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Image Deduplication in Face Recognition using Back Propagation Neural Network (BPNN)

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Abstract: **Deduplication has been widely used in backup systems and archive systems to improve storage utilization effectively. However, the traditional deduplication technology can only eliminate exactly the same images, but it is unavailable to duplicate images, which have the same visual perceptions but different codes. To address the above problem, we designed and developed a back propagation** based **Artificial Neural Network (ANN) classifier, which is efficient in terms of learning time, ROC and computational efficiency during testing/prediction/classification phase. In addition, with a large amount of data and a careful designing of architecture, we can define a better feature selection from CBFD (Complex Binary Feature Descriptor) thereby ensuring higher accuracy.**

Keywords: **Facial Recognition System, Complex Binary Feature Descriptor, Artificial Neural Network (ANN), Digital Image Processing (DIP).**

I. INTRODUCTION

Facial Recognition System

A facial recognition system is a computer application capable of identifying or verifying a person from a digital image or a video frame from a video source. One of the ways to do this is by comparing selected facial features from the image and a facial database. It is typically used in security systems and can be compared to other biometrics such as fingerprint or eye iris recognition systems.

Techniques used for 'Facial Recognition'

Traditional Recognition:-Some facial recognition algorithms identify facial features by extracting landmarks, or features, from an image of the subject's face. For example, an algorithm may analyze the relative position, size, and/or shape of the eyes, nose, cheekbones, and jaw. These features are then used to search for other images with matching features. Other algorithms normalize a gallery of face images and then compress the face data, only saving the data in the image that is useful for face recognition. A probe image is then compared with the face data. One of the earliest successful systems is based on template matching techniques applied to a set of salient facial features, providing a sort of compressed face representation.

Dimensional Recognition:- A newly emerging trend, claimed to achieve improved accuracies, is three-dimensional face recognition. This technique uses 3D sensors to capture information about the shape of a face. This information is then used to identify distinctive features on the surface of a face, such as the contour of the eye sockets, nose, and chin. One advantage of 3D facial recognition is that it is not affected by changes in lighting like other techniques. It can also identify a face from a range of viewing angles, including a profile view. Three-dimensional data points from a face vastly improve the precision of facial recognition. 3D research is enhanced by the development of sophisticated sensors that do a better job of capturing 3D face imagery. The sensors work by projecting structured light onto the face. Up to a dozen or more of these image sensors can be placed on the same CMOS chip—each sensor captures a different part of the spectrum.

Feature Learning

In machine learning, feature learning or representation learning is a set of techniques that learn a feature: a transformation of raw data input to a representation that can be effectively exploited in machine learning tasks. This obviates manual feature engineering, which is otherwise necessary and allows a machine to both learn at a specific task (using the features) and learn the features themselves: to learn how to learn.

Feature learning is motivated by the fact that machine-learning tasks such as classification often require input that is mathematically and computationally convenient to process. However, real-world data such as images, video, and sensor measurement is usually complex, redundant, and highly variable. Thus, it is necessary to discover useful features or representations from raw data. Traditional handcrafted features often require expensive human labor and often rely on expert knowledge. In addition, they normally do not generalize well. This motivates the design of efficient feature learning techniques, to automate and generalize this.

Feature learning can be divided into two categories: supervised and unsupervised feature learning, analogous to these categories in machine learning generally.

- In supervised feature learning, features are learned with labeled input data. Examples include neural networks, multilayer perceptron, and (supervised) dictionary learning.
- In unsupervised feature learning, features are learned with unlabelled input data. Examples include dictionary learning, independent component analysis, autoencoders, matrix factorization, and various forms of clustering.

Artificial intelligence (AI)

Artificial intelligence (AI) has been established as the area of computer science dedicated to production software capable of sophisticated, intelligent, computations similar to those that the human brain routinely performs. It includes methods, tools, and systems devoted to simulating human methods of logical and inductive knowledge acquisition, the reasoning of brain activity for solving problems. There are two main categories of AI developments. The first includes methods and systems that simulate human experience and draw conclusions from setoff rules, such as expert systems. The second includes systems that model the way the brain works, for example, artificial neural networks (ANNs).

