. This permits facial recognition to use Deep learning, particularly DCNNs, which have revolutionized human face recognition. DCNNs can learn hierarchical characteristics from raw pixel-level information in an auto manner, thus enabling the model to learn complex patterns that are difficult to handle otherwise. Their success is majorly associated with their ability to model non-linear relationships and learn discriminative features even in challenging situations such as changing illumination, angles, pose, or partial occlusion [2, 3].

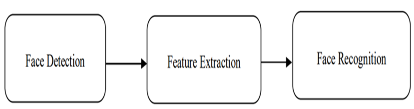

Figure 1. Face Recognition Process.

As shown in Fig. 1, facial recognition systems go through three stages: detection, feature extraction, and recognition. The automatic facial recognition system begins with face detection and establishes whether a face is present in the image. If faces are detected, it aims to locate these faces in the image. In the feature extraction stage, a feature vector known as the signature is retrieved from the recognized face; this vector must be sufficient enough to describe the face. Verifying the face's uniqueness and ability to differentiate between two distinct individuals is necessary. Notably, this process may be done using the face detection phase. Verification and identity are necessary for classification. Authorizing access to a desired identity needs verification, which involves matching two faces. On the other hand, to determine a face's identity, identification compares it to several different faces [4].

1.1 Related work

Several studies have offered alternative approaches to improving facial recognition accuracy on various datasets. P. Gupta, N. Saxena, M. Sharma, and J. Tripathi et al. [5] Utilized a CNN with Haar Cascade for preprocessing and a four-layer architecture, achieving 97.05% accuracy on the Yale Faces dataset. B. R. Ilyas, B. Mohammed, M. Khaled, and K. Miloud et al. [6] A deep neural network with Viola-Jones detection, ResNet50, and VGG16 was applied for feature learning. ResNet50 achieved 97.23% on Extended Yale B and 98.38% on the CMU PIE dataset. R. Ravi and S. Yadhukrishna et al. [7] Combining LBP, CNN, and SVM for expression recognition achieved 97.32% on CK+ but only 31.82% on the Yale Faces dataset. V. B. T. Shoba and I. S. Sam et al. [8] Proposed a hybrid system using SURF, HOG, and MSER, achieving 91.2% on Yale, 93.1% on FGNET, and 94.6% on MORPH datasets, focusing on improving age-invariant recognition. P. B and M. J et al. [9] Developed a real-time CNN-based system with 98.75% accuracy on AT&T datasets and 98.00% for real-time inputs by tuning convolutional parameters. T. Alghamdi and G. Alaghband et al. [10] Introduced a two-concurrent CNN (CCCNN) model achieving 100% accuracy on Extended Yale-B, 90.12% on AR, and 84.34% on LFW datasets. Y. Zhu and Y. Jiang et al. [11] Combining 2DPCA and LBP for robustness. Features are trained using a CNN for classification. The proposed method achieved 95% accuracy on the Jaffe and AR datasets. A. K. Dubey and V. Jain et al. [12] proposed a VGG16-based transfer learning model. It was tested on the CK+ dataset and JAFFE dataset.

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Nomenclature:

CNN	Convolutional Neural Network
DCNN	Deep Convolutional Neural Network
JAFFE	Japanese Female Facial Expression Database
LFW	Labeled Faces in the Wild Dataset
ORL	Olivetti Research Laboratory Face Database
ReLU	Rectified Linear Unit
SSD	Single Shot MultiBox Detector

The model achieved 94.8% accuracy on CK+ and 93.7% on JAFFE. S. Hangaragi, T. Singh, and N. Neelima et al. [13] used a deep neural network with Viola-Jones detection, achieving 94.23% on the LFW dataset, demonstrating robustness under variable configurations. A. Rajpal, K. Sehra, R. Bagri, and P. Sikka et al. [14] Evaluated DNNs (LeNet-5, AlexNet, Inception-V3, VGG16) with LIME for interpretability, with VGG16 achieving the highest accuracy: 100% on Yale, 97.5% on AT&T, and 97% on LFW. K. Jha, S. Srivastava, and A. Jain et al. [15] Integrated HOG detection, DHE enhancement, and DCT-ULBP for feature extraction achieved 94.58% accuracy on ORL, outperforming traditional methods. Y. El Madmoune, I. El Ouariachi, K. Zenkouar, and A. Zahi et al. [16] Proposed Krawtchouk Moments CNN (KMCNN) for noise-robust recognition, achieving 92.03% on Yale-B, 96% on ORL, and up to 73.97% on LFW under noisy conditions.

