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Feature Extraction and Reconstruction of Medical Images using Two-Dimensional Principal Component Analysis

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Abstract. Two-Dimensional Principal Component Analysis (2DPCA) is a classical technique used to reduce the cost of computation than standard PCA. In 2DPCA, images are treated as vectors and appear image as a matrix which is further computed and results as Eigenvalues consisting of lower dimensionality as compared to PCA. 2DPCA depends on the image matrix which is a computationally most efficient method than PCA used to enhance feature extraction speed and high accuracy. 2DPCA is represented as an image matrix, its Co-Variance matrix is computed with the image matrix directly without converting into a 1D vector, and Eigenvectors are obtained for feature extraction. 2DPCA computes an accurate Co-Variance matrix and finds Eigenvectors most efficiently. K-Nearest Neighbor (KNN) algorithm is used for classification. 2DPCA is the best method to obtain reconstruction accuracy than PCA. The main advantage of 2DPCA is less time required for feature extraction and to provide the highest reconstruction accuracy. For testing and evaluating 2DPCA performance, we are conducted several experiments using different databases such as IRMA, WANG, etc., for different medical images and observed that reconstruction accuracy depends on increasing the number of principal components.
Keywords. 2DPCA, Co-Variance Matrix, Feature Extraction, Medical Images

1. Introduction

PCA is also called Karhunen-Loeve expansion, a classical method extensively used in computer vision, image compression, signal processing, human face representation, knowledge representation, and recognition effectively. PCA is an important method for feature extraction and image representation. In PCA, matrix transformation of the image takes place into high dimension vectors and its covariance matrix is obtained consuming high-dimension vector space. Due to the large size of the covariance matrix, the evaluation of the covariance matrix accurately is difficult, and also to obtain corresponding Eigenvectors requires much more time. The main drawback of PCA is its computational complexity is very high. For XXY size images, the number of training images is greater than XXY which makes the database as larger, and also to perform PCA requires $M(XXY)^3$ computations which is expensive for even medium-size images. For reducing computational cost and ensuring lower dimensionality than PCA, a different technique known as 2DPCA is developed. 2DPCA was represented by Yang et al., in 2004 and applied for face representation and recognition. The main advantage of this technique is based on 2D images; the covariance matrix is directly obtained on the image matrix without converting to vectors. 2DPCA can derive Eigenvectors most accurately at a faster rate which requires less time because of the small covariance matrix and sufficient principal components as compared to PCA. 2DPCA is a straightforward classical technique for feature extraction which depends on a simple image matrix. 2DPCA is the most efficient method for extracting features from images with higher accuracy than conventional PCA. 2DPCA is the best method to achieve recognition and higher reconstruction accuracy than PCA.

PCA is used for image recognition and various linear discrimination techniques were developed in that image is converted into a 1D vector. 2DPCA is also used for face representation and recognition for achieving higher recognition accuracy than PCA. 2DPCA is equally treated as block-based in which the image is divided into the various block of equal sizes and the features are extracted from these blocks of images where each block is considered as one line of the image. Original 2DPCA extension is equivalent to Extended 2DPCA (E2DPCA) in which covariance is equal to the PCA average covariance matrix diagonal. We can further develop PCA and arbitrary extension to n-dimension PCA (nD-PCA) which is directly applied to n-order than 1D vectors and 2D matrices. Complete 2DPCA for feature extraction rather than original 2DPCA achieves both high recognition rates with reduced feature coefficients required for face recognition. 2-Direction 2DPCA or $2D^2$ PCA is used for effective face representation and recognition. 2DPCA is an unsupervised transformation technique and the main key of 2DPCA is the image covariance matrix which corresponds to pixels arrangement for image and different covariance matrix produces different information and its alternate version is derived with pixel rearrangement which is known as Generalized PCA. Generalized 2DPCA (G2DPCA) is used to overcome the problem such as computational complexity, the need for storage image retrieval, enhancing image quality, and reducing image transmission time.

