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Face Recognition Using the Subspace and Deep Learning Algorithms for Cases of Sufficient and Insufficient Data

Serkan KESER[1*]

[1]*Kirsehir Ahi Evran University, Department of Electrical and Electronics Engineering, Kirsehir, Türkiye*

(ORCID: 0000-0001-8435-0507)

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Abstract
In face recognition, the distance criterion significantly influences the recognition rate. Misclassified test signals can be accurately reassigned to the correct class using various distance measures and the nearest neighbor algorithm. This study uniquely explores the recognition performance of DCVA, Fisherface subspace classifiers, and Convolutional Neural Network (CNN) in face recognition, an aspect not thoroughly explored in the literature. Accordingly, this study introduces a Discriminative Common Vector-based (DCVA) algorithm utilizing various distance measures for face recognition for the first time. Additionally, the Fisherface-based algorithm uses different distance measures and nearest neighbors. Experiments were conducted on three different face databases. The images were downsampled to simulate both sufficient and insufficient data conditions. Experimental results indicate that the Correlation distance measure generally outperforms the Euclidean distance for the DCVA and Fisherface-KNN algorithms under both data conditions. The Fisherface-KNN algorithm surpasses the classical Fisherface in performance for various distance measures and nearest neighbor numbers and yields better recognition rates than the DCVA algorithm in sufficient data conditions. Moreover, while DCVA and Fisherface-KNN achieved superior results for two smaller face databases, CNN demonstrated better performance for larger databases.

1. Introduction

The application of speech, face, and object recognition systems is rapidly expanding across various fields. The primary objectives of these systems are to perform the recognition process with minimal delay while ensuring robustness, user security, scalability, and high recognition rates. It is crucial for these systems to provide accurate results under various environmental conditions and noise levels to maintain robustness. Additionally, they need to be scalable, meaning they should handle increasing data volumes or a larger number of users without significant performance degradation. Moreover, facial recognition systems must securely store personal data. A crucial condition for achieving high recognition rates is the appropriate classifier selection. Numerous classifiers such as CNN, ANN, KNN, SVM, Fisherface, and CVA are utilized for face recognition [1-7]. Among these, CVA is prominent as a subspace classifier with a high recognition rate and low computational complexity. It has been applied in various fields, including voice recognition, face recognition, image denoising, speaker recognition, and feature selection [8-13]. The number of samples and sample sizes in the training set classes are critical for CVA. If the size of a sample in the training set exceeds the total number of samples in all classes, an insufficient data case occurs; otherwise, a sufficient data case occurs. In the sufficient data case, the difference and indifference subspaces are intermixed and therefore the recognition rates may decrease. DCVA, a classifier mainly used in face recognition applications, is based

*Corresponding author: *skeser@ahievran.edu.tr*

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on the effective subspace classifier CVA [7]. The principal characteristic of DCVA is its ability to find a vector representing common properties for each class during training, termed the common vector. During the testing phase, the feature vectors of the test signal are acquired by projecting the test signal into the indifference subspace. Subsequently, the test signal is assigned to the class with the smallest Euclidean distance between the common vectors from the training phase and the feature vectors of the test signal. Fisherface is another effective subspace method employed in face recognition [9]. In the Fisherface method, training signals are initially projected using optimal basis vectors that maximize class separation during training. Then, the test vector is projected using these basis vectors, and this projected test vector is assigned to the class with the smallest Euclidean distance between the projected test vector and the projected training vectors across all classes [9]. A primary disadvantage of the DCVA and Fisherface methods is their reliance solely on Euclidean distance criteria. Conversely, a test signal misclassified according to Euclidean distance can be correctly classified using different distance measures or varying the number of nearest neighbors. Thus, more advantageous distance measures than Euclidean can be identified in the recognition process by employing different distance measures. Similarly, the literature includes studies comparing recognition performances based on different distance measures [14-19,42]. In [42], it was demonstrated that cosine and correlation distance outperformed the Euclidean distance of the original SIFT for the ORL face database. This paper also shows that the correlation distance measure provides better results than the Euclidean distance. The primary reason for this superior performance is the correlation distance's robustness to variations in lighting conditions, face positions, and facial expressions, contributing to improved accuracy in face recognition algorithms.

