A Design Of Eigenvalue Based CNN Tool For Image Retrieval

Ramesh Babu P, E Sreenivasa Reddy

Abstract: *Now there are several methods for retrieving images. TBIR, CBIR and SBIR (Semantic Image Retrieval) are some significant methods among them. We propose in this article an effective CNN tool for image retrieval based on eigenvalues. This work is the expansion as a cyber-forensic tool of our newly suggested CNN-based SBIR scheme. Eigenvalues play a prominent role in apps for image retrieval. Eigenvalues are useful in the measurement and segmentation of an image's sharpness and compression process. In this research we used PCA algorithm to generate eigenvalues with corresponding images from an input image. The generated eigenvalues with corresponding images are trained by AlexNet (A pre-trained deep layer convolution neural network (CNN)). After the training process eigenvalues are given as input to the AlexNet (CNN Tool) and the corresponding images are retrieved based on eigenvalues. We noted that output images based on their eigenvalues are obtained with an outstanding 96.44 percent accuracy due to AlexNet training.*

Keywords **:** ***Eigenvalues, AlexNet, PCA, Image Retrieval, deep learning and CNN Tool.***

I. INTRODUCTION

The ability of computers to rapidly and effectively retrieve information from image data sets depends on the artifacts found in the images has a significant impact on the progress of latest image retrieval technologies. Eigenvalues play a major role in apps for image processing. Image Compression (also known as dimension reduction) is one of the applications that is relatively simple to comprehend. Image compression was the means to reduce the size of a graphics file to make it easier to store.

PCA (Principle Component Analysis) was the one of the first methods for Image compression based on eigenvalues. The idea was to remove items such as facial gestures and spontaneous pixel disturbance if you discover the primary components of facial images and project the facial images on these main parts, making it simpler to define the face.

In this paper we are proposing a CNN tool design for image retrieval based on eigenvalues. We used PCA technique for generating eigenvalues from an input image. AlexNet trains the Eigenvalues generated with the respective images. Following the training phase, eigenvalues are provided to the AlexNet as input and the respective images are obtained based on their eigenvalues. Now we will go through the brief outline of the key concepts of this research proposal.

A. About IR (Image Retrieval):

IR (Image Retrieval) is one of computer vision's most interesting and fast-growing research fields. An image retrieval system is nothing but a computer system that allows you to search and retrieve images from various image databases or data sets. Many conventional and popular image retrieval techniques use some technique of adding labels to the images, such as subtitles, search terms, title or facts, so that image retrieval can be done across the words of annotation [5][6].

Moreover, the attention of this paper is only on image retrieval based on its eigenvalues, it is also important to know the other image retrieval systems. There are several techniques for recovering images. Some of the significant techniques of image recovery are shown in the figure below.

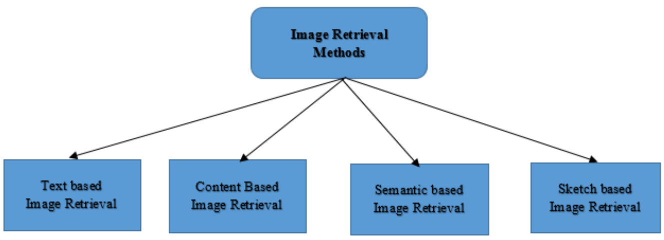

Fig 1: Various Important Image Retrieval Methods

The diagram below demonstrates the overall image retrieval process. In this user, an image as input is queried and the IR system extracts the features from the input image and matches the query image with the knowledge data set images, which is the image database of already extracted features. Then the closest distance between them is found and the finest image as output is retrieved.