M.S. Bartlett et al.,[1] developed a new method in which data labeling can be directly considered to obtain better recognition and experimental results showed good performance with 2DPCA with less complexity than PCA, LDA, or ICA methods. Yang. J et al., [2] proposed various techniques of bilateral projection methods like $2D^2$ PCA, Bilateral 2DPCA, Generalized low-rank approximation of matrices, Bidirectional PCA, etc., and considered image in two directions and reduces feature matrix to less size than original 2DPCA and also developed kernel-based 2DPCA which is non-linear to improve the feature extraction. Jian Yang et al., [3] tested 2DPCA performance on ORL, AR and Yale face databases for faces and achieved a high recognition rate for all images and proved it is the most efficient method than PCA. Hui Kang et al., [4] developed the Generalized 2DPCA to overcome the problems of existing PCA such as computational complexity, the storage requirement for image retrieval, image enhancement to ensure image quality, and reducing image transmission time. Liwei Wang et al. [5] proved that 2DPCA a feature extraction method to existing technique, block-based PCA, and they make a note that 2DPCA is also known as IMPCA. WANG Li-Wei et al., [6] used the FERET database and demonstrated and proved that PCA outperforms PCA on the data set which consists of simple images.

Zhang. D. et al., [7] considered simultaneous rows and column directions and developed 2-Directional 2DPCA ($2D^2$ PCA) efficiently. They performed experiments using FERET and ORL face database and proved that $2D^2$ PCA obtains slightly high accuracy than 2DPCA. Hongchuan Yu et al., [8] used the nD-PCA algorithm for Higher-order Singular Value Decomposition (HO-SVD), and for evaluating nD-PCA performance, several experiments are done on the FRGC 3D facial database. Anbang Xu et al., [9] developed complete 2DPCA for feature extraction of images and constructed directly two covariance matrices for images with the original matrix and its Eigenvectors are computed for extraction of images and experiments are done using ORL database for faces and with improved performance. Wang. L. [10] introduced a technique known as Extended 2DPCA (E2DPCA) which is an extension to 2DPCA in that some covariance information is eliminated by 2DPCA which can be used for recognition and experiments are done using ORL database and proved that both recognition time and accuracy are improved than the original 2DPCA. Venkatramaphanikumar. S. et al., [11] introduced Modular 2DPCA (M2DPCA) and experiments are done using Yale, ORL and AR databases and observed good recognition rate with less computational time under varying illuminations. Min qui Mao et al., [12] proposed 2DPCA Hashing (2DPCAH) method in which 2D images are used to extract features directly with 2DPCA and 2DPCAH provides hashing with this extracted 2DPCA data and applied iterative quantization methods to rotation matrix to reduce quantization error and performed some experiments showing the results of 2DPCAH, 2DPCA-RR and 2DPCA-ITQ are more effective than conventional PCAH. Sri Sutarti et al., [13] conducted the research using 4 trials with various training and testing data using AT & T data base and they achieved

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high accuracy by using many images in training as compared to testing data. Srinivasa Reddy et al., [14] demonstrated the method of retrieval of different medical images using 2DPCA.
In this paper, Section 2 deals with the Method of 2DPCA along with its reconstruction procedure for medical images and also explained k-nearest neighbor classification. In Section 3, 2DPCA algorithms used for Feature Extraction and Image Reconstruction and k-nearest neighbor algorithm are derived. Simulation results with evaluated and computed values in tabular form along with images and discussion with results are presented in Section 4. Finally, the last section presents the conclusions about the 2DPCA algorithm and its implementation using the Mat Lab with experimental analysis.