This study proposes the DCVA algorithm, which utilizes different distance measures, and the Fisherface-KNN algorithm, which classifies based on various numbers of nearest neighbors and distance measures. Each image in the face database is downsampled to evaluate scenarios with both sufficient and insufficient data. The focus of the study is an in-depth performance comparison of DCVA, Fisherface-KNN, and CNN, using three different face databases. An examination of the average recognition results obtained by the proposed DCVA and Fisherface-KNN algorithms reveals that the correlation distance generally outperforms the Euclidean distance. Additionally, the Fisherface-KNN algorithm typically delivers better results than the classical Fisherface across various distance measures and numbers of nearest neighbors. In cases with sufficient data, Fisherface-KNN achieves higher recognition rates than DCVA.

A deep learning method, previously used as an expressive classifier in literature, was also employed through CNN [31-34]. The author in [37] introduced a face recognition method based on principal component analysis (PCA). However, PCA has limitations when handling variations in lighting conditions and facial expressions, which results in lower recognition rates. Another widely used approach is the application of support vector machines (SVMs) for face recognition [38]. SVMs effectively capture complex patterns in face images, though their computation time increases significantly with large datasets. Recent advances in deep learning, especially with CNNs, have achieved considerable success in face recognition. In [39], the well-known pre-trained AlexNet architecture was proposed. Following AlexNet, many CNN-based approaches for face recognition, such as FaceNet [40] and VGGFace [41], were developed.

Thus, the recognition performances of face databases of three different sizes were examined using DCVA, Fisherface-KNN, and CNN. The rest of the paper is structured as follows: Section 2 introduces the classifiers DCVA, Fisherface-KNN, and CNN, as well as the cases of sufficient and insufficient data. In Section 3, the face databases are presented, and the experimental results are discussed. Finally, Section 4 provides the conclusions.

2. Proposed methods

2.1. Proposed Subspace Methods

This study conducted tests using different distance measures for DCVA and Fisherface-KNN. For DCVA, the nearest neighbor algorithm cannot be applied because it identifies a common vector for each class. In contrast, an algorithm using KNN decision criteria is proposed for Fisherface. The proposed Fisherface algorithm is based on the KNN structure and incorporates different distance measures, such as Cityblock, Correlation, Euclidean, and Spearman. The KNN algorithm predicts the class of a test vector based on the number of nearest neighbors, where the value of K, representing the number of nearest neighbors, directly influences the classification outcome and must be determined experimentally [14].

Table 1 presents the computational complexity of the classifiers along with a description of their parameters. As shown in Table 1, DCVA has low, Fisherface+KNN medium, and CNN high memory and computational complexity values.

Table 1. Comparison of computational complexity and resource usage of the DCVA, Fisherface+KNN, and CNN.

Classifier	Computational Complexity	Resource Usage (Memory and CPU)	Explanation
DCVA	$O(T \cdot K \cdot n^2)$	Low	T: Number of classes K: Number of samples per class n: Data dimension
Fisherface+KNN	$O(n^3) + O(K \cdot n)$	Medium	n^3: Complexity of PCA and LDA operations K: Number of nearest neighbors
CNN	$O(l \cdot m \cdot f^2 \cdot c)$	High	l: Number of layers m: Number of filters f: Filter size c: Input channels (e.g., 3 for RGB images)

2.1.1. The Proposed DCVA Algorithm

DCVA is superior to other subspace classifiers, especially in terms of low computational complexity. This advantage comes from using a discriminative common vector belonging to a class. [7]. If there are T different classes in the training set, where each class contains K samples, there will be a total of $M=KT$ samples. If we denote the sample of the r*th* signal with class i as x_r^i in n-dimensional space, the within-class scatter matrix S_w is found as follows:

$$S_w = \sum_{i=1}^{T}\sum_{r=1}^{K}\left(\left(\mathbf{x}_r^i - \boldsymbol{\mu}_i\right)\left(x_r^i - \boldsymbol{\mu}_i\right)^T\right) \quad (1)$$

where $\boldsymbol{\mu}_i$ denotes the mean vector of the ith class. The projection matrix is found by the eigenvectors corresponding to S_w's smallest eigenvalues, spanning the indifference subspace [7].

