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KPCA and Eigen-Face-Based Dimension Reduction Face Recognition Method

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ABSTRACT

The practice of identifying people depending on their facial traits is known as face recognition. With rising security demands and technological advancements, obtaining information has gotten much easier. This work creates a face identification application that compares the results of several methods. The main goal is to recognize the face and retrieve information from a database. There are two main steps to it. The first stage is to discover the distinguishing elements in an image and save them. The second step is to compare it to existing photographs and provide the data associated with that image. Face detection algorithms include the Principal Component Analysis (PCA) mechanism and Eigen Face. To lower the complexity of image identification, we employed Kernel-PCA to identify the number of components in an image and further lowered the dimension data set. Experimental results prove that if we reduced the number of dimensions of an image, then a smaller number of Eigen faces will be produced and it will take less time to identify an image.

KEYWORDS: *Principal Component Analysis, Kernel-PCA, Dimension Reduction*

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INTRODUCTION

Face recognition is the most popular and widely utilized biometric technique among the many biometric procedures. In comparison to other techniques, it is less expensive, more natural, and more effective. Face recognition techniques can be classified into several groups. Some approaches detect the entire face, while others detect only certain parts of the face [1-3]. Data acquisition has been an issue for biometric systems such as fingerprint, voice, iris, fuzzy extractor, Keystroke dynamics, and Hand geometry [4]. In the case of fingerprint biometrics, the individual involved should keep her finger in the proper position and orientation, while in the case of speaker recognition, the microphone should be in the proper position and distance from the speaker. However, because the facial recognition method is non-intrusive, the face can be matched invisibly, even if the user is unaware that he or she is being identified.

RELATED WORK

Authors in [5] employed the Fourier Transform face recognition approach to correctly identify a person as well as for emotions/various facial expressions. This process enlarges an image first, then calculates its singular value decomposition (SVD) to generate a matrix with singular values, followed by its singular value decomposition, which extends and produces a single numerical value, rather than a matrix, which has been used to evaluate images. Independent Component Analysis (ICA) is primarily used to recognise faces in video sequences [6]. Face recognition from videos is more difficult because of the enormous amount of data contained in the video. Using ICA and PCA. Authors in [7] investigated facial identity and expression.

FACE RECOGNITION PROCESSING FLOW

It involves the following steps:

(a) Capture: pick up the behavioral samples, (b) Extraction: Exclusive data is extracted from the samples and the template is produced, (c) Comparison: The template is compared with a new sample, and (d) Result: The system decides whether the new samples are matching or not. Fig 1 depicts a general face recognition process flow.

