Machine Learning Model of Human Face Recognition
for Autism Spectrum Disorder Children

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Abstract

Autism spectrum disorder (ASD) is a complicated developmental disorder characterized by persistent difficulties in social interaction, speech and nonverbal communication, and repetitive activities. Because there is no medical test for ASD, diagnosing it might be difficult. ASD can be particularly difficult, with serious consequences for social interaction. In this study, we develop a machine learning model of human face recognition for autism children. We considered ORL database. For the face recognition, the data dimensionality reduction approaches such as principal components analysis (PCA), kernel principal component analysis (KPCA), independent component analysis (ICA) and factor analysis (FA) are investigated and compared. We have applied different classifiers and validated their performance through classification rate. We observed SVM showed the best performance with ICA methods for face recognition. This proposed system assists in the detection and recognition of human faces in autistic children.

Keywords: Face Recognition, PCA, KPCA, ICA, FA, ASD

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1 Introduction

Autism spectrum disorder (ASD) is a neuro developmental condition that affects children in their first three years of life [1]. Individuals with ASD have had problems understanding the emotions and thoughts of others. It is difficult for individuals to communicate with others because of this in society. Individuals with autism spectrum disorders may have a particularly difficult problem recognizing faces, which can have serious consequences for social interaction. Face recognition is the first step in social interaction and must occur before sophisticated social cues can be elicited. The researchers found 112 studies with over 5,000 individuals and analyzed them using meta-analysis, a method of combining and weighing all data in order to arrive at an objective result [2]. On tests of face identity processing, they discovered that over 80% of ASD people perform worse than the general population. In this article, we proposed a machine learning model for autism children to detect and recognize the human faces.The ORL database of faces was used for this purpose. The issue of huge dimensionality of input data is well-known in the field of digital image recognition.

Of image to be recognized (regardless of technique) is made up of thousands of pixels, each of which is defined by a multi-byte value. Face recognizing is the time-consuming and difficult computational tasks. Many reduction methods have been developed to address the problem of high dimensionality. In our study, we used the principal components analysis, kernel principal component analysis, independent component analysis and factor analysis data dimensionality reduction techniques and applied various classifiers in the ORL database. Mandal et al.[3] developed the Nearest Center Classification (NCC) criterion was used to face recognize SVMs using the standard eigenface technique.They used AR and FERET databases.Harfash et al.[4] suggested a machine learning model using Kernel PCA (KPCA) and kernel LDA that combine PCA and LDA (KDA). They showed that PCA/LDA/KPCA and KDA are capable of extracting significant features and drastically reducing the dimension of images, resulting in good face recognition accuracy.Huang et al.[5] investigated and compared different linear PCA and nonlinear approaches.They suggested that in the reduced subspace, a nonlinearity measure is calculated to quantify the degree of nonlinearity of a data set. Vinay et al.[6] proposed two dimensionality reduction techniques: SVD (Singular Value Decomposition) and PCA (Principal Component Analysis) for SURF-based face recognition.They showed and compared to other existing approaches such as the SURF-PCA method, the SURF-SVD method is more effective for face recognition, according to simulations conducted on four exemplar datasets. Georgy et al. [7] proposed a few several variations of a two-step methods involving the Karhunen-Loeve Transform (KLT) and Linear Discriminant Analysis (LDA).They found that with a large number of eigenvalues, the KLT provides a

good estimation of input data. Lei et al. [8] developed a face recognition model with Independent Component Analysis (ICA) successfully and explored that the performance of ICA is good for optimizing independent components of face recognition using the ORL Database and Towson database of faces.The goal of our study that develop a machine learning model autism children to detect and recognize the human faces easily.

The following concise summary of the contribution is given as follows:

– The study creates a machine learning-based system to improve face recognition for children with autism spectrum disorder (ASD).

– The work investigates and compares four-dimensionality reduction methods: Principal Component Analysis (PCA), Kernel Principal Component Analysis (KPCA), Independent Component Analysis (ICA), and Factor Analysis (FA) to improve face recognition performance.

– Different classifiers are tested, and the research finds that the Support Vector Machine (SVM) combined with ICA offers the best results for face recognition.

– The proposed system aims to support children with ASD by improving their ability to recognize and understand human faces, helping to overcome challenges in social interactions.

– The system could be applied in therapeutic tools to help children with ASD improve social and communication skills, addressing a key area of difficulty in their development.