$$\mathbf{P} = \mathbf{V}\mathbf{V}^T \quad (2)$$

The common vectors of the classes are obtained as follows:

$$x_{com}^i = P x_r^i, \; r=1, 2, \ldots, K, i=1, 2,.., T \quad (3)$$

The S_{com} is found using the following equation:

$$S_{com} = \sum_{i=1}^{T}\left(x_{com}^i - \mu_{com}\right)\left(x_{com}^i - \mu_{com}\right)^T, i = 1, \ldots, T \quad (4)$$

The eigenvectors associated with the nonzero eigenvalues of the S_{com} matrix provide the projection vectors for the DCVA:

$$J(\mathbf{W}_{opt}) = argmax\left|\mathbf{W}^T S_{com}\mathbf{W}\right|. \quad (5)$$

The feature vectors can be written as follows:

$$\Omega_i = \left[< x_r^i, w_1 > \cdots < x_r^i, w_{C-1} >\right] \quad (6)$$

where Ω_i are the discriminative common vectors. Then, the feature vectors of test images are found by:

$$\Omega_{test} = W_{opt}^T x_{test} \quad (7)$$

where $W_{opt}^T = [w_1, w_2, \ldots, w_{T-1}]^T$ and $\Omega_{test} \in \mathbb{R}^{(T-1)\times 1}$. The operations described above were performed for the insufficient data case ($M < n$). In the case of sufficient data ($M > n$), the common vector of the ith class is obtained from the projection of the mean feature vector (μ_i) of that class onto the indifference subspace:

$$x_{com}^i = \mathbf{P}\mu_i \quad (8)$$

In case of sufficient data, the smallest k eigenvalues are selected to correspond to a certain z percentage of the sum of the eigenvalues [23],

$$z = \frac{\sum_{i=1}^{k}\lambda_i}{\sum_{i=1}^{n}\lambda_i} \quad (9)$$

where n represents the total number of eigenvalues and k indicates the count of the smallest selected eigenvalues. The DCVA algorithm's block diagram is illustrated in Figure 1. The abbreviation DCV stands for Discriminative Common Vectors.