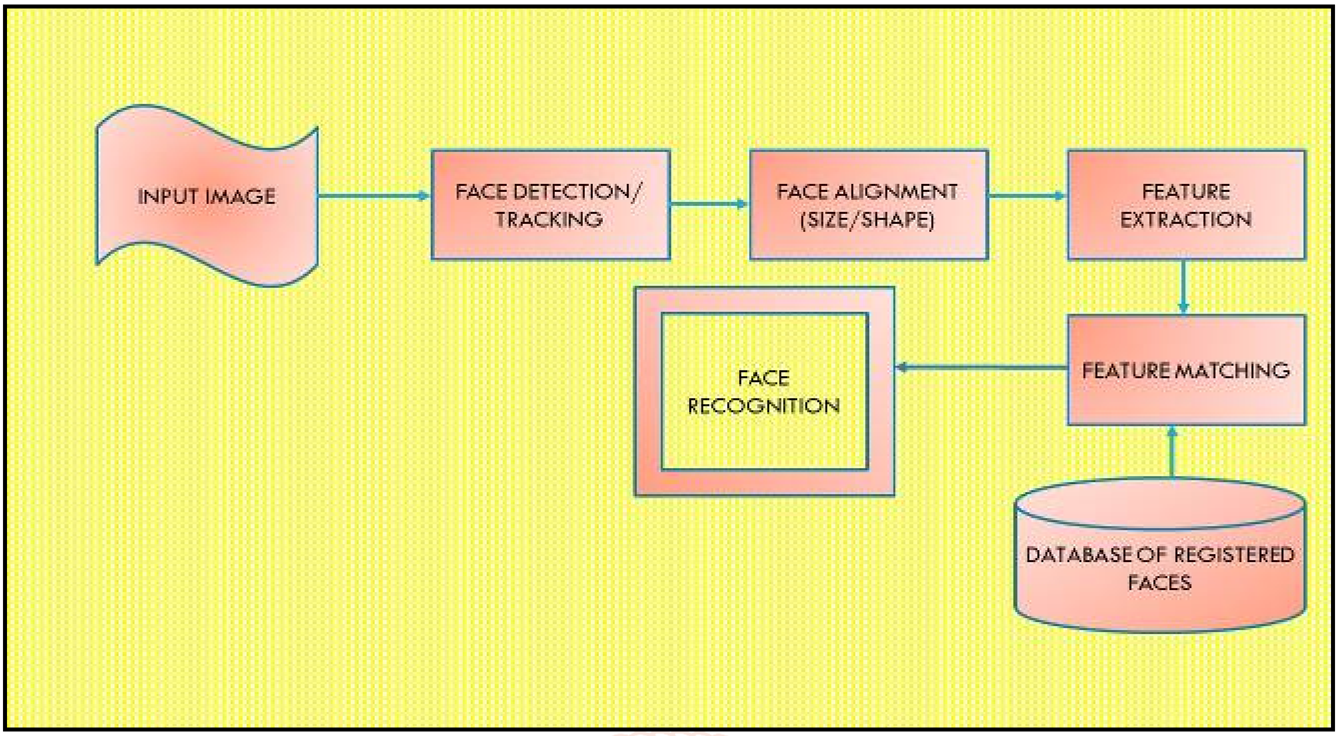

Fig 1: Face Recognition Process Flow

The face detection step fragments the face areas from the background and if the face has to be detected from a video, it has to be continuously tracked by the system. It provides rough approximations of the location and measurement of each detected face. The goal of the face alignment phase is to improve localization accuracy and normalise faces. Facial parts are analyzed and marked based on their location. Geometrical transformation techniques are used to locate parts of the face. The feature extraction is executed to attain useful information that can be distinguished between faces of dissimilar peoples and stay steady with regard to the geometric and photometric deviations. The extracted element vector of the input face is matched against those of enrolled faces in the database for face matching; it yields the uniqueness of the face when a match is established or point to an unknown face otherwise.

PRINCIPAL COMPONENT ANALYSIS (PCA)

It is a tool for reducing the number of dimensions in data. It helps us to lower the data's dimension without losing too much info. PCA decreases the dimension by identifying the most significant orthogonal linear combinations (principal components) of the source variables. The first principal component covers the majority of the data variance. The second principal component is orthogonal to the first principal component and captures the remainder of the first principal component's variation, and so on. The number of principal components is equal to the number of initial variables. These principal components are uncorrelated, and they're arranged in such a way that the first few explain the majority of the variance in the original data. The PCA is a DD (dimension- diminution) method that can be used to lessen a large set of variables into a small set that also covers most of the information in the large set. PCA is an orthogonal transformation that tries to draw straight lines through data. Every line represents a component analysis which is a relationship between dependent and independent variables. The first PCA follows the longest dimension of the data with the least error rate. The second PCA crosses the first PCA perpendicular and adjusts the errors created by the first PCA.

KERNEL PCA

A linear technique is PCA. That is, it can only be used on datasets that can be separated linearly. For datasets that are linearly separable, it performs admirably. However, if we apply it to non-linear datasets, we may end up with a dimensionality reduction that isn't optimal. Kernel PCA projects a dataset into a higher-dimensional feature space, where it can be linearly separated, using a kernel function. Support Vector Machines are a similar concept. To appreciate the value of kernel PCA, consider the fact that N points in $d < N$ dimensions cannot be linearly separated in general. Kernel PCA is a PCA extension that allows nonlinear data to be separated using kernels. The basic idea is to project data that is linearly inseparable into a higher-dimensional space where it may be split linearly. Fig 2 depicts the KPCA process flow.