1.2 Convolutional neural networks

Hubel and Wiesel discovered convolutional neural networks(CNNs) in 1962 [17]. When it comes to classifying images in data, CNNs are among the most popular deep-learning models [18]. It is the most widely used deep learning method for recognizing patterns in images, classifying images, and extracting other features from images [19]. The human brain's visual receptive fields serve as an inspiration for CNN architecture. These methods aim to develop a learning framework that outperforms the conventional feature extraction method (handcrafted features) by combining the extraction with the classifier. One important aspect of deep learning for the classification of images is its use of CNN architectures [20]. Different types of convolutional neural networks exist. Convolutional, max-pooling, and fully connected layers are essential components of CNNs, as shown in Fig. 2. The input layer's construct must match the input data exactly. The output layer's construct must match the learning data exactly. The layers among the input and output layers are called hidden layers [21].

1.3 Problem statements and research challenges

Several factors impact the performance of facial recognition. Many studies were capable of reaching 100% accuracy; however, elements that fall into the two categories of extrinsic and intrinsic factors have prevented a sufficient standard. The physical characteristics of human appearance, such as aging, plastic surgery, facial expression, and so on, are included in the intrinsic factor [22]. The variations in the human face's appearance, such as low resolution, occlusion, noise, posture variation, illumination, etc., are included in the extrinsic factor. So, the following are the significant factors that affect the facial recognition process: Aging, Facial expression, Low Resolution, Occlusion, Noise, Illumination, Pose Variation, Large-scale systems, and Plastic Surgery.

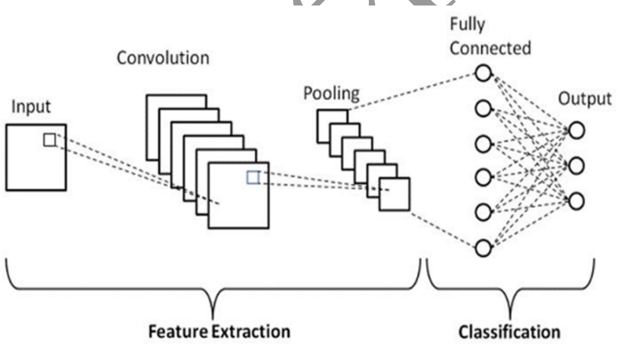

Figure 2. Basic CNN architecture [21].

2. Methodology

The primary objective of this paper is to implement an algorithm designed to enhance image classification performance through a deep convolutional neural network approach for automated facial recognition. Designing a CNN model from scratch requires carefully selecting optimal layers within the model architecture.

2.1 Datasets

For evaluating the performance and generalization of our CNN-based face recognition system, we used five datasets: ORL [23], Yale [24], Extended Yale B [25], JAFFE [26], and LFW [27]. These datasets, shown in Table 1, were selected for their variety of facial expressions, illumination, and poses to guarantee thorough testing across multiple situations.

2.1.1 ORL

To evaluate pose-invariant face recognition's resilience against changes in viewpoint, poses, and illumination, researchers often employ the ORL dataset, which has 400 images of 40 subjects (10 images per subject) recorded in different orientations and illumination situations.

2.1.2 Yale

The Yale Face Database is used to evaluate emotion-invariant person recognition performance. This database consists of 165 grayscale images of 15 subjects showing 11 emotions, such as happy, sad, and shocked. This database aims to tackle the difficulty of recognizing faces with various emotional expressions.

2.1.3 Extended Yale B

The Extended Yale B database evaluates model resilience to significant illumination variations and addresses the difficulty of high illumination variations The database comprises 2,452 images of 38 subjects captured under 64 illumination situations.

2.1.4 JAFFE (Japanese Female Facial Expression Database)

Evaluating expression-based recognition, the JAFFE dataset focuses on recognizing emotion with its 213 grayscale images of 10 Japanese female participants showing seven emotions, such as neutral, happy, and angry.