TABLE I: Differences in approach between conventional computing and ANNs

Characteristics	Conventional computing (including expert systems)	Artificial neural networks
Learning method	By rules (didactically)	By example (Socratic ally)
Functions Processing style	Logically Sequential	Perceptual pattern Parallel

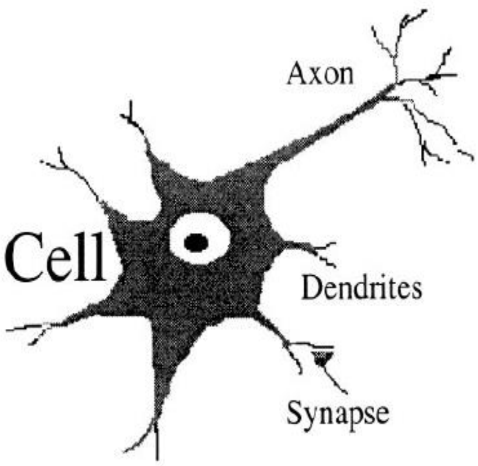

Fig. 1: Neuron cell

Expert systems are knowledge-based systems, an extension of conventional computing and are sometimes called the fifth generation of computing. This knowledge base allows an expert to define the rules that simulate a process of thinking and provides a simple way to draw conclusions and solve problems by following a set of rules. The idea of expert systems is that logical thinking can be modeled by compiling lists of logical propositions and performing logical transformations upon them. Expert systems are used for medical diagnosis and other diagnostic problem solving [41, 42]. It provides a guide for prediction and decision making in environments involving uncertainty and vagueness. Medical practice, for example, is often hampered by incomplete and inexact scientific models of human health and disease, and incomplete or sometimes inaccurate data about individual patients.

ANNs are digitized models of a human brain, computer programs designed to simulate the way in which human brain processes information. ANNs learn (or are trained) through experience with appropriate learning exemplars just as people do, not from programming. Neural networks gather their knowledge by detecting the patterns and relationships in data. The brain is an excellent pattern recognition tool. When we look at a pen, we know it is a pen because biological neurons in a certain area of our brain have come across a similar input pattern on previous occasions and have learned to link that specific pattern with the object description 'pen'. Sinceour brain contains billions of neurons, which are fully interconnected, we can learn and recognize an almost endless variety of input patterns.

An average brain contains ~100 billion neurons, each of which has 1000–10000 connections with other neurons. Neurons consist of a cell body which includes nucleus that controls the cell activity, many fine threads, dendrites, that carry information into the cell, and one longer thread known as the axon which carries the signal away (Fig. 1.1). Impulses pass along the axon to the synapse, the junction between one neuron and the next and signals are passed from one to the next in an all-or-none fashion. Neurons are organized in a fully connected network and act like a messenger in receiving and sending impulses. The result is an intelligent brain capable of learning, prediction, and recognition.

Artificial neural networks

An artificial neural network [43, 44] is a biologically inspired computational model formed from hundreds of single units, artificial neurons, connected with coefficients (weights) which constitute the neural structure. They are also known as processing elements (PE) as they process information. Each PE has weighted inputs, transfer function, and one output. PE is essentially an equation, which balances inputs and outputs. ANNs are also called connectionist models as the connection weights represent the memory of the system.

Although a single neuron can perform certain simple information processing functions, the power of neural computations comes from connecting neurons in a network. The supposed intelligence of artificial neural networks is a matter of argument. Artificial neural networks rarely have more than a few hundred or a few thousand PEs, while the human brain has ~100 billion neurons. Artificial networks comparable to a human brain in complexity are thus still far beyond the creative capacity of the human brain. The human brain is much more complex and, unfortunately, many of its intellectual functions are still not well known. ANNs are capable of processing extensive amounts of data, however, and making predictions that are sometimes surprisingly accurate. This does not make them intelligent in the usual 'human' sense of the word, so the term computer intelligence may be a better way of describing these systems.