The layout of this article is as follows: The approach and methods of face recognition are discussed in Section 2.Section 2's subsections include face recognition, data dimensionality reduction techniques, and classifiers. Section 3 presents the results of the experiment as well as an explanation of the findings. Section 4 presents Discussion and Conclusion.
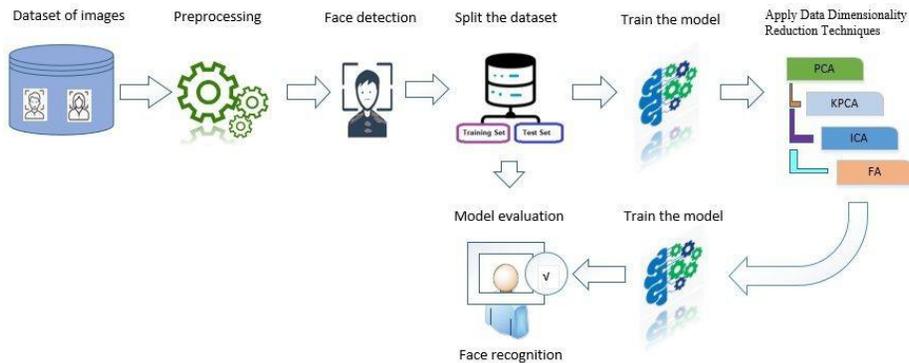
Fig.1: The flow diagram of the methodology of face recognition for ASD.

2 Approach and Methods

As shown in Figure 1, the proposed framework of face recognition for autism children consists of a sequence of steps. We followed these steps in our work to solve the face recognition issue using the ORL dataset.

2.1 Face Detection

This is one of the most important processes, which is characterized as the process of determining and extracting faces from input images or video images. Segmentation, extraction, and inspection of faces and likely facial features from an unregulated context are some of the methods that can be used to complete this task. To detect the face portion, we used the Viola-Jones algorithm. This algorithm should be able to operate in an unrestricted setting, which means it should be able to detect all visible faces in any image. Figure 2 two images before and after the face detection process.
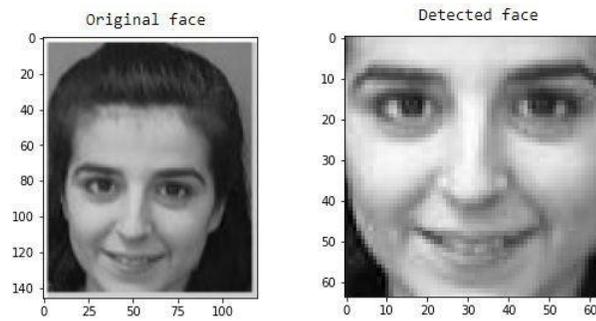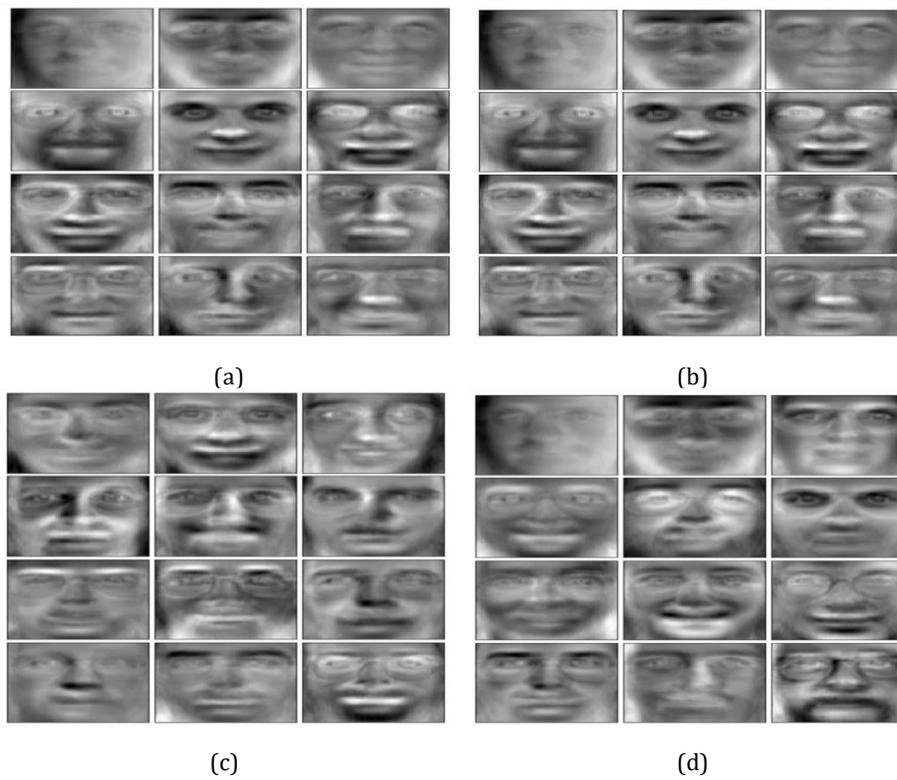
Fig.2: The face detection