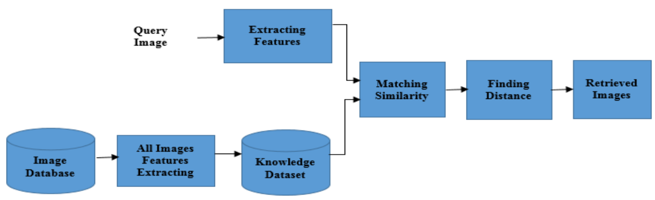

Fig 2: General process diagram of Image Retrieval

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B. About Eigenvalues:

Actually Eigen word derived from German language, Eigen means particular and Eigenvalue also called as Own Value. Eigen value is nothing more than a matrix's characteristic value. When performing DWT (Discrete Wavelet Transformation), the characteristic value containing the features is given to you. In computer vision and machine learning in particular, eigenvalues have many significant applications [13]. Well-known examples are PCA for dimensionality reduction (Principal Component Analysis) or Eigen Faces for face recognition.

Eigenvalues tell how essential it is to make up the completeness of the image for a particular set of Eigen vectors. We select the most important Eigen vectors based on these values expressed in percentages and reconstruct the image from them, which is basically the opposite method of PCA.

C. About PCA:

Also recognized as K-L or Hotelling transform is the principal component assessment (PCA). PCA belongs on the basis of statistical techniques to linear transformations. This method offers a strong tool for statistical analysis and pattern recognition that is often usage by means of a compression and dimensions reduction method in image processing. PCA is based on the Eigenvalues notion.

PCA discovers a fresh set of dimensions such that all dimensions are orthogonal (and therefore linearly independent) and ranked by data variance along them [10]. It implies that there is more significant axis of principle first. (More significant = greater variance / more information spread).

The simple step wise procedure of PCA is as follows:

Step 1: Put the entire d+1-dimensional dataset and ignore the labels so that our current dataset becomes d-dimensional.
Let our X data matrix be three students ' score:

Student	Math	English	Art
1	90	60	90
2	90	90	30
3	60	60	60
4	60	60	90
5	30	30	30

Step 2: Calculate the mean for every aspect of the entire dataset.

$$\mathbf{A} = \begin{bmatrix} 90 & 60 & 90 \\ 90 & 90 & 30 \\ 60 & 60 & 60 \\ 60 & 60 & 90 \\ 30 & 30 & 30 \end{bmatrix}$$

Matrix A

Now A matrix would be

$$\bar{\mathbf{A}} = [\,66 \quad 60 \quad 60\,]$$

Step 3: Calculate the entire dataset's covariance matrix

$$cov(X,Y) = \frac{1}{n-1}\sum_{i=1}^{n} (Xi - \bar{x})(Yi - \bar{y})$$

Covariance matrix of A can be compute using above formaula Also, the result would be a square matrix of d ×d dimensions.

$$\begin{array}{cccc} & Math & English & Arts \\ 1 & 90 & 60 & 90 \\ 2 & 90 & 90 & 30 \\ 3 & 60 & 60 & 60 \\ 4 & 60 & 60 & 90 \\ 5 & 30 & 30 & 30 \end{array}$$

'A' Matrix

$$\begin{array}{cccc} & Math & English & Art \\ Math & 504 & 360 & 180 \\ English & 360 & 360 & 0 \\ Art & 180 & 0 & 720 \end{array}$$

'A' Matrix
Covariance

Step 4: Calculate eigenvectors and the corresponding eigenvalues.

'A' eigenvalues are as follows

$$\det(A-\lambda I) = 0$$

det (A-λI) as identity matrix:

$$\det\left(\begin{pmatrix} 504 & 360 & 180 \\ 360 & 360 & 0 \\ 180 & 0 & 720 \end{pmatrix} - \lambda \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}\right)$$

Streamlining the matrix first,

$$\begin{pmatrix} 504 & 360 & 180 \\ 360 & 360 & 0 \\ 180 & 0 & 720 \end{pmatrix} - \begin{pmatrix} \lambda & 0 & 0 \\ 0 & \lambda & 0 \\ 0 & 0 & \lambda \end{pmatrix}$$

$$\begin{pmatrix} 504-\lambda & 360 & 180 \\ 360 & 360-\lambda & 0 \\ 180 & 0 & 720-\lambda \end{pmatrix}$$