There are many types of neural networks designed by now and new ones are invented every week but all can be described by the transfer functions of their neurons, by the learning rule, and by the connection formula.

Digital Image Processing

Image:

An image refers a 2D light intensity function f(x, y), where(x, y) denotes spatial coordinates and the value of f at any point (x, y) is proportional to the brightness or gray levels of the image at that point. A digital image is an image f(x, y) that has been discretized both in spatial coordinates and in brightness. The elements of such a digital array are called image elements or pixels.

A simple image model:

To be suitable for computer processing, an image f(x, y) must be digitalized both spatially and in amplitude. Digitization of the spatial coordinates (x, y) is called image sampling. Amplitude digitization is called gray-level quantization.

The storage and processing requirements increase rapidly with the spatial resolution and the number of gray levels.

Example: A 256 gray-level image of size 256x256 occupies 64k bytes of memory.

Types of image processing

- Low-level processing
- Medium level processing
- High-level processing

Low-level processing means performing basic operations on images such as reading an image resize, resize, the imagerotates, and RGB to gray level conversion, histogram equalization etc…, and the output image obtained after low-level processing is a raw image. The medium level processing means extracting regions of interest from the output of the low-level processed image. Medium level processing deals with the identification of boundaries i.e. edges.This process is called segmentation. High-level processing deals with adding of artificial intelligence to medium level processed signal.

Fundamental steps in image processing are

1. Image acquisition: to acquire a digital image
2. Image pre-processing: to improve the image in ways that increase the chances for success of the other processes.
3. Image segmentation: to partitions an input image into its constituent parts of objects.
4. Image segmentation: to convert the input data to a form suitable for computer processing.
5. Image description: to extract the features that result in some quantitative information of interest of features that are basic for differentiating one class of objects from another.
6. Image recognition: to assign a label to an object based on the information provided by its description.

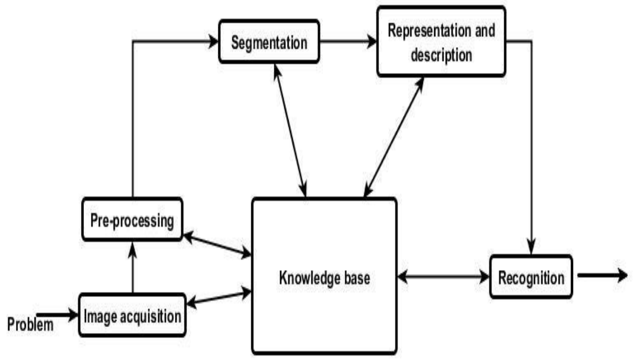

Fig. 2: Fundamental steps in digital image processing

Elements of Digital Image Processing Systems

A digital image processing system contains the following blocks as shown in the figure