2. Method of 2DPCA

2.1.2DPCA
Assuming each image is denoted by x by y matrix I then the linear transformation is represented by
$P = It$ (1)
Where t is the n-dimensional transformation (projection) axis and P is the transformed feature of the image on n is called the principal component vector. 2DPCA searches for optimal transformation by maximizing the total scattering of transformed data and the total scattering of transformed samples can be used to characterize the covariance matrix trace of transformed feature vectors such as
$J(t) = tr\,(S_t)$ (2)
Where $S_t = A\,[(P - A_p)(P - A_p)^T]$ (3)
The total power is equivalent to the sum of a trace of C_t, then trace of C_t is derived as

$$\begin{aligned} C_t &= tr\,\{A\,[(P - A_p)(P - A_p)^T]\} \\ &= tr\,\{A\,[(I - AI)\,tt^T(I - AI)^T]\} \\ &= tr\,\{A\,[t^T(I - AI)^T(I - AI)\,t]\} \\ &= tr\,\{\,t^T A\,[(I - AI)^T(I - AI)\,t]\} \\ &= tr\,\{\,t^T C_t\,\} \end{aligned} \quad (4)$$

Therefore, $C_t = A\,[(I - AI)^T(I - AI)\,t]$ (5)
Where C_t is called image covariance matrix and alternately it can also be expressed as
$J(t) = tr\,\{\,t^T C_t\,\}$ (6)
Where inner-scatter matrix of image C_t is derived as

$$C_t = \frac{1}{N}\sum_{k=1}^{N}(I_k - I^{\wedge})^T(I_k - I^{\wedge}) \quad (7)$$

Where $I^{\wedge}$ represents Image average.
Therefore, $I^{\wedge} = \frac{1}{N}\sum_{k=1}^{N} I_k$ (8)
Maximizing of vector t in equation (4) is corresponds to the largest Eigenvalue of C_t using Eigenvalue Decomposition or Singular Value Decomposition (SVD) algorithm.
But, one transformation axis is not sufficient for representing data accurately, so many Eigenvectors of C_t are required and the number of Eigenvectors (V) is selected based on a predefined threshold (θ)
Let $e_1 \geq e_2 \geq e_3 \ldots\ldots\ldots \geq e_n$ be Eigenvalues of C_t which are arranged in non-increasing order. Then choosing V, first Eigenvectors, so that its corresponding Eigenvalues satisfy the condition

$$\theta = \leq \frac{\sum_{i=1}^{V} e_i}{\sum_{i=1}^{n} e_i} \quad (9)$$

For feature Extraction, let $t_1, t_2, \ldots\ldots, t_v$ are the V selected highest Eigenvectors of C_t.. Each image is transformed into the V dimensional subspace based on equation (1).
The transformed (Projected) image
$P = [\,P_1 \ldots\ldots\ldots\ldots\ldots P_v]$ is then x by V matrix which is given as
$P = IT$ (10)
Where $T = [t_1 \ldots\ldots\ldots\ldots\ldots t_d]$ is y by the transformation matrix

2.2. Column-Based 2DPCA

Original 2DPCA is known as row-based 2DPCA, but the alternate method of 2DPCA is column-based which can be represented by using a Column instead of a row. This is similar to the original 2DPCA in which input images are transposed previously.

Using Equation (7), replacing image I using transposed image I^T and treated it as column-based image Co-Variance Matrix, R as

$$R= \frac{1}{N}\sum_{k=1}^{N}\left(I_k{}^T - I^{\wedge T}\right)^T\left(I_k{}^T - I^{\wedge T}\right) \quad (11)$$

$$R= \frac{1}{N}\sum_{k=1}^{N}\left(I_k - I^{\wedge}\right)\left(I_k - I^{\wedge}\right)^T \quad (12)$$

Similarly, in Equation (1), the column-based optimal transformation matrix is derived by calculating Eigenvectors R(b) corresponding to the q highest Eigenvalues as

$$P_{col} = B^T I \quad (13)$$

Where B= $[b_1 \ldots\ldots\ldots\ldots\ldots b_q]$ is x by q column-based optimal transformation matrix.

2.3. Image Reconstruction using 2DPCA

A combination of principal components with Eigenvectors are used to reconstruct the image in 2DPCA. Assuming orthonormal Eigenvectors that correspond to the first V highest Eigenvectors of the image Co-Variance matrix C_t are $T_{1,}T_{2,\ldots\ldots\ldots\ldots,}T_v$.