2.1.5 LFW (Labeled Faces in the Wild)

To evaluate how well facial recognition systems work in real life, researchers use the LFW dataset, which includes 13,233 images of 5,749 subjects captured in natural settings and shows large ranges of background, pose, illumination, and occlusion.

Table 1. Overview of the datasets.

Dataset	Number of Images	Number of Individuals	Key Features	Challenges
ORL	400	40	Different orientations, illumination	Pose and illumination variation
Yale	165	15	Multiple expressions	Emotional expression variation
Extended Yale B	2,452	38	64 illumination conditions	Extreme illumination variations
JAFFE	213	10	7 emotional expressions	Expression-based recognition
LFW	13,233	5,749	Collected in the wild	Real-world variability

2.2 Preprocessing

Before training and evaluating our facial recognition model, we applied several preprocessing techniques to homogenize the datasets, which improved its predicted performance. The First Step of preprocessing is Face detection and image cropping. A face detection algorithm, Single Shot MultiBox Detector (SSD) [28], was employed to detect faces and cropping in each image. Maintaining a constant image size and converting the image to a grey scale provides uniform input to successive models, allowing for fast processing and analysis. The dataset has been split into testing and training sets using a k-fold for all datasets except LFW. The hold-out data was split, 80% for training and 20% for testing. We employed data augmentation approaches to the dataset as the final preprocessing step to increase the model's robustness and generalizability. The clean, standardized, and improved data from the model ensures real-world variation representation according to these preprocessing steps. This makes the model more adaptable, which enhances its accuracy in recognizing faces in various settings.

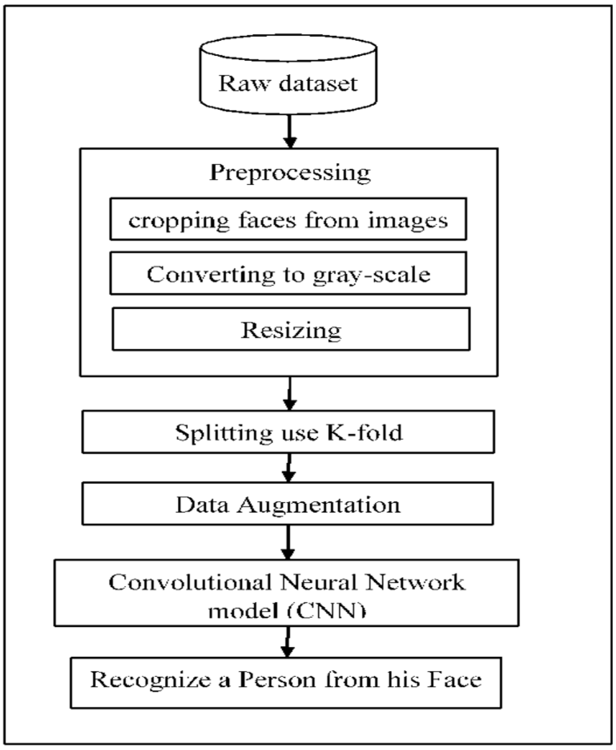

Figure 3. Block Diagram of the Proposed Model.

2.3 Proposed model

Convolutional neural networks, built from scratch, handle facial recognition tasks. Their design allows for the extraction and categorization of facial features using several convolutional and fully connected layers.

2.3.1 The architecture of the model

Three convolutional layers using a set of kernels extract the feature map from the input images, which is then downsampled at the pooling layer. In our first convolutional layer, we apply 16 3x3 filters on input images with the parameters (100, 100, 1), where the one is for greyscale images. The backpropagation technique improves the filters during training after they are first started randomly. Then, after applying the ReLU activation function, the feature map's spatial dimensions are reduced to half by implementing a Max-pooling layer with a 2x2 filter size and two strides. The second convolutional layer has 32 filters of size 3x3 with ReLU activation, and the 2x2 Max-pooling layer with a stride of 2 follows this third convolutional layer. It has 64 filters with size 3x3, a ReLU activation, and a 2x2 Max-pooling layer with a stride of 2. After we generate two-dimensional feature maps using convolutional and pooling layers, we flatten them to a one-dimensional vector using the Flatten layer. The fully connected layers use this vector to process the features retrieved. The fully connected layers are simply regular neural network layers where each neuron is connected to all units in the previous layer. There is only one fully connected layer with 128 units with ReLU activation; a Dropout layer with a 0.4 rate prevents overfitting by randomly dropping 40% of the neurons in the training phase. For multi-class classification problems, the output layer applies the Softmax activation function, as shown in Fig. 3.