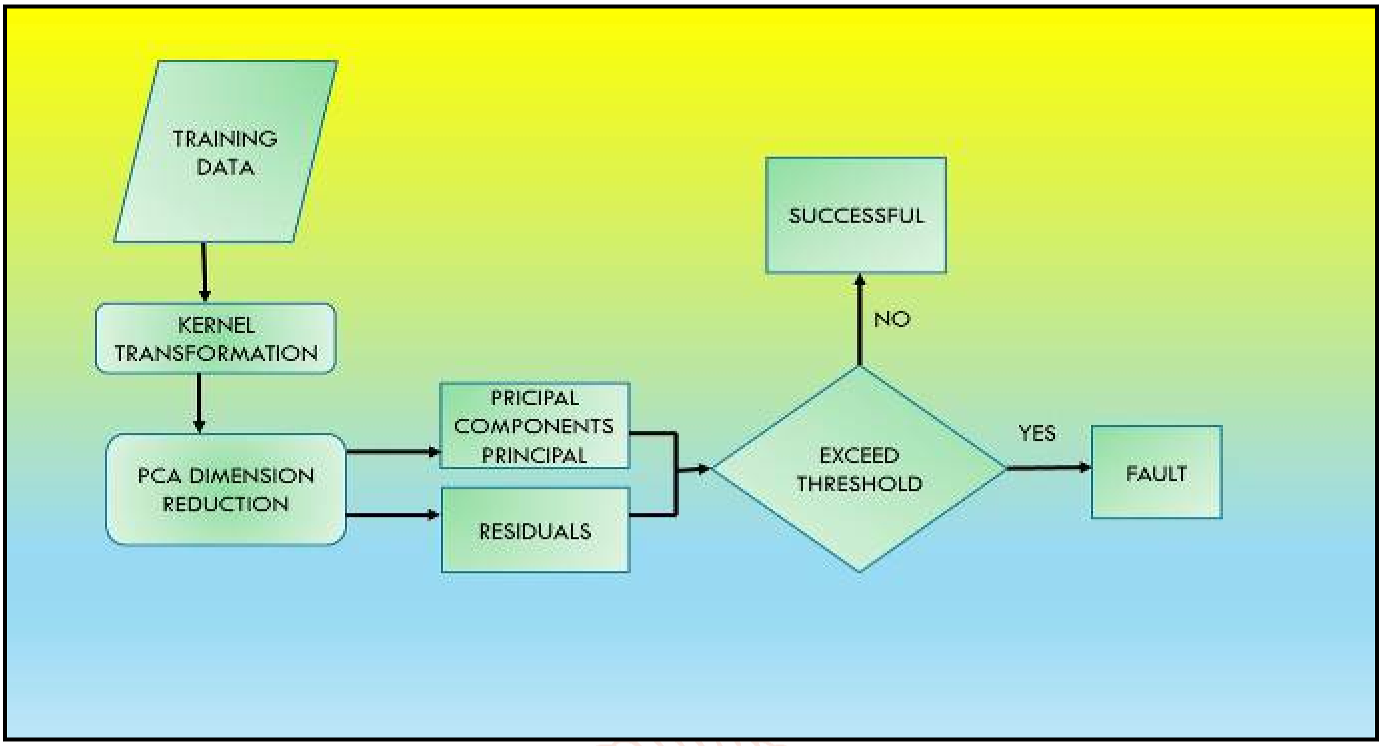

Fig 2: KPCA Process Flow

FACE RECOGNITION USING PCA

Face recognition is handled by Eigen face in PCA, which aids in the creation of initial training sets. Images from the set are compared to a fresh face. Face space has been defined and eigen faces with the highest eigenvalues have been preserved in the training set. Eigen face values have been changed as a result of the addition of new faces. Eigenfaces calculate a set of weights based on the input photos. Check an image against face space, and if it's a face, classify the weight samples as known or unknown faces. The PCA processing of a new face is shown in Fig 3.

PROPOSED METHOD

- **Collect the data:** Create a dataset of images.
- **Produce a dataset with a mean zero:** Subtract the mean from every dimension of the data.
- **Calculate Covariance Matrix:** For 2D (Dimensional) data, the matrix will be 2 X 2 and for n Dimensional data, the matrix will be n X n.
- **Compute Eigen vectors and Eigen Values for the matrix:** The Eigenvectors give statistics about the pattern of the data.
- **Gather components and create a feature vector:** The Eigenvector with the highest Eigen value is called the Principal Component. There is no damage in leaving an Eigenvector with a low value; just a small amount of information is lost. It also decreases the data's dimensionality. A matrix of Eigenvectors is referred to as a feature vector.
- Construct the Final Dataset: It can be constructed using below equation
- **Construct the Final Dataset:** It can be constructed using equation 3