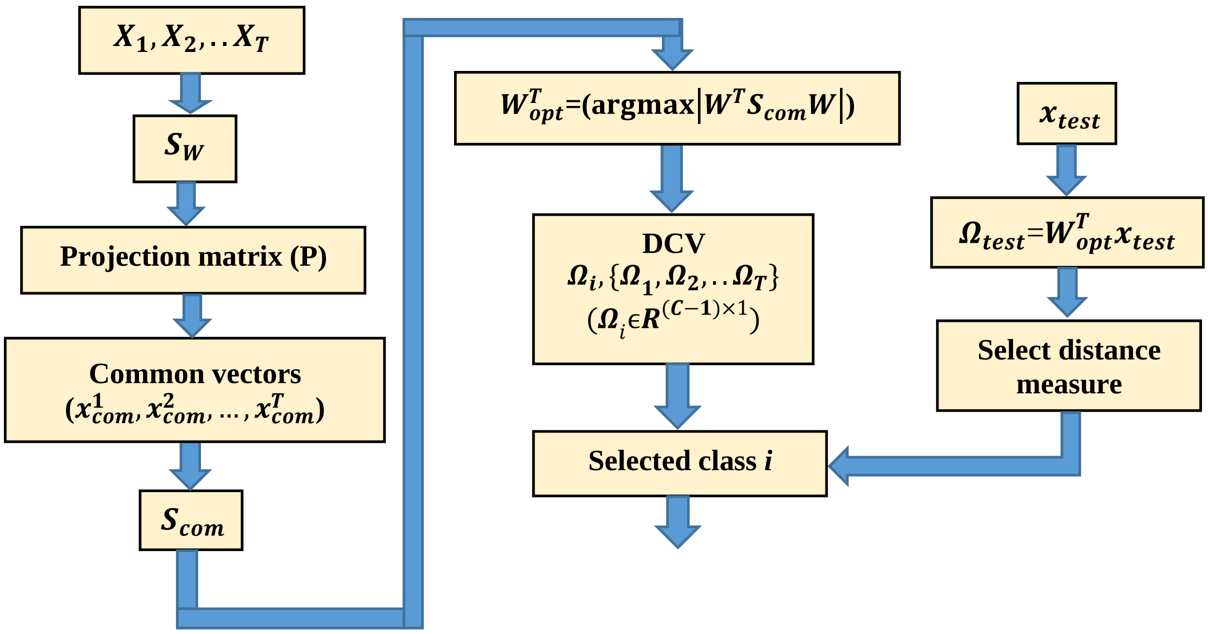

Figure 1. Block diagram of the proposed DCVA algorithm.

2.1.2. The Proposed Fisherface -KNN Algorithm

Fisherface is one of the important algorithms based on Linear Discriminant Analysis for face recognition due to its effort to maximize the discrimination between classes in the training process [9, 20]. The S_W is found using Eq. 1 mentioned above, and the between-class scatter matrix S_B is calculated by:

$$S_B = \sum_{i=1}^{T} N(\mu_i - \mu)(\mu_i - \mu)^T \qquad (10)$$

where N represents the number of samples in a class, μ_i is the mean of the *ith* class, and μ is the mean of all classes. The optimal basis vectors (U_{opt}) are determined as follows [9]:

$$U_{opt} = \underset{U}{argmax} \frac{|U^T S_B U|}{|U^T S_W U|}, \qquad (11)$$

In the Fisherface method, the above equations are valid for the sufficient data case ($M > n$). In the face recognition problem, in the case of insufficient data ($M < n$), the within-class scatter matrix S_W is usually singular. To overcome this problem, the Fisherface method projects the feature space dimension onto a lower-dimensional space using Principal Component Analysis (PCA). Using U_{opt}, feature vectors are found for each class as follows:

$$\Omega_i = U_{opt}^T X_i, \quad i = 1, 2, \dots, T \qquad (12)$$

where $\Omega_i \in \mathbb{R}^{(T-1)\times K}$ and K is the number of samples in the ith class. For classification, the test signal is first projected using U_{opt}, and then Ω_{test} ($\Omega_{test} \in \mathbb{R}^{(T-1)\times 1}$) is found by:

$$\Omega_{test} = U_{opt}^T x_{test} \qquad (13)$$

The block diagram of the Fisherface-KNN algorithm is given in Figure 2 below. The S_W and S_B scatter matrices are first found for the face images in the training set. The training process is performed using the KNN algorithm for the feature vectors (Ω_i). Then, the test signal (Ω_{test}) is found and assigned to the most appropriate class using the KNN algorithm.