2.3.2 Training and evaluation of the proposed model

The dataset was split into five folds using k-fold cross-validation to enhance model evaluation. The difference between the actual and predicted labels was calculated using the categorical cross-entropy loss function. Categorical cross-entropy measures how much the actual and predicted labels coincide in a multi-class classification problem. The Adam optimizer was used to minimize categorical cross-entropy loss. Adam is the conventional option, as it works great for models with variable learning rates and very sparse gradients. The model was trained with 50 epochs and a batch size of 32. During each epoch, we used our training data to update the model's weights, monitor overfitting, and ensure generalization throughout our validation data. The model weights were then saved post-training at the epoch where validation accuracy was the highest. This test's dataset was used to evaluate the model's accuracy and loss measures to infer the model's generalizability on unseen data, resulting in an accurate model.

3. Results and discussions

Being presented are the results of the conducted tests on five face recognition datasets: ORL, Yale, Extended Yale B, JAFFE, and LFW, evaluating the accuracy, precision, recall, and F1-score of the proposed CNN model. This occurred under two settings, firstly, data augmentation used during training, and secondly, data augmentation not used during training. Experimental outcomes depict data augmentation lifts robustness of poses, illumination variations, and emotional differences. Additionally, it informs about the model's capability to generalize over datasets. Through comprehensive comparisons between the two training strategies, we reveal the pros and cons of augmented data.

3.1 ORL dataset results

The model obtained an accuracy of 95.25%, precision of 96.08%, recall of 95.25%, and an F1-score of 95.78% when trained without augmentation. These measures display high performance; however, with a small dataset, the model may not generalize well to variations in the dataset, such as different poses. Training with data augmentation, however, produced vastly superior results. It achieved an accuracy of 97.50%, precision of 97.92%, recall of 97.50%, and F1-score of 97.20% on the model. These improvements indicate that data augmentation improved the model's robustness by exposing more diverse data. In Fig. 4, we can see the accuracy and loss for each fold, and in Fig. 5, we can see the confusion matrix with and without augmentation.

3.2 Yale dataset results

The model's accuracy of 96.97%, precision of 97.98%, recall of 96.97%, and F1-score of 96.77%, without data augmentation, achieves the accuracy of 93.33%, precision of 94.80%, recall of 93.33%, and an F1-score of 92.85% with augmentation indicates resilience. However, there is a possibility of overfitting to the augmented patterns. In Fig. 6, the accuracy and loss for each fold are presented, and Fig. 7 presents the confusion matrix with and without augmentation.

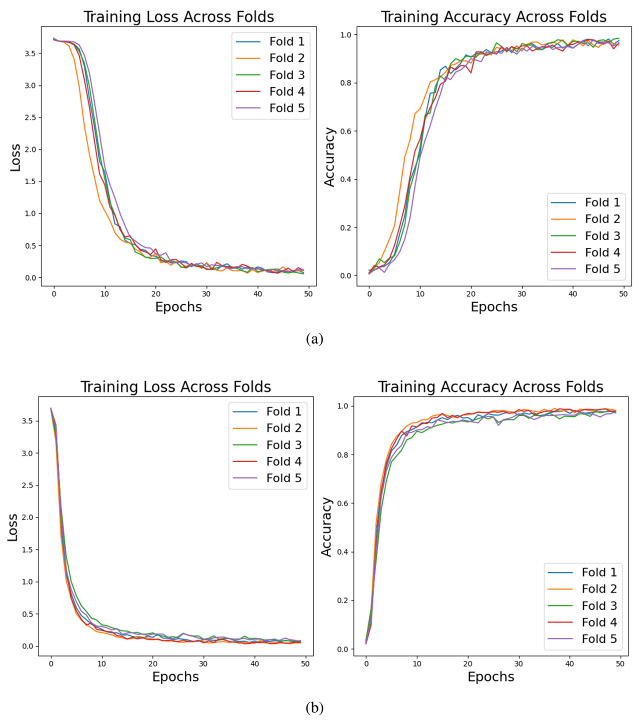

Figure 4. Accuracy and loss of 5-fold across ORL dataset (a) without (b) with data augmentation.