(a)

(b)

(c)

(d)

Fig.3: (a)The 12 Eigenfaces using PCA (b) The 12 Eigenfaces using KPCA (c) The 12 localized feature vectors for ICA and (d) The 12 localized feature vectors FA of the ORL dataset.

2.2 Data Dimensionality Reduction Techniques

In the field of face recognition, dimensionality reduction has been a major issue. We used four data dimensionality reduction techniques such as principal components analysis, kernel principal component analysis, independent component analysis and factor analysis.

Principal components analysis (PCA): PCA is a mathematical method developed by Karl Pearson in 1901 that can be used to perform operations such as prediction, redundancy reduction, feature extraction, and data compression. It finds a lot of use in image recognition and compression. It is a technique for reducing dimensionality in feature space by transforming the observed variable into a smaller dimensionality of feature space. It converts a matrix of observed variables (variables that are correlated) into a new coordinate system with fewer variables (variables that are uncorrelated variables) that can better describe the observed variables. The PCA face recognition method finds eigenvectors, also known as eigenfaces, which represent the training images' global features[4]. Since the main aim of PCA is to reduce dimensionality, the eigenvectors of the covariance matrix must be identified in order to deliver the best possible. The following is a algorithm of the steps involved in finding the principal components:

Algorithm 1: Principal Component Analysis (PCA) for Face Recognition

- Input: A training dataset DD with mm samples, each of dimension nn.
- Output: A reduced-dimensional representation of the dataset with principal components.
- Consider D_k of an m-dimensional training set D, k= 1 ,2,....,m
- Calculate the mean vector,

$$M_v = \frac{1}{m}\sum_{k=1}^{m} D_k \ \ (1)$$

- Find out the covarance matrix,

$$A = \frac{1}{m}\sum_{k=1}^{m}(D_k - M_v)(D_k - M_v)^u \qquad (2)$$

- Compute the eigenvalues/eigenvectors of the matrix A.
- Arrange the eigenvalues in order of declining eigenvalues.
- Choose the first f ≤ m eigenvectors and generate a new representation for the data set.

– A similarity measure is used to compare the projected test image to each projected training image. The training image is the one that comes nearest to the test image.

In the Figure(3a) showed the first 12 eigenfaces using PCA.

Kernel principal component analysis (KPCA): KPCA is a nonlinear form of PCA that is built with a kernel function. The data set can be mapped onto a higher dimensional feature space via a nonlinear mapping. The basic steps of KPCA are given below:

Algorithm 2: Kernel Principal Component Analysis (KPCA) for Face Recognition

– Input: A training dataset DD with mm samples, each of dimension nn. The chosen kernel function K(x,y)K(x,y).

– Output: A reduced-dimensional representation of the dataset with principal components in the kernel space.

– Consider a set of centered data $D_k \in$ Rn

$$\sum_{k=1}^{m} \phi(D_k) = 0 \quad (3)$$

– Find out the covarance matrix,

$$A = \frac{1}{m} \sum_{k=1}^{m} \phi(D_k).\phi(D_k)^u \qquad (4)$$

– Compute the eigenvalues/eigenvectors of the matrix A. – The kernel function is defined as:

$$K(D_i, D_j) = \phi(D_i).\phi(D_j) \qquad (5)$$

– Calculate the average of the training data.

– Choose the eigenvectors and generate a new representation for the data set.

– A similarity measure is used to compare the projected test image to each projected training image. The training image is the one that comes nearest to the test image.

In the Figure(3b) showed the first 12 eigenfaces using KPCA.