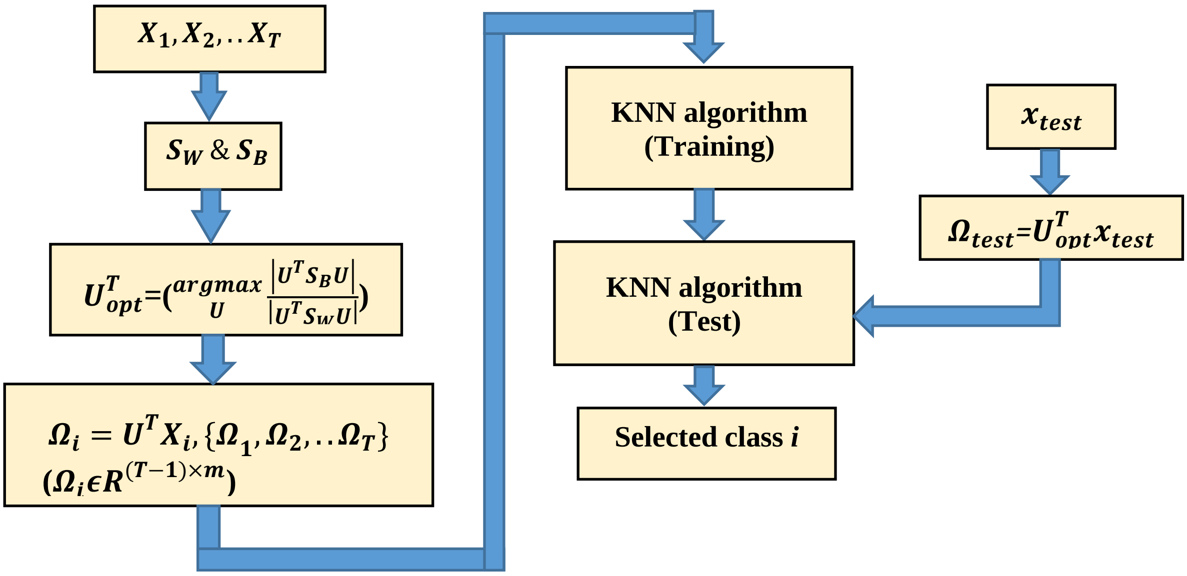

Figure 2. Block diagram of the proposed Fisherface-KNN algorithm.

2.1.3. Proposed CNN Model

In deep learning, a Convolutional Neural Network (CNN) is a class of artificial neural network, most commonly used for applications such as image and video recognition [26, 27], image classification, image segmentation [28, 29], and brain-computer interfaces [30]. The CNN model in Figure 3 was used in the study.

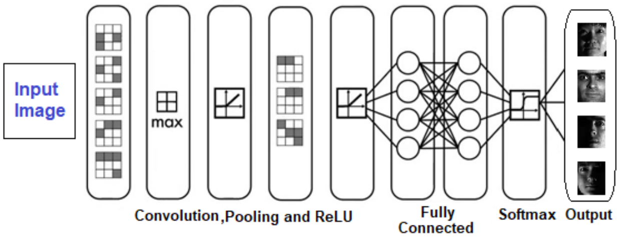

Figure 3. The proposed CNN method.

The layers of the proposed CNN model are listed in Table 2.

Table 2. The layers of the proposed CNN model

Layer level	Layers
1	Image Input (NxMx1 images)
2	Convolution (3x3 convolutions, 8 filters)
3	Batch Normalization
4	ReLU
5	Max Pooling (2x2 max pooling)
6	Convolution (3x3 convolutions,16 filters)
7	Batch Normalization
8	ReLU
9	Max Pooling (2x2 max pooling)
10	Convolution (3x3 convolutions,32 filters)
11	Batch Normalization
12	ReLU
13	Fully Connected
14	Softmax
15	Classification Output

The proposed CNN architecture includes three convolutional layers, two max-pooling layers, and three regularization layers. The training was conducted over 12 epochs with eight iterations, using a learning rate of 0.01. The network training employed the stochastic gradient descent with momentum (SGDM) optimizer.

2.2. The Cases of Sufficient and Insufficient Data

For DCVA and Fisherface, the difference and indifference spaces can be completely separated in the insufficient data case, while these spaces cannot be distinguished in the sufficient data case. To investigate the effect of the sufficient data case for DCVA and Fisherface-KNN, the sizes of the images were reduced using the downsampling method. The image is downsampled using the mathematical expressions below, resulting in sub-images.

$$\boldsymbol{I_s = I(k_i, k_j)} \qquad i\text{=1, 2 and } j\text{=1,2,} \qquad (14)$$

where $\boldsymbol{I}$ represents test images, $\mathbf{k_1}$ $(\boldsymbol{k_1 = 1, 3, 5, \dots, N-1})$ and $\boldsymbol{k_2}$ $(\boldsymbol{k_2 = 2, 4, 6, \dots, N})$ represent the pixel indices of the rows and columns of images and $\boldsymbol{I_s}$ represents the sub-images. Four sub-images are found as follows for the *p*th level,

$$\boldsymbol{I_{p1} = I(k_i, k_j)}, \qquad i\text{=1 and } j\text{=1,}$$

$$\boldsymbol{I_{p2} = I(k_i, k_j)}, \qquad i\text{=1 and } j\text{=2,}$$

$$\boldsymbol{I_{p3} = I(k_i, k_j)}, \qquad i\text{=2 and } j\text{=1,}$$

$$\boldsymbol{I_{p4} = I(k_i, k_j)}, \qquad i\text{=2 and } j\text{=2,}$$

The average of sub-images is found, and an **$N/(2^p) \times N/(2^p)$**-dimensional matrix is obtained for the *p*th level. Figure 4 below shows how the downsampling process is done, and DS indicates the downsampling process.