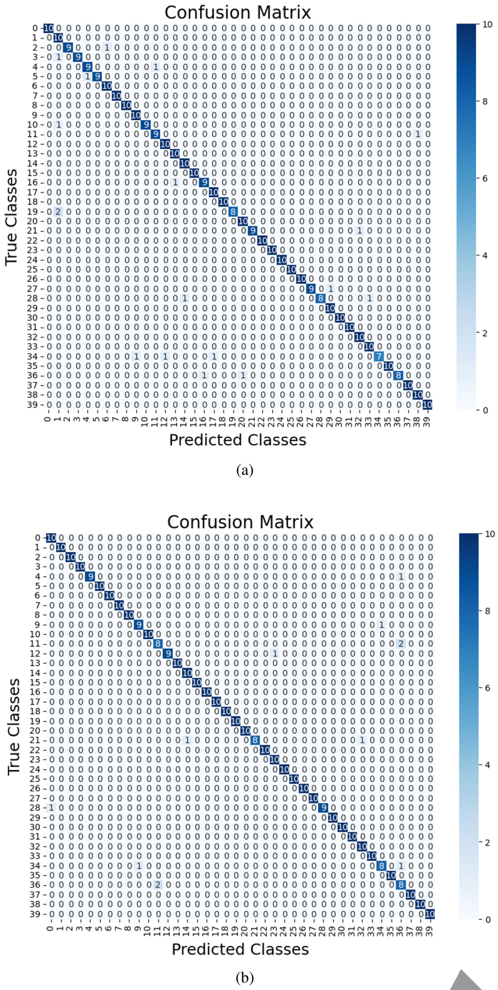

Figure 5. Confusion Matrix of 5-fold across ORL dataset (a) without (b) with data augmentation.

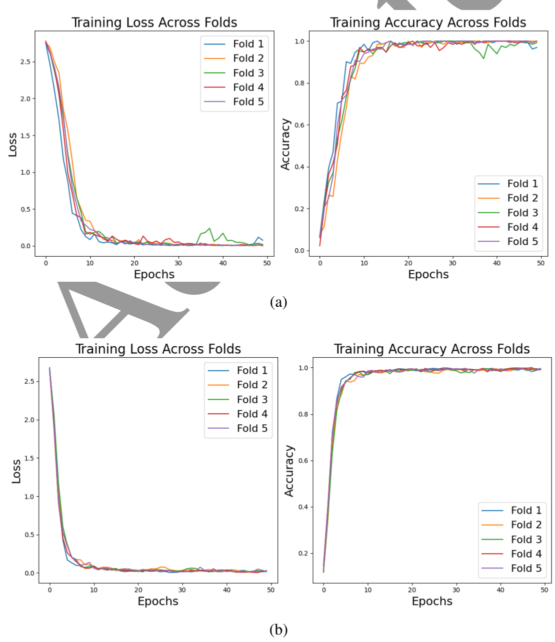

Figure 6. Accuracy and loss of 5-fold across Yale dataset (a) without (b) with data augmentation.