This is shortened matrix,

$$\det\begin{pmatrix} 504-\lambda & 360 & 180 \\ 360 & 360-\lambda & 0 \\ 180 & 0 & 720-\lambda \end{pmatrix}$$

$$-\lambda^3 + 1584\lambda^2 - 641520\lambda + 25660800$$

Now essential to resolve for λ

$$-\lambda^3 + 1584\lambda^2 - 641520\lambda + 25660800 = 0$$

Next resolving this equation for λ, we will get as

$$\lambda \approx 44.81966\ldots,\ \lambda \approx 629.11039\ldots,\ \lambda \approx 910.06995\ldots$$

These are Eigenvalues

Determine the eigenvectors equivalent to eigenvalues.

$$\begin{pmatrix} -3.75100\ldots \\ 4.28441\ldots \\ 1 \end{pmatrix}, \begin{pmatrix} -0.50494\ldots \\ -0.67548\ldots \\ 1 \end{pmatrix}, \begin{pmatrix} 1.05594\ldots \\ 0.69108\ldots \\ 1 \end{pmatrix}$$

Step 5: Category by lowering their eigenvalues, the eigenvectors choose k with the largest own values to form a d / k dimensional matrix W.

$$\begin{pmatrix} 910.06995 \\ 629.11039 \\ 44.81966 \end{pmatrix}$$

So, the eigenvectors that correspond to two peak their eigenvalues are:

$$W = \begin{bmatrix} 1.05594 & -0.50494 \\ 0.69108 & -0.67548 \\ 1 & 1 \end{bmatrix}$$

Step 6: Use this matrix d / k to convert the samples to the fresh subspace

During the last step, we're using the 2-dimensional matrix W that we've just calculated to transform our samples into the new subspace through the equation y = W ′ x where W′ is the matrix W transposition.

The below figures illustrates the operation of PCA for generating eigenvalues from an input image in the context of image retrieval:

Original Image

Fig 3: Images with their eigenvalues of 5, 10, 20 and 40 as generated by PCA

In this research, we have split and concatenated the image into blocks of 10*10 dimensions. For matrix we apply PCA that returns a set of eigenvalues, Eigen vectors and main elements. This creates images of Eigen that would be essential to the compressed image.

D. About AlexNet

The ILSVRC (ImageNet Large-Scale Visual Recognition Challenge) competition introduced AlexNet as the winner in 2012 and reached a 15.3 percent winning top-5 test error rate, compared to 26.2 percent attained by the second-best entry. The team built AlexNet, made up of Alex Krizhevsky, G. Hinton and Ilya Sutskever[12].

Though we used GoogLeNet in our previous research, to get better accuracy as per our current research AlexNet has been used for training purpose. Even though there are many more network topologies, AlexNet in our opinion was the first to make a breakthrough. AlexNet is a pre-trained neural network (CNN) of convolution. A CNN network of image sorting that has learned to extract strong and enlightening features from natural images and use them as a starting point for learning a fresh task. Actually AlexNet contains five convolutional layers and three fully connected layers, further it can be improved as per user's requirement in their research. In our research we extended this AlexNet up to 25 layers. After actual convolutions and fully connected layer, the ReLu is implemented. Dropout is useful afore the primary and the subsequent fully connected layer. The image size in our architecture chart should be 227 * 227 dimensions.

This paper used AlexNet as CNN tool for image recovery in this research. The eigenvalues obtained by the PCA algorithm are given to the AlexNet as input. The network has been thoroughly trained for accurate outcomes along with its input eigenvalues. And the respective images were obtained based on the query's eigenvalues.