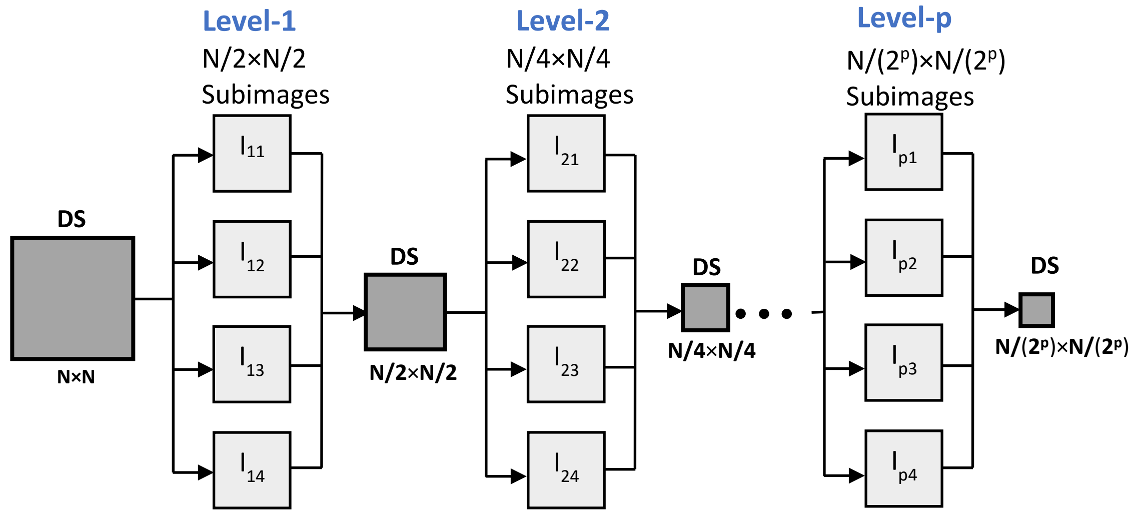

Figure 4. The downsampling process of an image for *p* level.

3. Experimental Studies

The experiments were conducted on a desktop PC with a 3 GHz (i5-7400) processor and 8 GB RAM under Windows 10. The ORL, YALE, and Cropped YALE (C-YALE) face databases were used in the studies. The ORL face database includes 400 images of size 112 × 92, with face records of 40 individuals taken at ten different poses. Each face image was manually reduced to 64 × 64 size. The YALE face database contains face images of 15 individuals, with ten different images per person. The C-YALE database consists of 2280 images for 38 individuals, aligned, cropped, and resized to 168 × 192. In this database, 40 images were used for training and 20 for testing, with 3-fold cross-validation. In the test phase, test signals were classified using different distances such as Correlation, Cityblock, Euclidean, and Spearman. The recognition process was performed according to the numbers of nearest neighbors (K=1, K=3, K=5). In the experimental studies, 10-fold cross-validation was used to evaluate the performance of the proposed algorithms for the ORL and YALE face databases. Some image sizes obtained for different *p*-values are shown in Figure 5 below.

Figure 5. Some images of the C-YALE database for p=0, p=1, p=2 and p=3.

All experimental results are given in the tables below. The symbol * indicates the sufficient data case, and the letter "p" shows the downsampling levels. CB, COR, EUC, and SP represent Cityblock, Correlation, Euclidean, and Spearman distances, respectively. As shown in Table 3, the best results for the proposed DCVA algorithm were generally obtained using the Correlation distance for sufficient and insufficient data cases across the three databases.