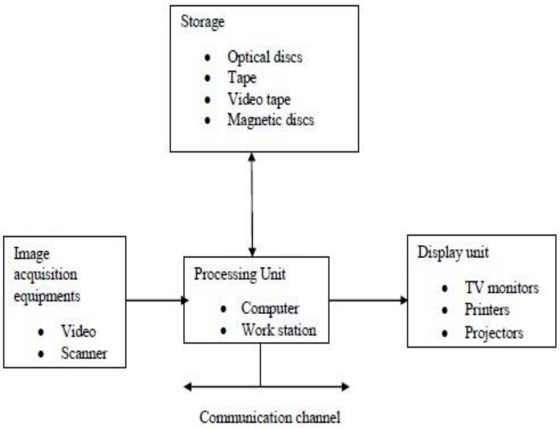

Fig. 3: Elements of digital image processing systems

The basic operations performed in a digital image processing system including

1. Acquisition
2. Storage
3. Processing
4. Communication
5. Display

II. LITERATURE REVIEW

Lu et al. in [1] proposed a compact binary face descriptor (CBFD) feature learning method for face representation and recognition. Given each face image, the first extract pixel difference vectors (PDVs) in local patches by computing the difference between each pixel and its neighboring pixels. Then, they learn a feature mapping to project these pixel difference vectors (PDVs) into low-dimensional binary vectors in an unsupervised manner, where 1) the variance of all binary codes in the training set is maximized, 2) the loss between the original real-valued codes and the learned binary codes is minimized, and 3) binary codes evenly distribute at each learned bin, so that the redundancy information in PDVs is removed and compact binary codes are obtained. Lastly, they cluster and pool these binary codes into a histogram feature as the final representation for each face image. Moreover, they propose a coupled CBFD (C-CBFD) method by reducing the modality gap of heterogeneous faces at the feature level to make their method applicable to heterogeneous face recognition. Extensive experimental results on five widely used face datasets show that our methods outperform state-of-the-art face descriptors.

Zhao et al. in [2] proposed a Markovian stochastic mixture approach for combining bottom-up and top-down face recognition: face recognition is performed from the results of face alignment in a bottom-up way, and face alignment is performed based on the results of face recognition in a top-down way. By modeling the mixture face recognition as a stochastic process, the recognized person is decided probabilistically according to the probability distribution coming from the stochastic face recognition, and the recognition problem becomes that "who the most probable person is when the stochastic process of face recognition goes on for an infinitely long duration". This problem is solved with the theory of Markov chains by properly modeling the stochastic process of face recognition as a Markov chain. As conventional face alignment is not suitable for this mixture approach, discriminative face alignment is proposed. And they prove that the Markovian mixture face recognition results only depend on discriminative face alignment, not on conventional face alignment. Their approach can surprisingly outperform the face recognition performance with manual face localization, which is demonstrated by extensive experiments.

Horiuchi et al. in [3] evaluated the influence coming from (a) longer lapse of time (15-year aging difference), (b) shooting angles (vertical and horizontal), (c) change of face expression (smiling and laughing), and (d) accessories (cap, sunglass, moustache and so on). As the images taken by CCTV on streets are not always ideal mug shots, these points are also crucial in selecting the best face recognition algorithms as a tool to fight against crimes. Police Info-Communications Research Centre (PICRC) attempts to evaluate the accuracy of face recognition technology by choosing some of the representative face recognition algorithms mentioned in MBE 2010 Still Face. For instance as for the evaluation of the point (a), after the representative face recognition algorithms compared the photographs of the people with those of their former selves already stored in the database step by step, the degree of face recognition accuracy was verified. It is confirmed that the latest face recognition algorithms are hardly influenced by the four points ((a)-(d)) mentioned above. This result can conclude that the analyses made in MBE 2010 Still Face should be reliable enough even for police organizations to choose suitable face recognition algorithms for criminal investigations.

Lei et al. in [4] presented a subspace-learning framework named Coupled Spectral Regression (CSR) to solve this challenging problem of coupling the two types of face images and matching between them. CSR first models the properties of different types of data separately and then learns two associated projections to project heterogeneous data (e.g. VIS and NIR) respectively into a discriminative common subspace in which classification is finally performed. Compared to other existing methods, CSR is computationally efficient, benefiting from the efficiency of spectral regression and has better generalization performance. Experimental results on VIS-NIR face database show that the proposed CSR method significantly outperforms the existing methods.

Huang et al. in [5] proposed a new method called discriminative spectral regression (DSR). The DSR maps heterogeneous face images into a common discriminative subspace in which robust classification can be achieved. In the proposed method, the subspace-learning problem is transformed into a least squares problem. Different mappings should map heterogeneous images from the same class close to each other, while images from different classes should be separated as far as possible. To realize this, they introduced two novel regularization terms, which reflect the category relationships among data, into the least squares approach. Experiments conducted on two heterogeneous face databases validate the superiority of the proposed method over the previous methods.

Fang et al. in [6] proposed a new data-driven feature-learning paradigm, which does not rely on category labels. Instead, they learn from user behavior data collected on social media. Concretely, they used the image relationship discovered in the latent space from the user behavior data to guide the image feature learning. They collected a large-scale image and user behavior dataset from Behance.net. The dataset consists of 1.9 million images and over 300 million view records from 1.9 million users. They validate their feature-learning paradigm on this dataset and find that the learned feature significantly outperforms the state-of-the-art image features in learning better image similarities. They also show that the learned feature performs competitively on various recognition benchmarks.