The resulting principal component vectors are

$P_v = I\,t_v$ where v= 1, 2, ..., v

Let E = $[P_{1,}P_{2,\ldots\ldots\ldots\ldots,}P_v]$ and

F = $[t_{1,}t_{2,\ldots\ldots\ldots\ldots,}t_v]$ then

$$E = IF \quad (14)$$

Since, $t_{1,}t_{2,\ldots\ldots\ldots\ldots,}t_v$ are orthonormal, from equation (14), computing the reconstructed image of sample I, then

$$I^{\sim} = VF^T = \sum_{i=1}^{V} P_i\ t_i^T \quad (15)$$

Assuming $I^{\sim}{}_i = P_i\ t_i^T$ (i= 1,2, ..., v) which can be the same size as image I and indicates the reconstruction of sub-image, I. So, image I is reconstructed approximately with the addition of the first V sub-images. If the chosen number of principal component vectors V=n is the total number of Eigenvectors of C_t.

If $I^{\sim}$ = I, then using principal component vectors image is reconstructed without loss of any information, otherwise if V<n, then reconstructed image $I^{\sim}$ is an approximation of original image I.

2.4. KNN- Classification

KNN-Classification method is used to match training and testing images. KNN is used to find Eigen Value from training images and next computing the ED between training and testing images. Images with the smallest can be considered as images with more similarities with testing images.

3. Algorithm for Proposed Method

3.1 2DPCA Algorithm for Feature Extraction and Image Reconstruction

1. Let Image database consists of a set of N training images $I_k = [I_{1,}I_{2,\ldots\ldots\ldots,}I_n]$ where (k=1, 2..., n).
2. Compute the Average (Mean) Matrix ($I^{\wedge}$)by using
   $$I^{\wedge} = \frac{1}{N}\sum_{i=1}^{N} m$$
   Where N= No. of Images and M= Image Matrix
3. Compute Matrix difference for each Image in Image Matrix (I_k) with I′. So, $I' = I_k - I^{\wedge}$.
4. Co-variance matrix (C_t) is computed using images of the training set
   $$C_t = \frac{1}{N}\sum_{k=1}^{N}(I')^T I' \qquad \text{or}$$

$$C_t = \frac{1}{N}\sum_{k=1}^{N}(I_k - I^{\wedge})^T(I_k - I^{\wedge})$$

Where I′= Difference Matrix and $(I')^T$ = Transpose of Difference Matrix

5. Compute the Eigenvalue and Eigenvector using Singular Value Decomposition (SVD) method, I V=e V.
   Where I= Square Matrix; e = Scalar Eigenvalue and V = Eigenvector
   The eigenvector is transformed (projected) depending on Eigenvalue originality with the largest
   $e_1 > e_2 > e_3 \ldots\ldots\ldots > e_n$.

3.2. K-Nearest Neighbor (KNN) Algorithm

To compute the distance between training and testing data, the KNN classification method is used. Euclidean Distance (ED) Matrix used to compute the distance between images is KNN which is calculated by using the formula:

$$d_x = \sum_{x=1}^{N}(t_{2x} - t_{1x})^2$$

Where t_1= training data; t_2= testing data; x= data variable and d_x = Distance

4. Simulation Results

Mat Lab software is used for testing and evaluating the performance of the 2DPCA algorithm. Using computed 2DPCA, simulation results are performed for different medical images by collecting from different databases such as IRMA and WANG, etc. KNN algorithm is used to calculate Euclidean distance between the images. Euclidean distance with minimum distance between images is concluded as images are similar. So, image similarity depends on the distance between the images.