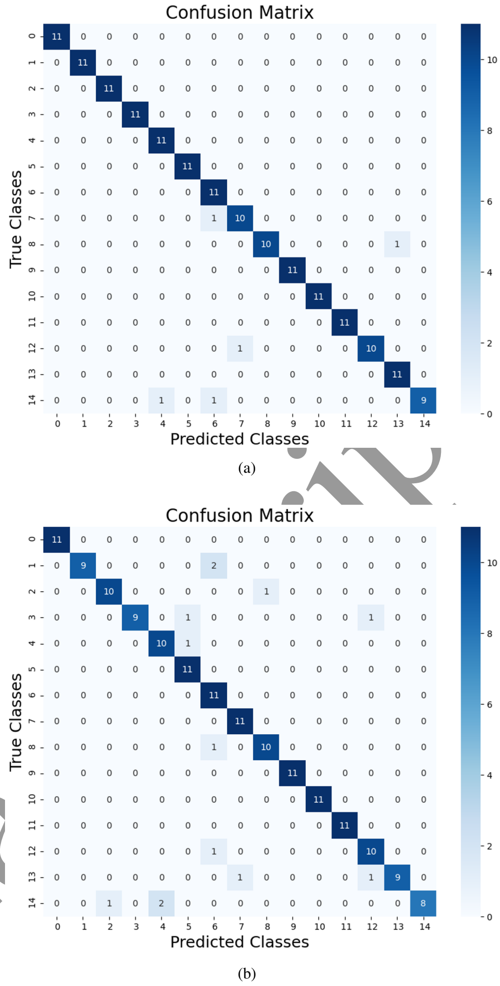

Figure 7. Confusion Matrix of 5-fold across Yale dataset (a) without (b) with data augmentation.

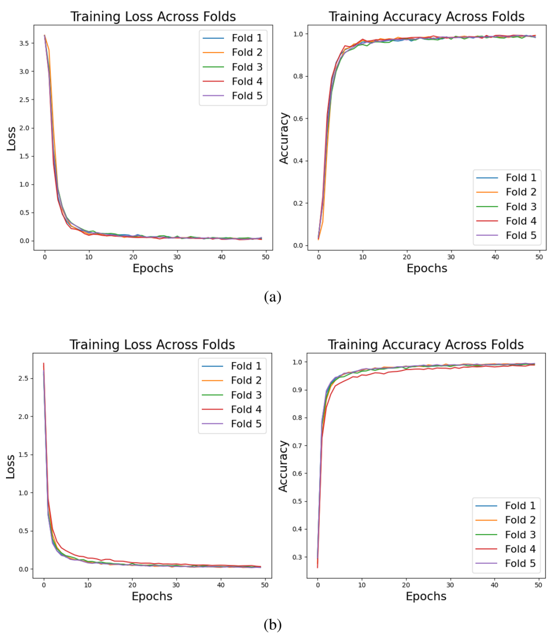

Figure 8. Accuracy and loss of 5-fold across Extended Yale B dataset (a) without (b) with data augmentation.

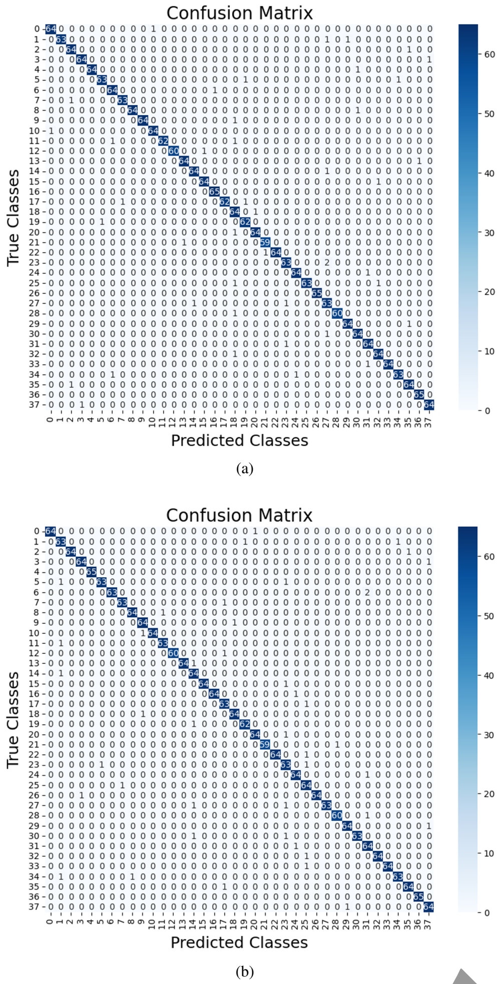

Figure 9**.** Confusion Matrix of 5-fold across Extended Yale B dataset (a) without (b) with data augmentation.