This presented, research article is structured as follows, describes implementation of image retrieval system, PCA, Eigenvalues, and AlexNet in Section One. Section two includes the associated latest research on image retrieval systems based on eigenvalues. Section three describes the definition of the problem. Section four discusses this research paper's suggested methodology and includes PCA data. The results are described in section five. This research paper is concluded in Section six

II. RECENT RELATED RESEARCHES

As a cyber-forensic tool using CNN-based deep learning, Ramesh Babu P et al [1] designed an effective framework for semantic-based facial image recovery scheme. Even though existing cyber forensic tools are not equipped with beneficial

semantic image retrieval methods, this CNN deep learning based semantic facial expression image retrieval system helps solve many actual-time problems with sentimental analysis, such as helping with automatic riding, trained 144 layers of deep training and obtained the best performance accuracy with 86.25%. Hailong Liu et al [5] recommends an image recovery scheme that uses fused deep learning characteristics to resolve The conceptual difference between short-level characteristics and large-level semantic characteristics of traditional CBIR method. First, LeNet-L's enhanced network structure is achieved by improving LeNet-5's convolutional neural network. Then, LeNet-5 and AlexNet extract two distinct profound convolutional characteristics. At last, the comparable image is acquired after the fusion by comparing the resemblance between the retrieved image and the distance function image in the database. The findings indicate that this technique has a better accuracy of retrieval.Zheng dang et al [6] implemented a novel strategy for a matrix's zero own value defined by the output of the network. Their loss may not endure from the mathematical instabilities of their Eigen decomposition's analytical differentiation and converges much quicker to the best solution. They proved the method's throughput in trying to match important point assignments in true pictures and outlier rejection for the PnP issue. Their new loss has enabled us to accomplish state-of - the-art outcomes for both cases.

Daniel L. Swets et al [7] explains the automated choice of image training features using multidimensional allowed to discriminate analysis concepts and the related ideal linear projection. They show the efficacy for Discriminating Structures for generic recovery from big dataset of commonly differing real-world objects described as "well-framed" opinions, and contrast them with main element assessment. Only this use of intensity pictures as input to the scheme is investigated in their studies. It may also be useful to use edge pictures as well as intensity pictures to render our system almost insensitive to lighting circumstances. In the Utmost Discriminating Structures space, it is necessary to explore the applicability of intensity in conjunction with images of edge map.

Nguyen Khang et al [8] suggested using Factorial Communications Analysis to retrieve content-based images. They also suggested a fresh search quality algorithm. The mathematical studies indicate that the findings of FCA are much better than tf * idf and marginally higher PLSA. The fresh recovery algorithm using inverted files increases the response time considerably without losing outcome accuracy. While studying the effect of parameter n_thres, they discovered that the list of applicants contained approximately 90 percent appropriate pictures with a size of 1/100 database. It implies that by tracking only 1/100 database, we can attain a accuracy of 90 percent if an suitable resemblance measure is used. This inspires us to plan in future projects to incorporate our archiving method with a utter impossibility of resemblance as CDM (Contextual Dissimilarity Measure).

Zhong Su et al [9] suggested a unique technique for generating image class features depicted by the favourable images given by feedback on subjective relevance. They used well known efficient PCA algorithm to reduce both the noise characteristics of the original image and the dimensionality of the characteristic spaces. The technique improves the pace of recovery and considerably decreases the memory without sacrificing the accuracy of recovery

III. PROBLEM DEFINITION

There are several image retrieval methods for retrieving of images. But the role these methods in effective retrieving of images is not up to the mark. In the case of TBIR, for example, there is a need for manual annotation, so that huge databases are strongly needed. Using this technique, we cannot retrieve the image features. There is mainly a subjectivity in TBIR for human perception. It increases the precision of the retrieval in the case of CBIR, but its feature set is inadequate. And there is primarily a conceptual difference between characteristics of higher and lower level, there is a need to use relevant feedback technique to decrease this semantic gap. In the case of SBIR similarity measurement and image retrieval works twice, thus leading to increased calculation performance and in this technique there is a major necessity for semantic features [15].