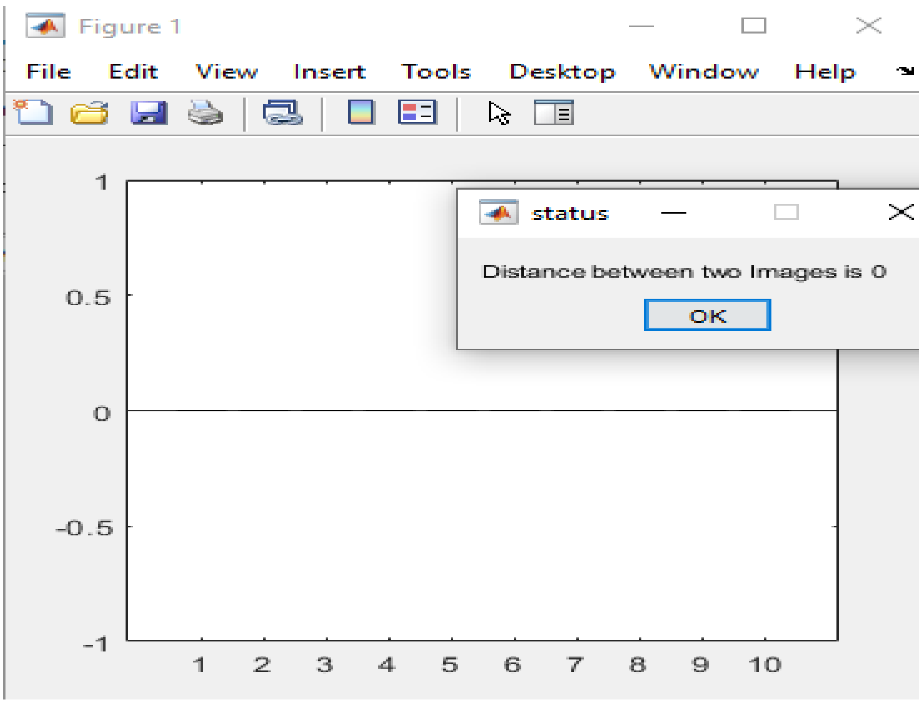


Figure 1(a). Images having the same features

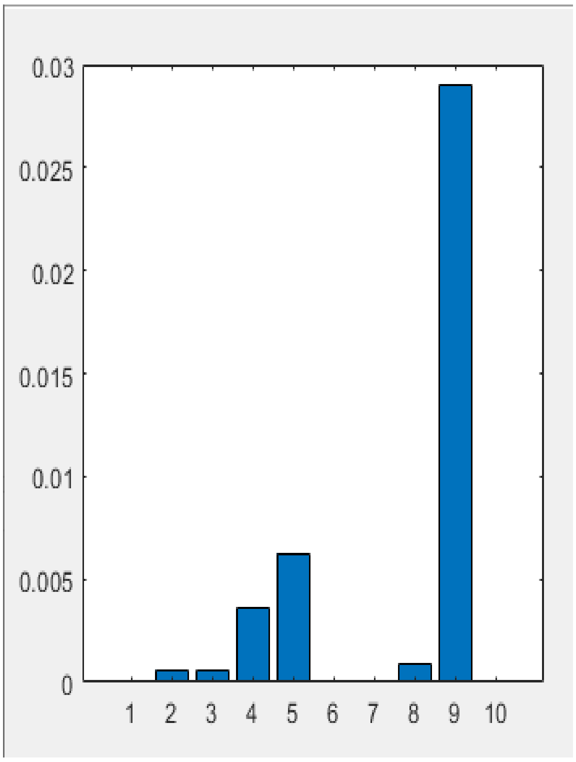


Figure 1(b) Images with similar features

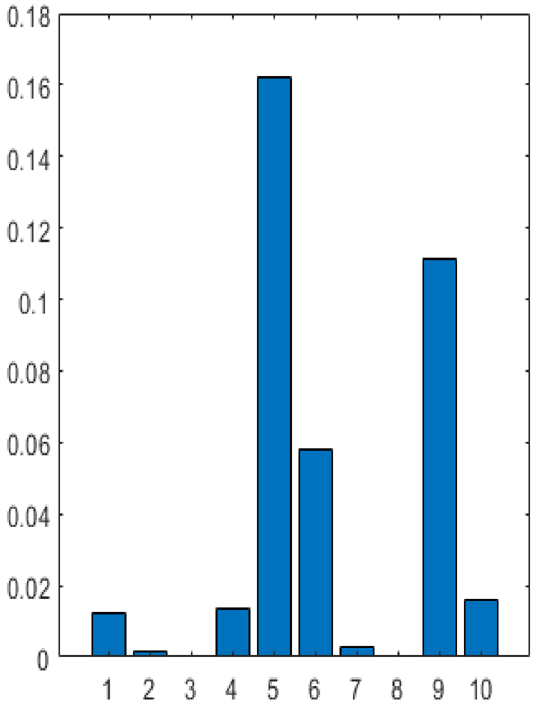
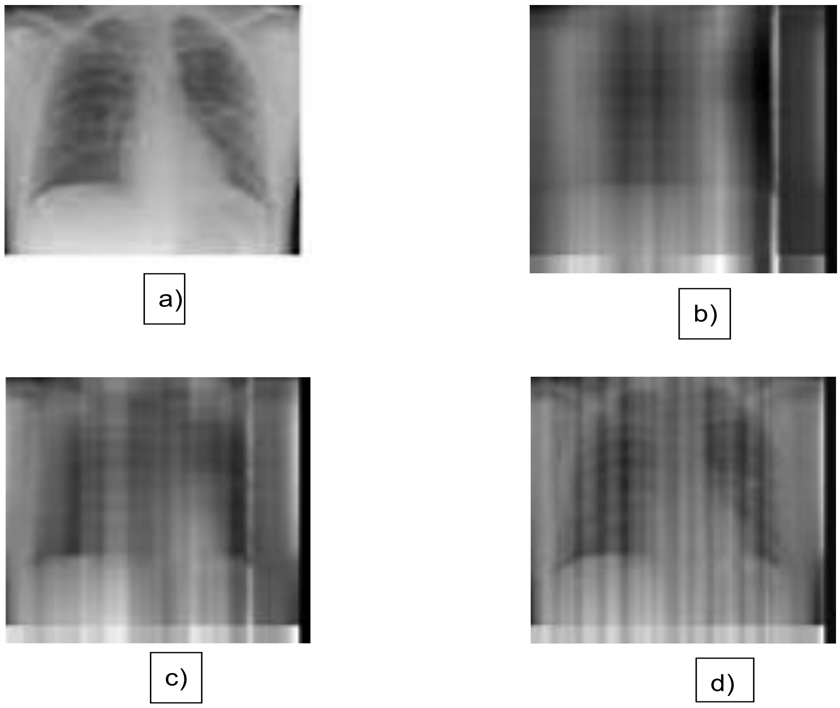


Figure 1(c) Images with different features

If two images having the same features, then the distance between two images is 0 and the output of the bar graph shows 0. If two images having similar features or belong to the same type, then the maximum height in the output of the bar graph is less than 0.1. If two images do not have similar features or belong to different types, then the maximum height in the output of the bar graph is greater than 0.1 as shown in figure 1(a), 1(b), 1(c) respectively. Figure2 shows the Reconstruction of X-Ray Medical Image using different principal components and observed that reconstruction accuracy increases with increasing the number of principal components with its values for the highest 20 are tabulated in table 1.

Table 1: 2DPCA values for X-Ray Image of Figure 2

Principal Component	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7	Z_8	Z_9	Z_{10}
2DPCA Value	3	21	3.2	43	3	18	33	12	3.5	14
Principal Component	Z_{11}	Z_{12}	Z_{13}	Z_{14}	Z_{15}	Z_{16}	Z_{17}	Z_{18}	Z_{19}	Z_{20}
2DPCA Value	3	3.8	45	4	2.3	1.5	9	24	10	18



(a) Original Image (b) Reconstruction using 20 PCs
(c) Reconstruction using 30 PCs (d) Reconstruction using 40 PCs
Figure 2. Original Image and Image Reconstruction