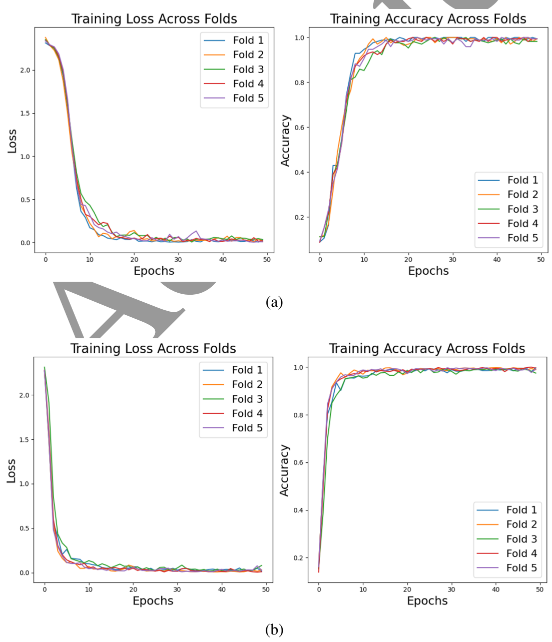

Figure 10**.** Accuracy and loss of 5-fold across JAFFE dataset (a) without (b) with data augmentation.

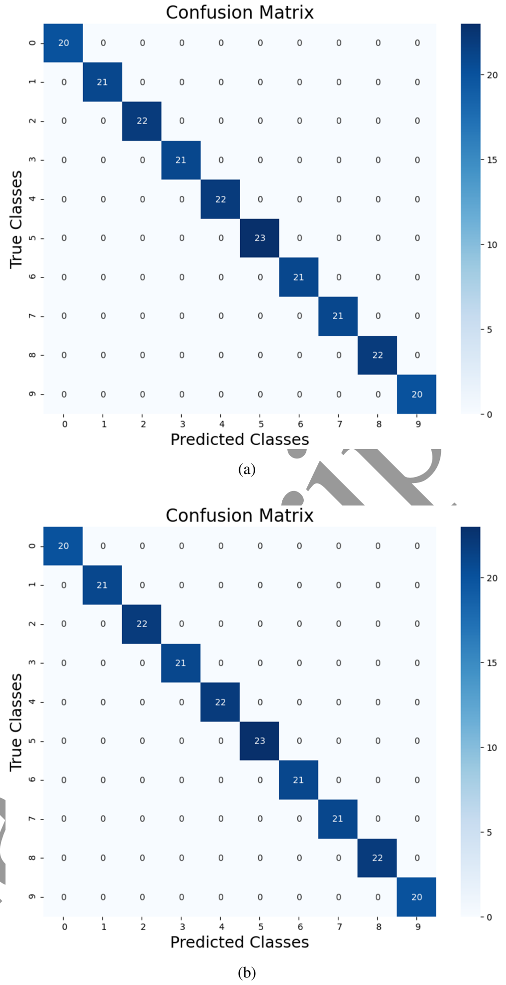

Figure 11**.** Confusion Matrix of 5-fold across JAFFE dataset (a) without (b) with data augmentation.

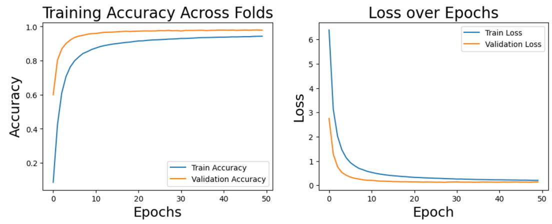

Figure 12**.** Accuracy and loss across LFW dataset.

3.3 Extended Yale B dataset results

The model's consistent accuracy of 98% across the board for the Extended Yale B dataset regardless of data augmentation indicates strong generalizability to illumination fluctuations caused by the dataset's actual variation. Thus, data augmentation is not needed. In Fig. 8, the accuracy and loss for each fold are shown, while in Fig. 9, the confusion matrix with and without augmentation is shown.