Table 3. Mean accuracy rates of the proposed DCVA algorithm for the ORL and YALE

	Mean accuracy rates (%)					
	Measures	**p=0**	**p=1**	**p=2**	**p=3**	**p=4***
YALE	**CB**	97.67	97.34	97.34	98	92
	COR	99.34	99.34	99.34	99.34	92
	EUC	98.34	98.34	98.34	98	93.34
	SP	96.34	96	96	96	86
		p=0	**p=1**	**p=2***	**p=3***	
ORL	**CB**	99.25	99.25	97.5	88.75	
	COR	100	100	98.25	90.25	
	EUC	99.75	99.75	97.5	90.5	
	SP	97.25	95.75	95.5	68.25	
		p=0	**p=1**	**p=2***	**p=3***	
C-YALE	**CB**	91.11	90.87	89.61	87.42	
	COR	91.81	91.42	90.25	88.22	
	EUC	91.62	91.38	90.13	87.91	
	SP	89.21	88.82	87.53	86.21	

Recognition rates for DCVA decreased significantly for face databases in the case of sufficient data. The average recognition rates of the Fisherface-KNN algorithm were found according to the number of nearest neighbors (K=1, K=3, K=5) and different distance measures. For insufficient data, the Correlation distance gave the best results for K=1, K=3, and K=5. In the case of sufficient data, Euclidean and correlation distance measures gave similar results for the YALE database. However, the best results were obtained using the Correlation distance for the C-YALE database. Regarding sufficient data, Euclidean and correlation distances gave similar results for the YALE database in Table 4. However, the best results were obtained using the correlation distance for the C-YALE database, as shown in Table 5.

Table 4. Mean accuracy rates of the proposed Fisherface-KNN (K=1, K=3, K=5) algorithm for the YALE database

	Mean accuracy rates (%)					
	Measures	**p=0**	**p=1**	**p=2**	**p=3**	**p=4***
K=1	**CB**	97.33	97.33	98.00	98.67	98.00
	COR	99.34	99.34	98.67	98.67	98.34
	EUC	99.00	98.67	98.67	98.67	98.34
	SP	96.00	96.00	97.34	92.67	92.67
K=3	**CB**	98.67	98.67	98.00	98.67	98.34
	COR	99.67	99.67	99.34	99.34	98.67
	EUC	99.34	99.34	98.67	99.34	98.67
	SP	98.67	98.67	98.00	93.34	94.67
K=5	**CB**	98.34	99.67	99.34	98.67	98.67
	COR	99.67	99.34	98.67	98.00	99.34
	EUC	98.67	97.67	98.67	99.34	99.34
	SP	98.34	98.00	98.67	98.67	94.67

Table 5. Mean accuracy rates of the proposed Fisherface-KNN algorithm for the C-YALE database

	Mean accuracy rates (%)				
	Measures	**p=0**	**p=1**	**p=2**	**p=3***
K=1	**CB**	89.32	88.82	88.02	86.97
	COR	90.21	89.84	89.24	88.96
	EUC	90.06	89.76	88.72	88.62
	SP	86.89	86.65	86.13	85.95
K=3	**CB**	90.08	89.62	88.81	87.77
	COR	90.96	90.53	90.18	90.01
	EUC	90.87	90.26	89.75	89.07
	SP	87.52	87.21	87.02	86.73
K=5	**CB**	89.93	89.52	88.74	87.58
	COR	90.68	90.23	89.93	89.65
	EUC	90.66	90.12	89.21	88.95
	SP	87.50	87.20	86.92	86.65

Table 6 provides the average recognition rates of the Fisherface-KNN algorithm for the ORL database. The Correlation distance generally gave the best results for insufficient data. while Euclidean performed better in the sufficient data case.