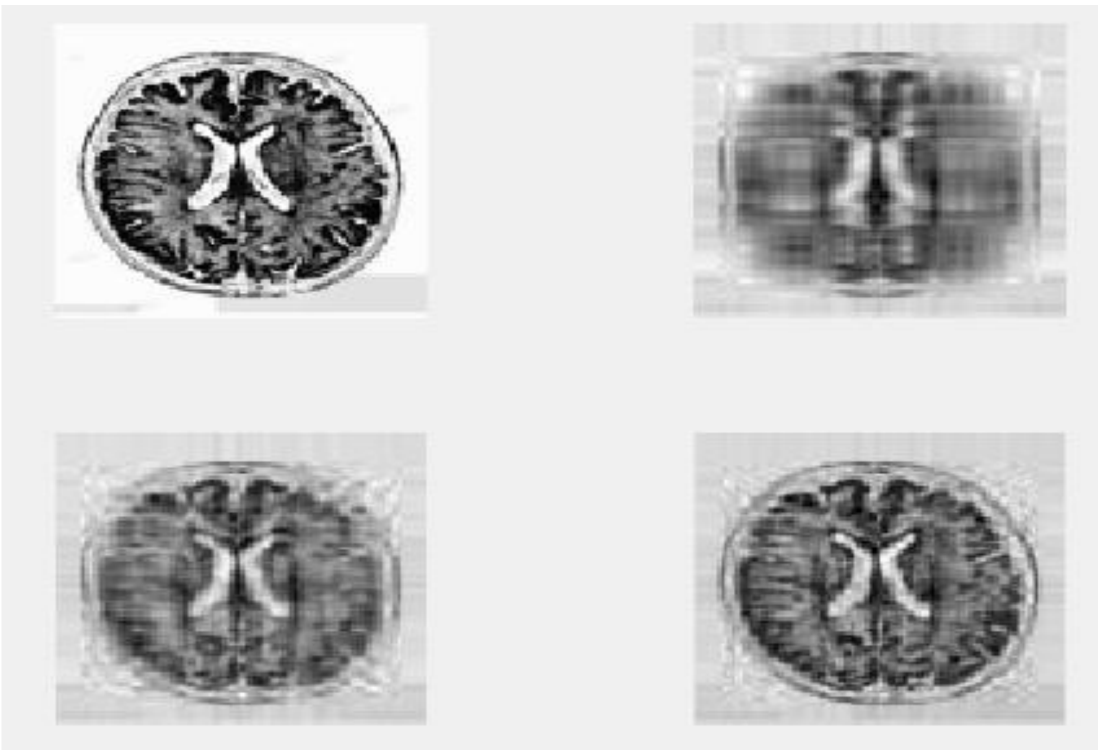


Figure 3. Original Image and Reconstruction using 20 PCs, 40 PCs, 60 PCs respectively