In addition, dimensionality reduction will not favour the decrease of memory utilization in larger image data sets by these three image recovery techniques. PCA is the best method for addressing this reduction in image dimension [10]. We use this PCA method in our proposed framework design to produce eigenvalues for respective images and can be obtained based on these eigenvalues input respective images. Even though PCA has some drawbacks to perform distributed class data sets and to evaluate covariance matrix accurately, it is playing important role in deep learning and image processing fields due to its little noise compassion, not as much of memory requirement and increased efficiency in the case dimensionality reduction.

IV. PROPOSED METHODOLOGY

This paper proposes a novel design, based on eigenvalues for image retrieval using CNN based pre-trained deep learning network called AlexNet. We used PCA algorithm for generating eigenvalues from input images. The clear illustration about AlexNet and PCA discussed in introduction part. This proposed approach examines the possibility and potential benefits of learning the tools for image analysis in the principal component analysis (PCA) domain of convolutional neural networks (CNN). In order to create eigenvalues, we engaged the PCA on images. Finally, deep learning will be performed for classification through a pre-trained conventional neural network called AlexNet. Convolution neural networks are a sort of artificial neural network used in various fields such as image classification and segmentation.

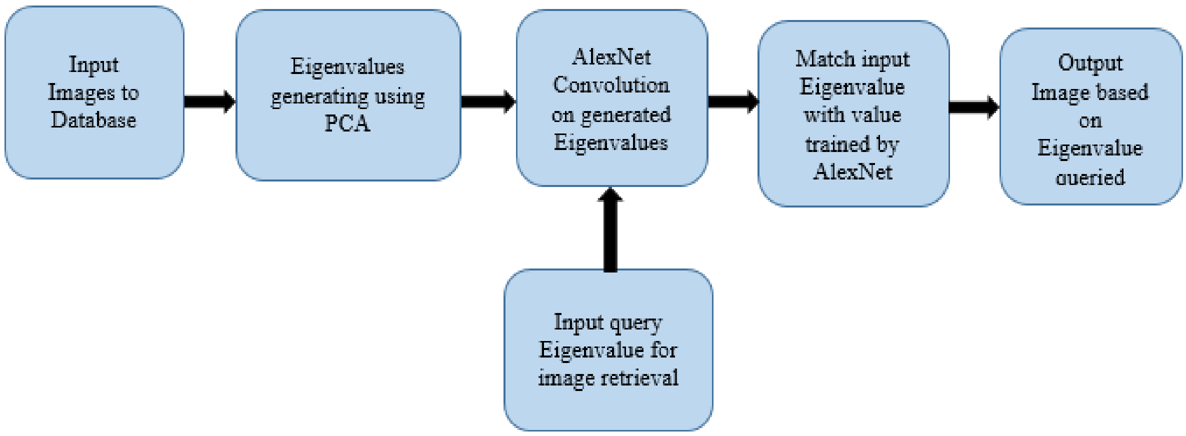


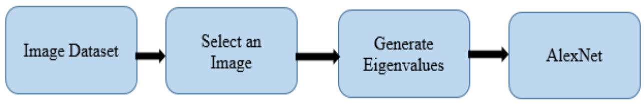
Fig 4: Overall process diagram of the proposed design