Table 6. Mean accuracy rates of the proposed Fisherface-KNN (K=1, K=3, K=5) algorithm for the ORL

	Mean accuracy rates (%)				
	Measures	**p=0**	**p=1**	**p=2***	**p=3***
K=1	**CB**	98.50	98.50	99.25	98.50
	COR	99.00	99.25	99.25	98.75
	EUC	99.00	99.00	99.25	98.75
	SP	96.25	97.75	98.25	93.25
K=3	**CB**	99.00	98.50	98.50	98.50
	COR	99.00	99.25	99.00	99.00
	EUC	99.25	99.00	99.25	99.25
	SP	97.50	98.75	95.75	92.00
K=5	**CB**	98.25	98.00	98.00	98.00
	COR	98.50	99.00	98.50	98.25
	EUC	98.75	98.50	98.50	98.75
	SP	96.75	98.50	92.50	90.25

Table 7 presents the average recognition rates for the CNN model under both sufficient and insufficient data cases for the three face databases.

Table 7. Mean accuracy rates of the CNN for the three databases

Databases	Mean accuracy rates (%)				
	p=0	**p=1**	**p=2**	**p=3**	**p=4***
YALE	93.34	92	88.67	88.67	87.34
	p=0	**p=1**	**p=2***	**p=3***	
ORL	95.25	92.5	86.25	85	-
	p=0	**p=1**	**p=2**	**p=3***	
C-YALE	93.97	93.48	92.89	91.62	-

Table 8 compares the highest recognition rates of the DCVA, Fisherface-KNN, and CNN algorithms. The best results were generally achieved using the Correlation distance for subspace algorithms. The DCVA algorithm yielded higher average recognition rates than Fisherface-KNN for the ORL database, but Fisherface-KNN outperformed DCVA for the YALE database. Additionally, for ORL and YALE databases, the average recognition rates of CNN were lower than those of DCVA and Fisherface-KNN. However, CNN achieved higher recognition rates for the C-YALE database than DCVA and Fisherface-KNN. The reason for CNN's lower recognition rates on small databases is that CNN requires a large amount of data to learn the features of faces, and when working with a small dataset, there is not enough variety of examples to learn these features. Due to insufficient data, the model cannot fully learn the necessary features to distinguish between different faces, leading to low recognition rates.

Table 8. The highest accuracy rates of the DCVA and Fisherface-KNN algorithms

Mean accuracy rates (%)								
DCVA			**Fisherface-KNN**			**CNN**		
ORL	**YALE**	**C-YALE**	**ORL**	**YALE**	**C-YALE**	**ORL**	**YALE**	**C-YALE**
100 (COR)	99.34 (COR)	91.81 (COR)	99.25 (COR&EUC)	**99.67** (COR)	90.96 (COR)	95.25	93.34	**93.97**

4. Conclusion

This study developed DCVA and Fisherface-based algorithms and explored the effects of different distance measures and the number of nearest neighbors on recognition rates. Additionally, a Convolutional Neural Network (CNN) was employed. The performances of the two subspace classifiers and CNN were examined under both sufficient and insufficient data cases. For the subspace classifiers, the Correlation distance generally provided higher recognition rates compared to Euclidean distance. In the sufficient data case, Fisherface-KNN outperformed DCVA, suggesting that Fisherface-KNN delivers better results when difference and indifference subspaces cannot be easily distinguished.

The findings show that the choice of distance measures in subspace algorithms and the number of nearest neighbors in Fisherface-KNN can lead to better results than Euclidean distance. For the ORL and YALE databases, CNN produced lower average recognition rates compared to DCVA and Fisherface-KNN. However, for the C-YALE database, CNN achieved higher recognition rates, highlighting that subspace methods are more effective for smaller databases, while CNN excels with larger datasets. The lower recognition rates of CNN for small databases are attributed to insufficient data, which prevents the model from fully learning the distinguishing features between different faces.

The Correlation distance, which measures the direction and correlation between two vectors, is particularly robust to changes in lighting and brightness in face images. While brightness variations negatively affect other distance measures, such as Euclidean distance, Correlation distance remains stable against these variations. Consequently, the experiments demonstrated higher accuracy rates when using Correlation distance.

This study focuses on three classifiers and small databases. However, future research will aim to include more classifiers and larger databases, as well as investigate recognition performance using hybrid classifiers.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics.

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