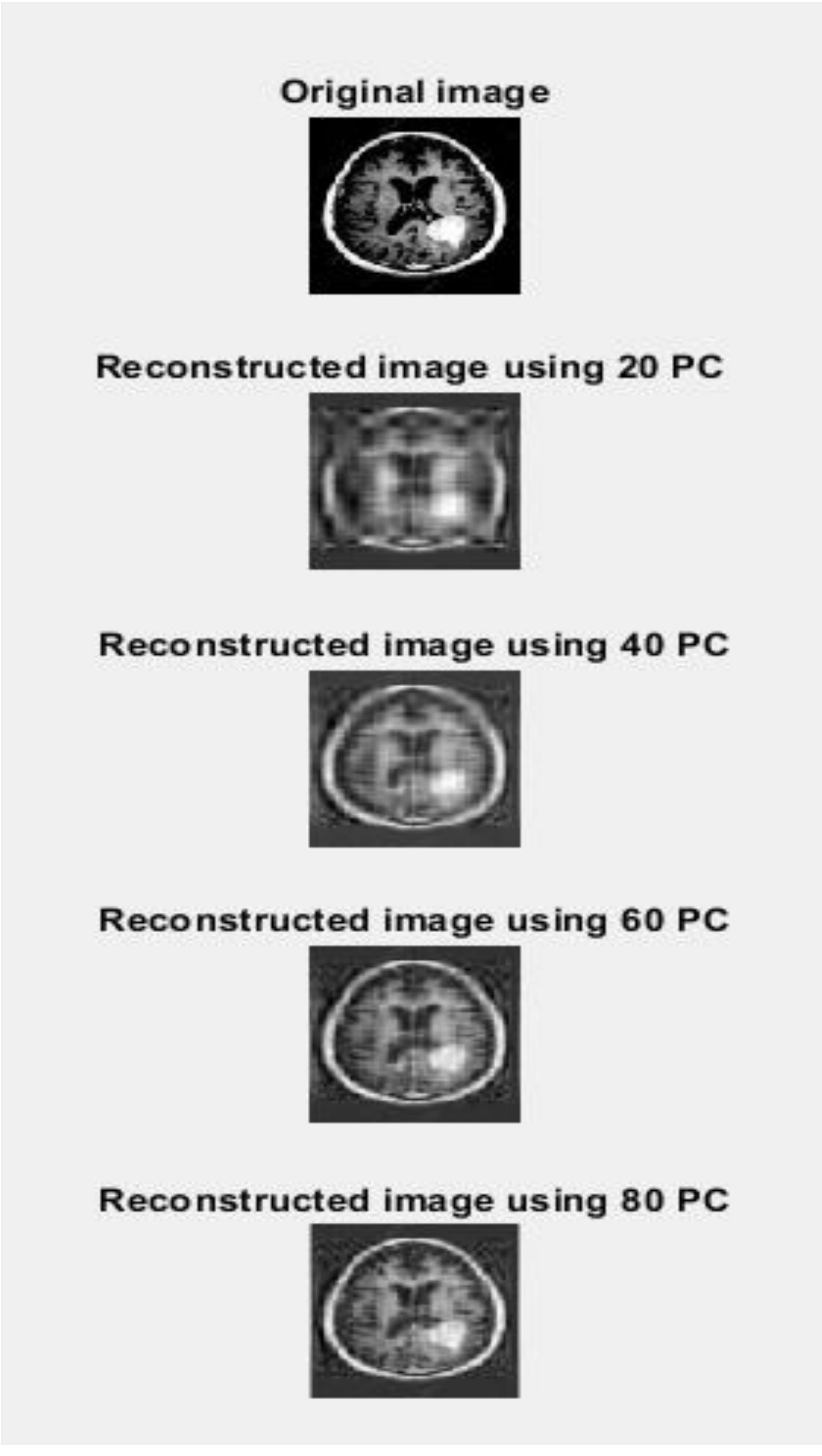


Figure 4. Original Image and Reconstructed Image using 20 PCs, 40 PCs, 60 PCs, and 80 PCs

Table 2: 2D PCA Values for Normal Image of Figure 3

Principal Component	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7	Z_8	Z_9	Z_{10}
2DPCA Value	104	118	131	140	143	146	155	149	146	147
Principal Component	Z_{11}	Z_{12}	Z_{13}	Z_{14}	Z_{15}	Z_{16}	Z_{17}	Z_{18}	Z_{19}	Z_{20}
2DPCA Value	154	161	132	129	120	109	126	168	208	256

Similarly, Figure 3 and Figure 4 show the Reconstruction of MRI medical images for both Normal and Abnormal (tumor) images respectively, and also observed that the reconstruction quality increases with increasing the number of principal components with its values for the highest 20 are tabulated in table 2. Feature Extraction and Reconstruction is carried for different medical images and obtained the reconstruction accuracy of 90% for X-Ray images and 95% for MRI images and also observed that reconstruction accuracy depends on increasing the number of principal components (image features).

5. Conclusion and Future Scope

In this paper, we are presented 2DPCA because of the advantages such as computing the Co-Variance matrix in less time and with high accuracy. 2DPCA is used to reduce computational cost, complexity, and also used in dimensionality reduction. Simulations are performed using Mat Lab by collecting medical images from different databases such as IRMA and WANG etc. Feature Extraction and Reconstruction is performed for different medical images and achieved the reconstruction accuracy of 90% for X-Ray images and 95% for MRI images. Here, we are concluded that the reconstruction accuracy increases by increasing the number of principal components. Reconstruction of Medical Images by using different algorithms is the scope of future work.

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