A. Algorithm of Deep CNN for Proposed Design:

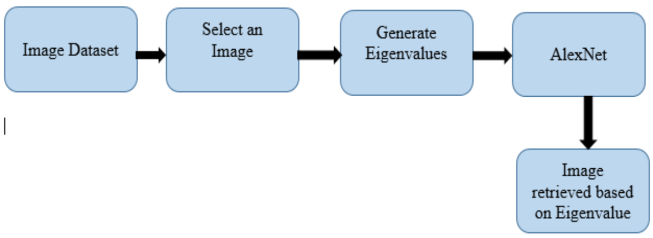
Step 1: Input image layer which has input image dimension 227x227x3 with normalization as zero centre.
Step 2: The stride [4 4] and padding [0 0 0 0] for 96 11x11x3 convolutions.
Step 3: ReLU convolution layer repeats till 21st layer. Conducts a threshold process for each input component.
Step 4: Cross Channel.
Step 5: The stride [2 2] and padding [0 0 0 0] to do down-sampling by 3x3 max pooling.
Step 6: The stride [1 1] and padding [2 2 2 2] for 256 5x5x48 convolutions.
Step 7: ReLU (Rectified Linear Unit)
Step 8: Cross channel normalization with 5 channels per element.
Step 9: The stride [2 2] and padding [0 0 0 0] for 3x3 max pooling.
Step 10: The stride [1 1] and padding [1 1 1 1] for 384 3x3x256 convolutions.
Step 11: ReLU.
Step 12 The stride [1 1] and padding [1 1 1 1] by 384 3x3x192 convolutions
Step 13: ReLU.
Step 14: The stride [1 1] and padding [1 1 1 1] for 256 3x3x192 convolutions.
Step 15: ReLU.
Step 16: the stride [2 2] and padding [0 0 0 0] for 3x3 max pooling.
Step 17: 4096 fully connected layer (A fully connected layer multiplies the input by a weight matrix and then adds a bias vector).
Step 18: ReLU.
Step 19: 50% dropout
Step 20: 4096 FCL (fully connected layer)
Step 21: ReLU.
Step 22: 50% dropout
Step 23: 1000 FCL (fully connected layer)
Step 24: Softmax.
Step 25: Sorting Output - Cross entropy ex with 'tench' and 999 other classes.

B. Phase wise Methodology Process:

Training Phase:



Testing Phase:



In training phase, AlexNet is trained using eigenvalues which are generated through PCA. We used a method of PCA for generating eigenvalues of the given input image. The generated eigenvalues will be trained by the AlexNet for classification. In testing phase, everything is the same like in training phase but the trained eigenvalues of an images will be matched with the input queried eigenvalue and then based on that corresponding image will be retrieved.The second step is to use the pre-trained conventional neural network (AlexNet) for classifying images based on eigenvalues and test it to determine the object class of a given unknown eigenvalue.

C. Network Layer Graph of CNN (AlexNet):

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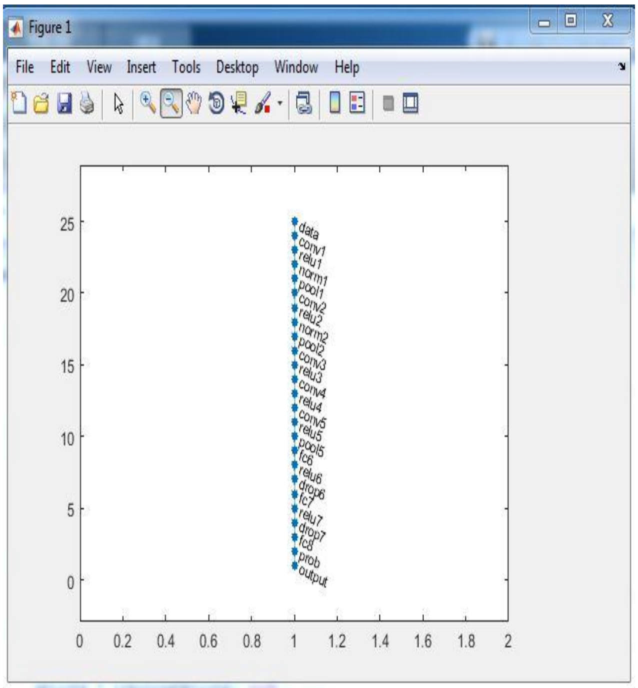

Fig 5: Layer Graph

Network contains 25 layers, we can visualize the above layer graph by plotting lgraph file of the network. The component of the layer graph is input, Input are the images of dimension 227-by-227-by-3, where 3 indicates the color channel. This dimension of the images is required by the first layer. The image input layer is the first component of the network's Layers characteristic. The below tabular diagram illustrates of layer wise computation of AlexNet with 25 layers:

Table 1: Illustration of layers

s

V. EXPERIMENTAL RESULTS

The proposed eigenvalue based facial image-retrieval design is analysed using the Yale facial dataset. This Yale facial dataset consists of different gray scale facial images, which includes the face features of happy, sad, wink, surprise, oval face, round face, moustache face with glasses, sad face with glasses and sad face with No glasses and so on. We have trained the network by using happy face expression of 15 persons.