Lu et al. in [7] proposed an unsupervised feature learning method to learn hierarchical feature representation. Since different face regions have different physical characteristics, they propose to use different feature dictionaries to represent them, and to learn multiple yet related feature projection matrices for these regions simultaneously. Hence, position-specific discriminative information can be exploited for face representation. Having learned these feature projections for different face regions, they performed spatial pooling for face patches within each region to enhance the representative power of the learned features. Moreover, they stack their JFL model into a deep architecture to exploit hierarchical information for feature representation and further improve the recognition performance. Experimental results on five widely used face datasets show the effectiveness of their proposed approach.

III. PROBLEM FORMULATION

Existing Work

In literature, a compact binary face descriptor (CBFD) feature learning method for face representation is proposed recently. Inspired by the fact that binary codes are robust to local changes such as varying illuminations and expressions, they aimed to learn compact binary codes directly from raw pixels for face representation. Specifically, they learned a feature mapping to project each local pixel difference vector (PDV) into a low-dimensional binary vector, where the variance of all binary codes in the training set is maximized so that the redundancy information in PDVs is removed. To make the learned binary codes compact, they expected that the loss between original PDVs and learned binary codes are minimized and the learned binary codes are evenly distributed at each bin. Then, they clustered and pool these compact binary codes to obtain a histogram representation of each face image.

Problem Formulation

Based on the comparison we have seen that CBFD is associated with SVM like classifiers to predict a user. As analyzed, SVM is slow compared to other classifiers like Artificial Neural Networks. In addition, the accuracy of SVM decreases as the feature set distributes further and starts to overlap. RBF SVM also performspoorly with highly overlapped feature-space. This can be seen in the results of "lighting" dataset where accuracy is reduced to 60%.

Proposed Solution

We propose a back propagation based artificial neural network classifier, which is efficient in terms of learning time, ROC and computational efficiency during testing/prediction/classification phase. In addition, with a large amount of data and a careful designing of architecture, we can define a better feature selection from CBFD thereby ensuring higher accuracy.