$$Final\ Dataset = Row\_Feature\_Vector\ X\ Row\_Data\_Adjust$$

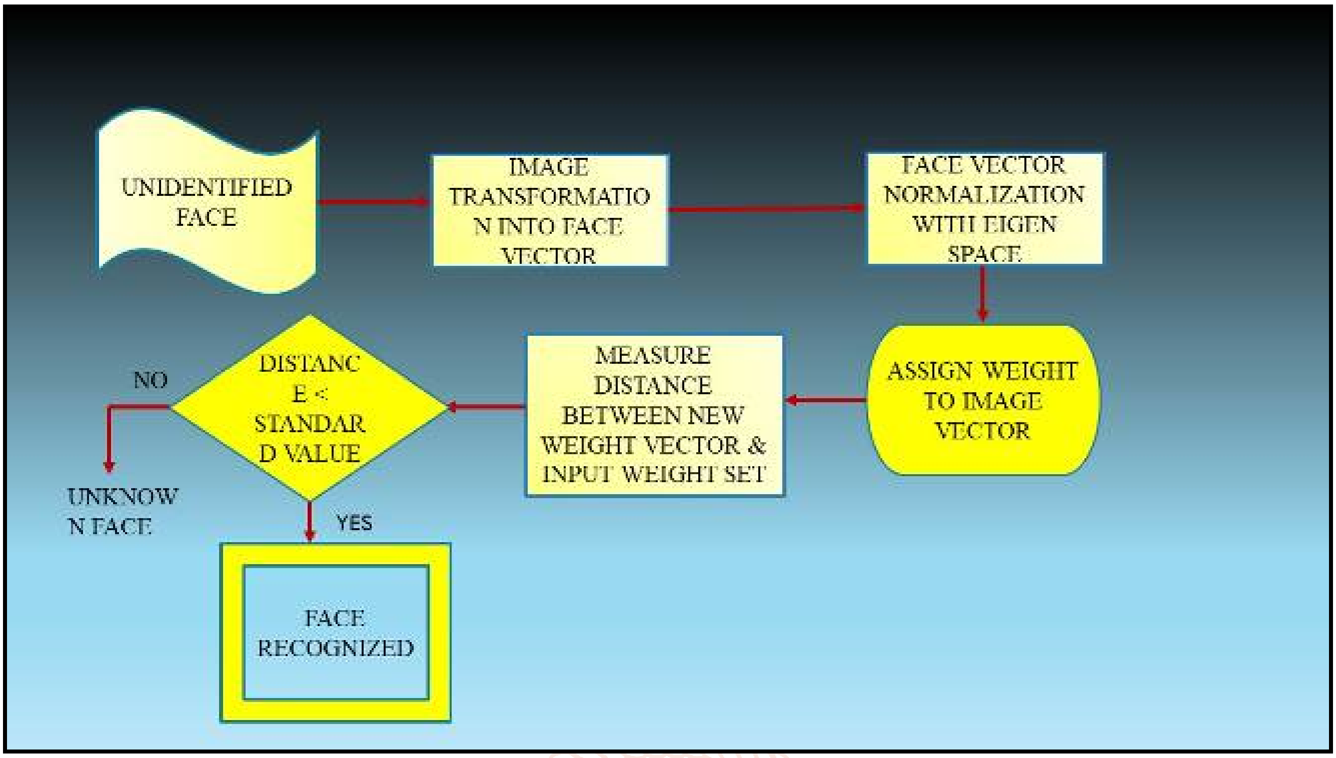

Fig 3: Principal Component Analysis Processing

RESULTS

To detect a face, we employed PCA and Eigen face approaches. There are a total of Eighteen data sets. An image is chosen, and math is performed with the data set. The answer is found if there is a match. Fig 4 to Fig 7 depict the results of the KPCA method.