3.4 JAFFE dataset results

The model's accuracy, precision, recall, and F1-score with and without data augmentation reached 100%. Still, the model's loss was 0,0035 without data augmentation and 0.0008 with data augmentation, indicating that data augmentation improved classification with fewer false positives or negatives. Figure 10 showcases the accuracy and loss for each fold, and Fig. 11 shows the confusion matrix with and without augmentation.

3.5 LFW (Labeled faces in the wild)

The LFW dataset was balanced as a part of our preprocessing step to improve the model's performance. To be more precise, classes with more than 50 images were downsampled to make the distribution uniform, while classes, with less than 50 images used data augmentation. This step aimed to increase the model's generalizability for different face representations and reduce class imbalance. As a result of these preprocessing steps, the model achieved an accuracy of 98.24%, precision of 98.337%, recall of 98.24%, and an F1-score of 98.19%. This indicates that the model's capacity for recognizing and classifying faces in images was enhanced via downsampling and data augmentation. These findings are presented in Fig. 6, which displays the accuracy and loss. Experiments demonstrated how the proposed CNN model works in various scenarios and provides illumination for the effects of data augmentation and dataset-specific features. Data augmentation significantly enhanced performances for smaller or less diverse datasets like ORL and JAFFE. This is done by increasing the variability in position, illumination, and emotion. However, caution is needed when applying augmentation since it causes overfitting on datasets like Yale's. After being enhanced, ORL and JAFFE networks had the largest increases in accuracy and loss reduction. Since the fundamental Extended Yale B variety consistently performed well regardless of augmentation, it shows signs of sufficiency. By implementing augmentation and balancing, LFW achieved strong generalizability, a requirement for resolving the class imbalance. Although Yale showed resiliency, its performance with augmentation showed signs of overfitting. Data augmentation's effectiveness in enhancing performance depends on the magnitude and variability. Also, Preprocessing methods like balancing were crucial in handling imbalanced datasets like LFW. Table 2 compares the proposed models with and without data augmentation with the current approaches.

Table 2. Comparison of Face Recognition Effectiveness Proposed Model with and without Data Augmentation with Current Approaches.

References	ORL	Yale Face	Extended Yale B	JAFFE	LFW
[14]	97%	—	—	—	—
[15]	94%	—	—	—	—
[16]	96%	—	—	—	—
[5]	—	97%	—	—	—
[7]	—	31%	—	—	—
[8]	—	91%	—	—	—
[6]	—	—	97%	—	—
[10]	—	—	100%	—	—
[16]	—	—	98%	—	—
[11]	—	—	—	96%	—
[12]	—	—	—	93%	—
[10]	—	—	—	—	84%
[14]	—	—	—	—	97%
[16]	—	—	—	—	73%
Proposed model with augmentation	97%	93%	98%	100%	98%
Proposed model without augmentation	95%	96%	98%	100%	—

4. Conclusion and future scope

The results of the experiments provide light on the impacts of data augmentation and dataset-specific characteristics,and also demonstrate the numerous contexts in which the proposed CNN model operates. Data augmentation notably improved performances in less diversified or smaller datasets such as ORL and JAFFE by making stance, illumination, and emotion variances more robust. However, applying augmentation is not always beneficial since it can cause overfitting on datasets like Yale's. The two networks that showed the greatest improvement in accuracy and loss reduction after augmentation were ORL and JAFFE. While, the basic variety of Extended Yale B seemed enough since it regularly performed well, even without augmentation. Strong generalizability was obtained by LFW via augmentation and balancing, which were necessary to solve the class imbalance. Despite displaying resilience, Yale's performance with augmentation indicated overfitting. So although data augmentation often improves performances, how well it does so is size and variability-dependent. Additionally, preprocessing techniques such as balancing were essential to deal with unbalanced datasets like LFW.

This research provides a route for improving facial recognition models. A promising option for future research is to modify the model for online facial recognition, enhancing its efficiency and applicability for real-time use. Furthermore, refining data augmentation methods may enhance performances, especially on datasets such as Yale, where differences in accuracy were observed. Also, investigating advanced architectures and transfer learning techniques may enhance robustness and generalization across various real-world situations.

Authors' contribution

All authors contributed equally to the preparation of this article.

Declaration of competing interest

The authors declare no conflicts of interest.

Funding source

This study didn't receive any specific funds.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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