A. CNN Testing:

Its network needs 227* 227* 3 input images, specify extra enhancement activities to be performed on the training images: randomly flip the training pictures along the vertical axis and randomly translate them up to 30 pixels and scale them horizontally and vertically up to 10 percent. Data reduction helps to prevent overfitting and retention of accurate training image data by n.

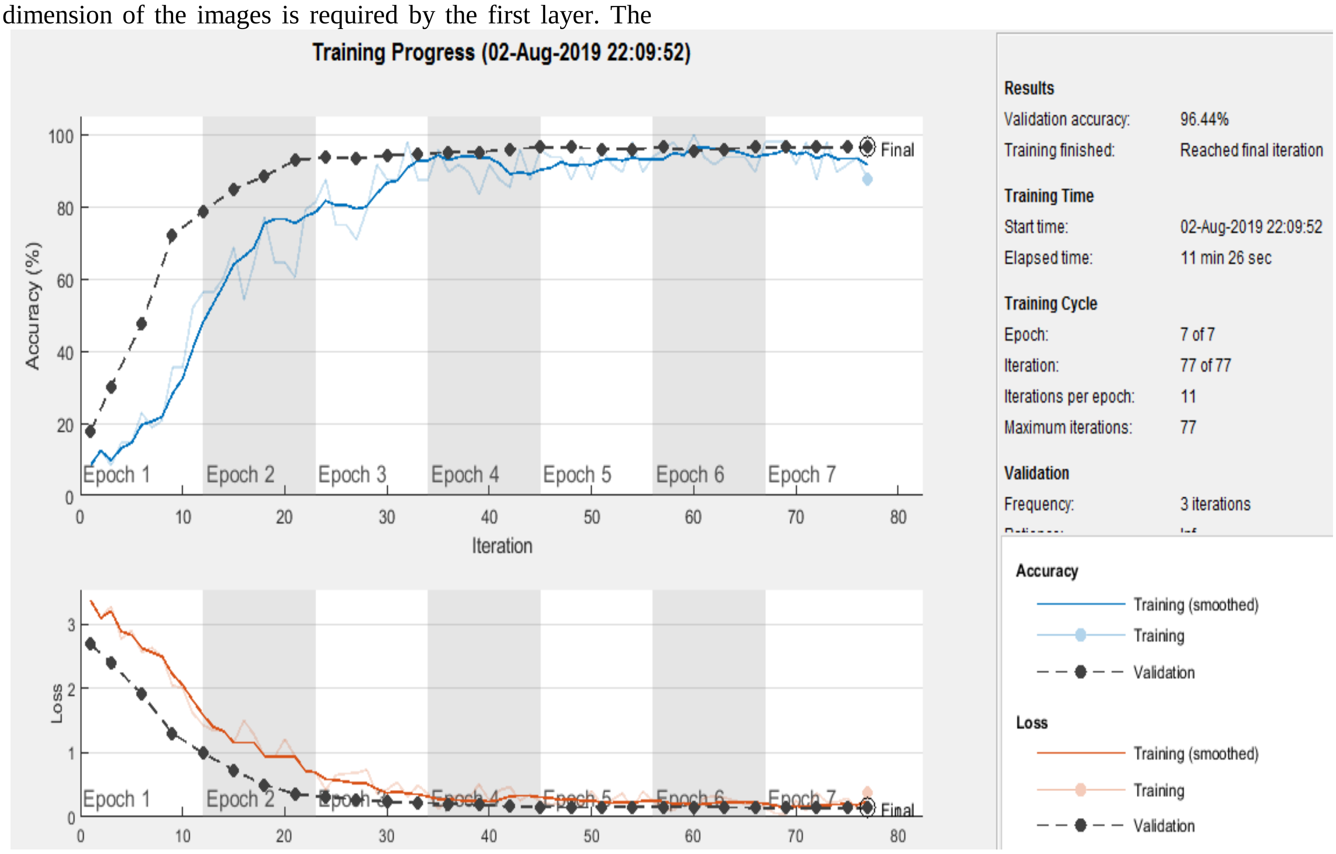

Fig 6: Training Process

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B. Results

It takes approximately 15 minutes to complete the training process. During our observation network has taken 11:26 seconds for completion of training with an accuracy of 96.44 %, Total iteration, Training cycle parameter as iteration per epoch are 11, Maximum iterations are 77. We have tested the 15 people's happy expression and generated 50 eigenvalues per each person.

Testing result of images:

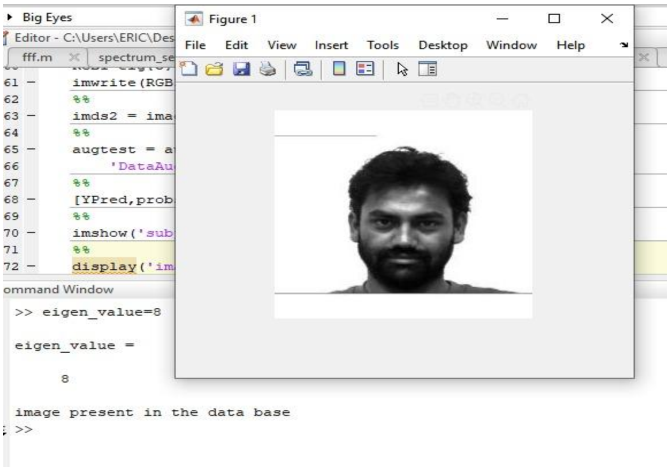

Fig 7: Output of a retrieved image with eigenvalue of 8

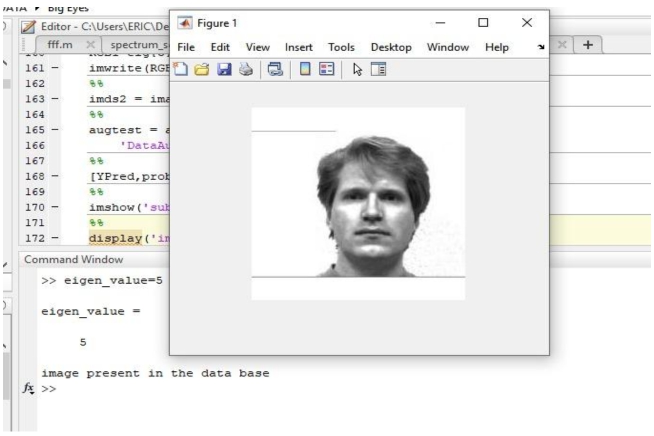

Fig 8: Output of a retrieved image with eigenvalue of 5

VI. CONCLUSION

This paper represents about the design of eigenvalue based CNN tool for image retrieval using pre trained deep convolution neural network (CNN) called AlexNet. Eigenvalues are useful for image reduction in dimensionality. We used the PCA algorithm in this research to generate eigenvalues from an input image. Our recommended CNN deep learning based image retrieval system based on its eigenvalue has low sensitivity to noise and needs less memory. Finally, our network has achieved highest result with 96.44 % accuracy after 25 layers of deep learning. The elapsed time is 11minutes and 26 seconds, Validation frequency is 3 iterations, Training cycle parameter as iteration per epoch are 11 and Maximum iterations are 77.In this research, we definitely hope that our proposed design will represent the interests of novice researchers and learners who are actively involved in image processing, deep learning based cyber forensics and image retrieval applications

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