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IV. PROPOSED METHODOLOGY

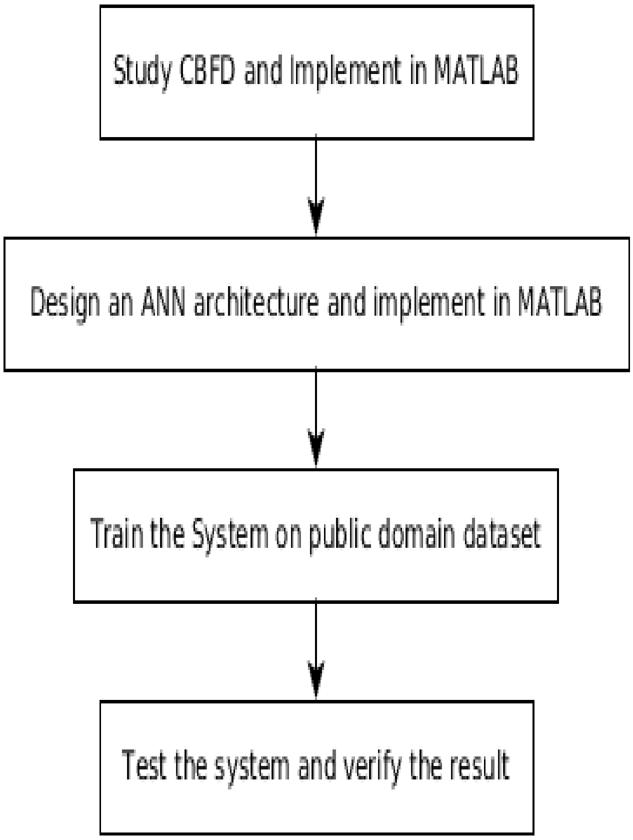

Fig 4: Proposed Research Methodology

In the overall approach of using artificial intelligence in using it for the detection or identification of biometric data. The procedure, which is followed to extract the feature, is crucial as it is the one and the only factor involved in determining the way designed classifiers moves in lieu of identifying the desired template which in this case are facial images that are intended to provide some idea of facial detection systems of the future in deduplication of people. In our system, the images are used to calculate the complex binary feature descriptors which are nothing but complex mathematical gradient oriented vectors describing the image features for feeding to the classifiers. Then the design of the artificial neural network is carried out following the procedure for its neurons, hidden layers, input, output and dimensions as in rows and columns. Then the training of the system is done using public domain set which is a process in which the neural network learns the detection on the bases of the features and learns for identitythan in classes or desired output, which will be further used to recognizes the testing dataset.

After all, this is done; the testing phase can be carried out. As shown in results the image which is selected has to be matched with training images and the corresponding image has to brought to light which the system does with good accuracy.

V. SIMULATION AND EXPERIMENTAL RESULTS

We proposed to develop a back propagation based Artificial Neural Network (ANN) classifier, which is efficient in terms of learning time, ROC and computational efficiency during testing/prediction/classification phase. Also, with a large amount of data and a careful designing of architecture, we can define a better feature selection from CBFD (Complex Binary Feature Descriptor) thereby ensuring higher accuracy. We have used MATLAB R2013B software for developing our proposed algorithm. The final output of the designed algorithm is presented in the form of a table.

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TABLE I: Test Results

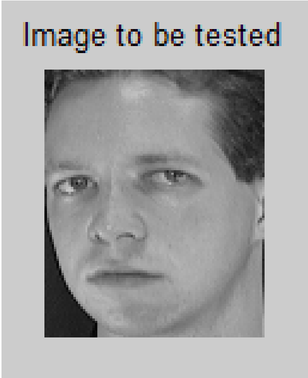
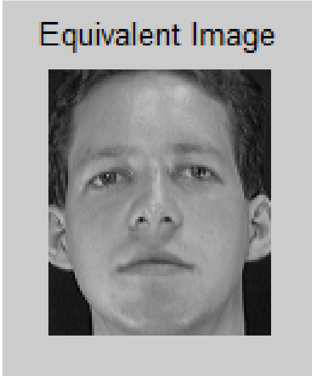
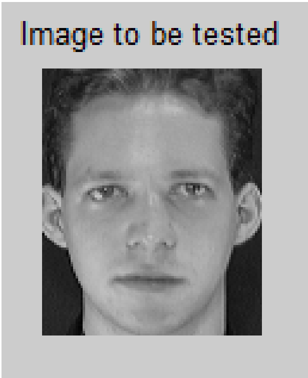
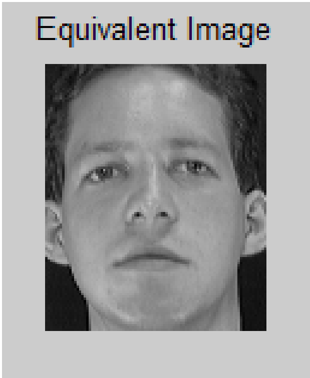
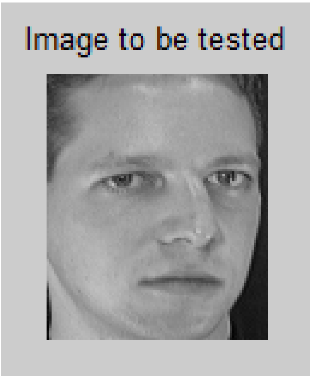
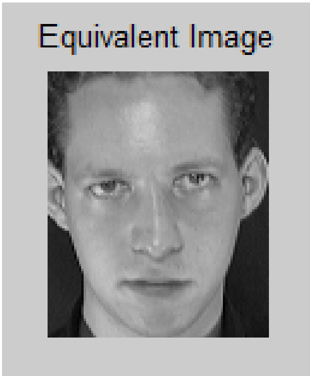
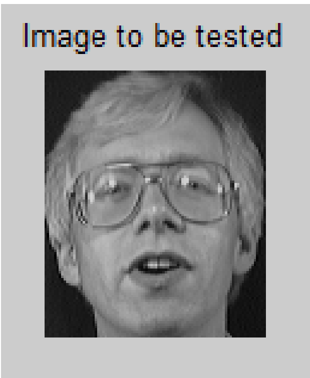
Images to Probe	**Images from Gallery**
 **Fig 5(a)**	 **Fig 5(b)**
 **Fig 6(a)**	 **Fig 6(b)**
 **Fig 7(a)**	 **Fig 7(b)**
 **Fig 8(a)**	 **Fig 8(b)**