Independent component analysis (ICA): ICA is a statistical approach for separating the components of a multidimensional random vector that are statistically as independent as possible. The data is represented in terms of statistically independent variables in ICA, which is a type of redundancy reduction approach. The search for a linear transformation that reduces the statistical dependency between the components of a random vector is

known as ICA [9]. ICA's purpose is to give an independent decomposition and representation of images. To put it another way, the purpose is to reduce the statistical dependence between the basis vectors as much as possible. Maximum nongaussianity is an important principle in ICA estimation. The central limit theorem states that sums of nongaussian random variables are closer to gaussian than sums of gaussian random variables. ICA outperforms PCA in terms of data representation because PCA only analyzes second order moments and uncorrelates data, but ICA analyzes higher order statistics and finds independent source components from their linear mixes [10]. The following are the basic steps for determining the independent components:

Algorithm 3: Independent Component Analysis (ICA) for Face Recognition

- Input: A training dataset DD with mm samples, each of dimension nn.
- Output: A reduced-dimensional representation of the dataset with independent components.
- Consider D_k of an m-dimensional training set D, k= 1 ,2,....,m
- Calculate the mean vector,

$$M_v = \frac{1}{m} \sum_{k=1}^{m} D_k \quad (6)$$

- Find out the covarance matrix,

$$A = \frac{1}{m} \sum_{k=1}^{m} (D_k - M_v)(D_k - M_v)^u \quad (7)$$

- The covariance matrix A is factorized by the ICA of x into the following form:

$$A = R\triangle R^u \quad (8)$$

where $\triangle$ is a real positive diagonal matrix

- R transforms D into X in such a way that the new data X's components are independent.

$$D = RX \quad (9)$$

In the Figure(3c) showed the 12 localized feature vectors for ICA. Factor analysis (FA): FA is a type of statistical analysis that looks for underlying factors or exogenous variables among a set of observations. By minimizing the number of variables, it aids data interpretation. It takes the maximum common variance of all variables and converts it to a single score. It is used to condense a group of observed variables into an unobserved variable termed factors and to explain the variance among the observed variables.A factor, also known as a latent variable, is linked to numerous observed

variables with similar response patterns. Every factor responsible for a certain percentage of the variability in the observed variables. A m-dimensional mean-centered observed vector D=(D1,D2,...,Dm) is reduced into a vector F=(F1,F2,...,Fn) of n latent variables (factors) and a vector v of m independent disturbance variables in FA [11] ,

$$D = \wedge F + v \quad (10)$$

where $\wedge$ is a factor matrix, and P_{ij} denotes the relative relevance of factor F_j to D_i.In each element of D, the disturbance term v accounts for independent noise. In the Figure(3d) showed the 12 localized feature vectors for FA.

2.3 Classifiers

The six common classifiers such as k-nearest neighbor (KNN), Logistic regression, Passive aggressive, Bagging, Support Vector Machine-radial basis function and Support Vector Machine-polynomial were used for classification. Under very mild conditions, the kNN classifier has shown outstanding performance on data with a high example size, such as approaching infinity, in which its error rate approaches the Bayes optimum [12].The logistic function, which is at the core part of the procedure, is called logistic regression.The probability of a target variable is predicted using logistic regression[13].For large-scale learning, passive aggressive is commonly utilized. It operates by reacting passively to accurate classifications and aggressively to any mis-classifications[14].Bagging is used with decision trees to increase model stability in terms of reducing variance and enhancing accuracy [15]. Support Vector Machine is a very effective method for pattern identification in general [16]. SVM techniques are based on a set of mathematical functions known as the kernel. The kernel's job is to take data and turn it into the structured form. Different functions such as linear, nonlinear, polynomial, Gaussian kernel, Radial basis function (RBF), sigmoid etc. We use two kernels Radial basis function (RBF) and polynomial of SVM.

3   Analysis of Results

We used the Cambridge ORL(Olivetti Research Labs) database, which is open to the public and contains 10 grayscale images of 40 persons standing upright [17]. A 20 x 20 pixel subimage is derived from these images. We used Viola-Jones algorithm for face detection showed in Figure 2. In experiment, the performance of four dimension reduction strategies was tested with the classifiers for an objective comparison. The classifiers k-nearest neighbor (KNN), Logistic regression, Passive aggressive, Bagging, Support Vector Machine-radial basis function and Support Vector Machine-

polynomial were denoted as C1,C2,C3,C4,C5 and C6. The data dimensionality reduction techniques principal components analysis, kernel principal component analysis, independent component analysis and factor analysis were denoted as PCA, KPCA, ICA and FA. We considered the number of components K where the value of k is considered 25, 50 and 75. The results of accuracy followed by the classifiers were shown in table 1. We analyzed the classification results of accuracy, the maximum result (98.25%) of this dataset was generated by C5 for ICA with K=50. The error-rate of the ORL dataset of different classifiers are shown in Figure 4.