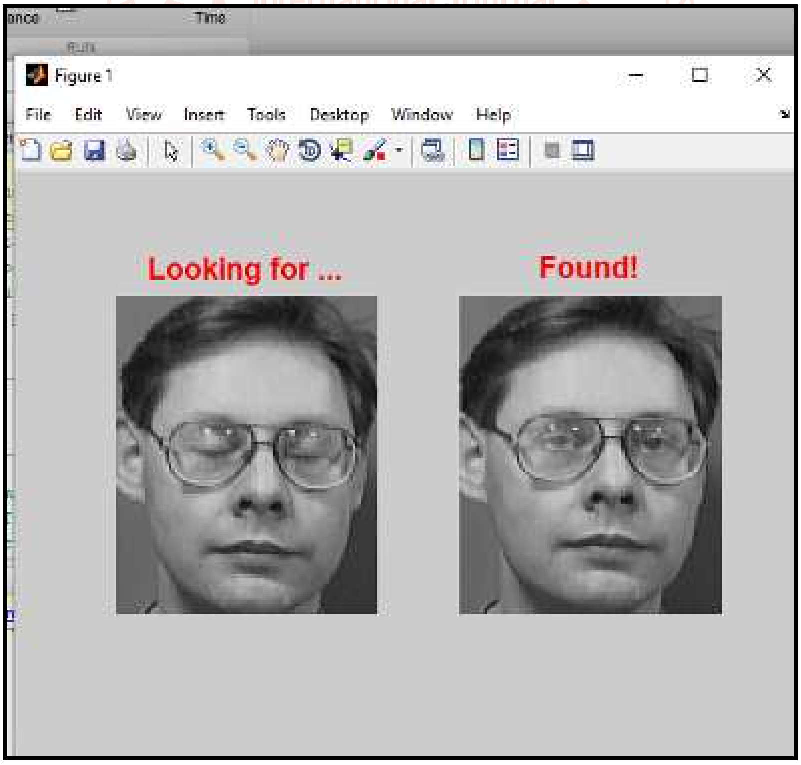

Fig 4: Image Match With little variation

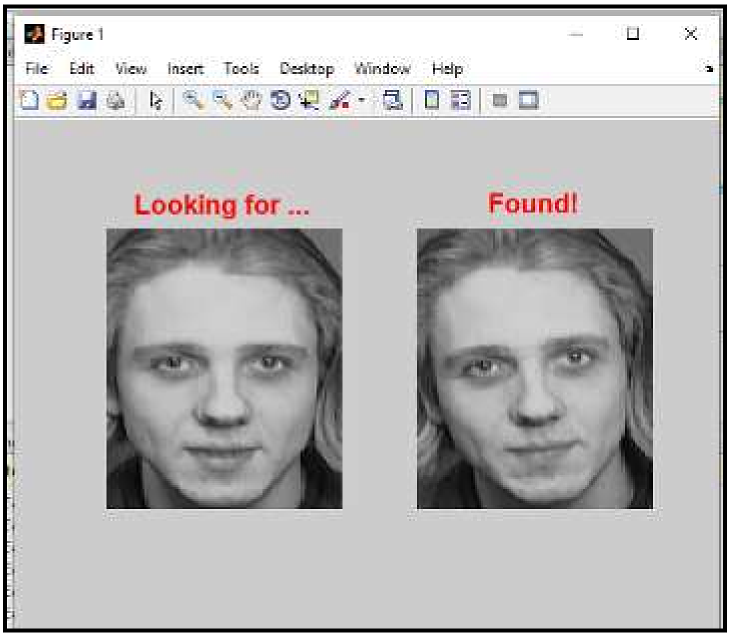

Fig 5: Exact Image Found

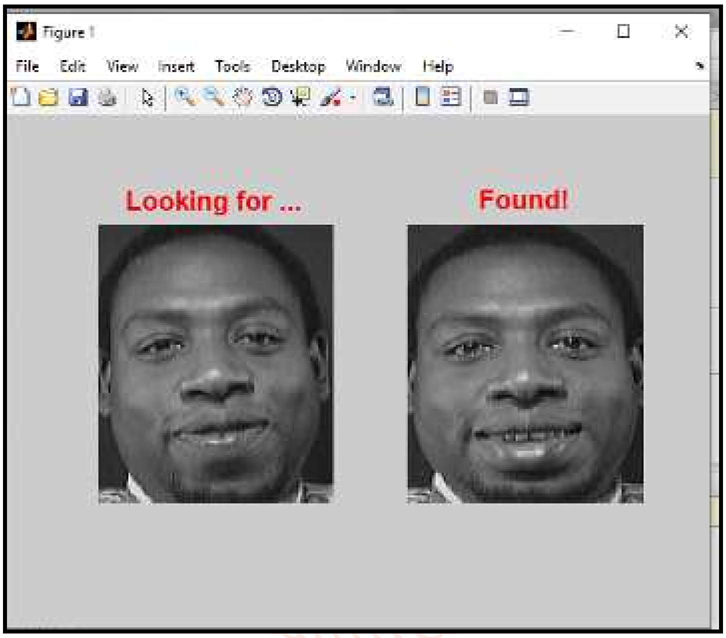

Fig 6: Image Match With least Distance Value

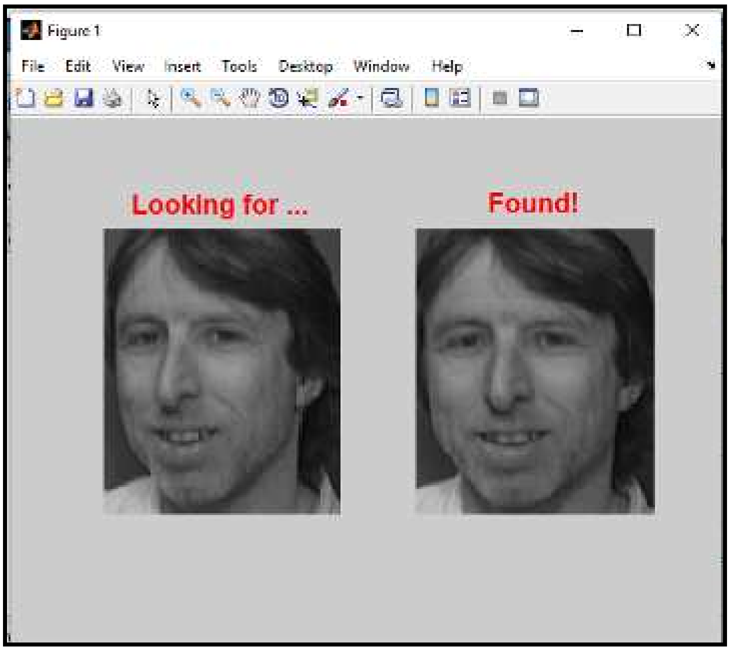

Fig 7: Image Match with Pose Variation

PURE PCA APPROACH

There are two sets Train and Test. The Image in Train is tested against image in Test as shown in Fig 8.

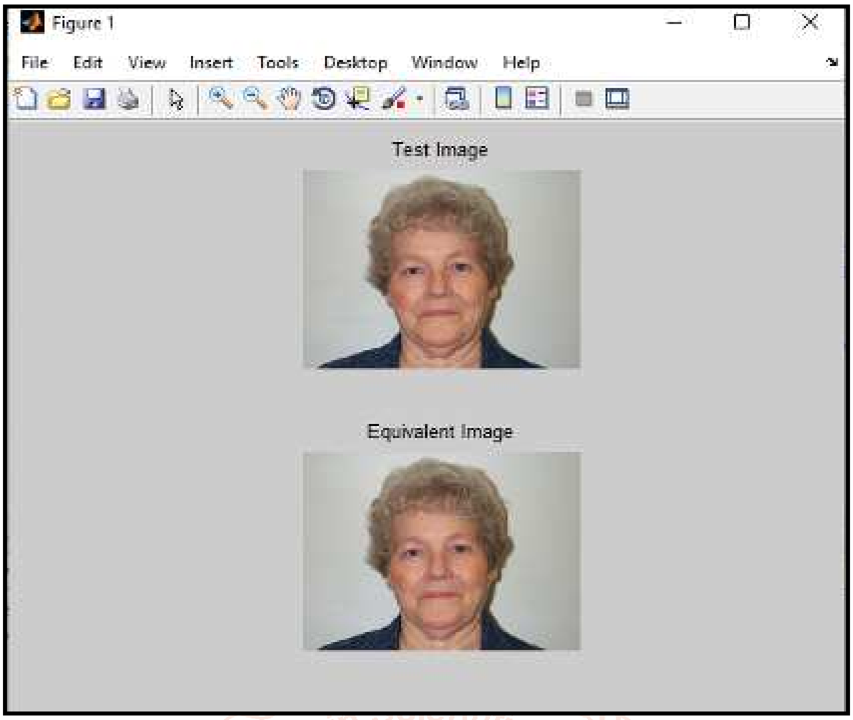

Fig 8: Exact Image Found

CONCLUSION

Each picture would provide the same amount frr the comparison, but not every pixel has useful data. Background and hair pixels, for example, would arbitrarily increase or decrease the distance. We'd also need the faces to be properly aligned in all photographs for direct comparison, and we'd expect that the head rotation was consistent. To solve this problem, the PCA technique generates a set of main components known as Eigen faces. Eigen faces are pictures that indicate the most significant differences among all of the pictures in the database. By computing the average for each pixel in the picture, the recognizer first finds an average face. The differences between each Eigen face and the average face are represented by each Eigen's face. The most important variances between all photos and the average picture will be represented by the first Eigen face, while the least significant differences will be represented by the last Eigen face. In this work, we have compared the results of PCA and KPCA methods. We have reduced the dimensions of the available data with the help of the Kernel PCA method.

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