Fig 9(a)

Fig 9(b)

Fig 10(a)

Fig 10(b)

Fig 11(a)

Fig 11(b)

Fig 12(a)

Fig 12(b)

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Fig 13(a)

Fig 13(b)

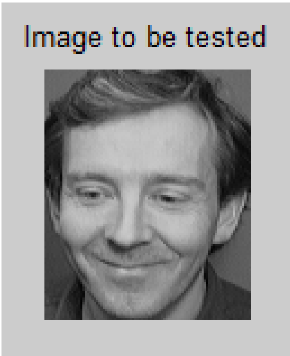

Fig 14(a)

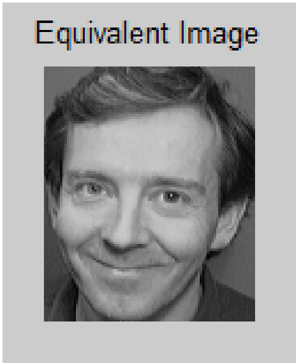

Fig 14(b)

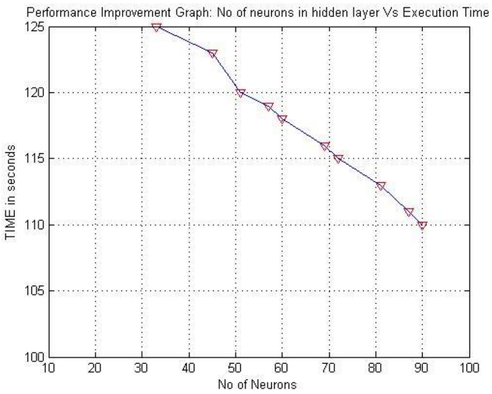

Fig. 15: Numbers of neurons VS Time

The above figure shows the plot between different numbers of neurons in the hidden layer of time. This graph depicts that the time consumptions decrease as the number of active neurons increase.

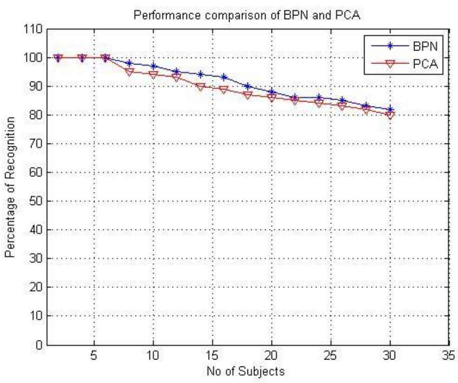

Fig. 16: Accuracy

The above figure shows the comparison of accuracy as in percentage of recognition for the two different neural network type, one is backpropagation and the other is principal component analyses. The backpropagation outperforms the latter in the percentage of recognition.

VI. CONCLUSION AND FUTURE SCOPE

Deduplication is a technology that can be used to reduce the amount of storage required for a set of files by identifying duplicate "chunks" of data in a set of files and storing only one copy of each chunk. The deduplication process is simple: for each chunk being stored, attempt to locate an existing instance in the chunk store. If none is found, the new chunk is added to the chunk store; otherwise, the new chunk is a shared chunk. We designed and develop a back propagation based Artificial Neural Network (ANN) classifier, which is efficient in terms of learning time, ROC and computational efficiency during testing/prediction / classification phase. In addition, with a large amount of data and a careful designing of architecture, we can define a better feature selection from CBFD (Complex Binary Feature Descriptor) thereby ensuring higher accuracy.

The future work is to develop the architecture, which could work with cloud-based database and perform real-time deduplication.

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