4   Discussion and Conclusion

In this study, we considered the ORL dataset of 400 images. PCA, KPCA, ICA and FA dimension reduction methods have been used and six classifiers were used to investigate the dataset. When we evaluated the performance of these Table 1: Accuracy of dimension reduction techniques classification by various classifiers

| Classifiers		C1	C2	C3	C4	C5	C6
Number of Dimensionality components reduction techniques							
K=25	PCA	93.75	95.50	90.75	90.50	96.00	97.25
	KPCA	90.75	93.50	92.25	90.50	95.50	95.50
	ICA	96.50	95.00	90.00	95.00	97.25	97.00
	FA	94.75	96.00	95.25	95.25	96.75	96.75
K=50	PCA	94.00	97.50	94.50	97.25	96.50	97.75
	KPCA	93.50	96.75	95.50	95.75	96.00	96.00
	ICA	95.75	97.25	96.25	98.00	**98.25**	98.00
	FA	95.50	97.50	96.00	97.50	97.25	97.25
K=75	PCA	94.25	96.75	94.75	96.25	96.50	97.75
	KPCA	93.75	97.50	96.50	96.50	96.75	96.75
	ICA	95.25	97.25	95.75	97.25	97.00	96.50
	FA	94.25	97.00	96.00	96.00	96.50	96.50
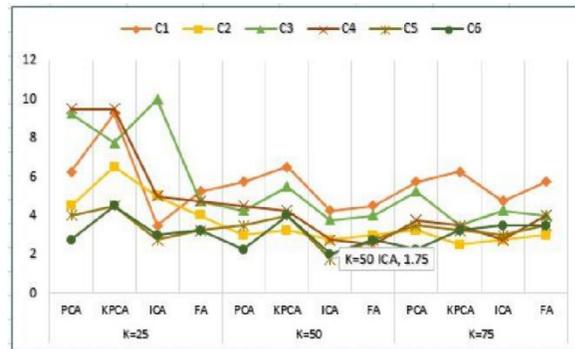
Fig.4: The error-rate of dimension reduction techniques followed by various classifiers

classifiers, SVM-RBF(C6) was the most frequent classifier to explore the best result for this dataset for ICA technique. We compared our model to different studies and comparisons are shown in table 2. Alaa et al.[18] developed PCA-NN, a face recognition system based on PCA followed by a feedforward neural network (FFNN), and LDA-NN, a face recognition system based on LDA followed by an FFNN. From their experiment, the highest results for LDA-NN as 97.00 % accuracy for ORL dataset. Huang et al.[5] evaluated linear PCA and nonlinear approaches. They observed the results of accuracy 97.75% using PCA-SVM for this dataset. We can recognize human faces easily using this SVM method with

Table 2: A comparison of our model to that of other previous research.

Dataset	Authors	Methods	Accuracy (%)
ORL face-dataset	Alaa et al.	LDA-NN	97.00
	Huang et al.	PCA-SVM	97.75
	Proposed model.	ICA-SVM	98.25

ICA technique. The aim of this study is to learn to recognize faces easily by paying attention to social signals.

The limitation is that the study uses the ORL database, which may not be fully representative of facial variations in children with autism spectrum disorders (ASD). A larger and more diverse data set is needed for better generalization. Although the study explores various dimensionality reduction techniques, it does not investigate deep learning approaches, which have shown significant advances in face recognition tasks. The model's effectiveness is validated using classification rates, but its real-world applicability in assisting ASD children in social interactions is not tested in practical scenarios.

Future research should utilize larger and more diverse datasets, including real-world facial images of children with autism spectrum disorder (ASD), to improve model generalization and accuracy. Incorporating deep learning techniques, such as

convolutional neural networks (CNNs) or transformer-based models, could further enhance face recognition performance and reduce dependency on manual feature extraction. The proposed system should be tested in realworld environments with autistic children to evaluate its practical effectiveness in improving social interactions and communication.

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