

NEURAL NETWORKS BASED IMAGE RETRIEVAL SYSTEM USING ROSENBLATT'S PERCEPTRON ALGORITHM

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ABSTRACT

Now a day's many applications based on an Image based classification systems has become a challenging task. Many systems based on the image based recognition but that takes an original Image as the input query and compare with the retrieval Image through the machine and retrieves based on more complicated task. The aim and Objective of this Paper is to classifying the Image using Rosenblatt's Perceptron Algorithm, a Neural Network concepts for more efficient and effective results. Pattern recognition techniques are associated a symbolic identity with the recognition of the pattern. In this work will be analysis different neural network methods in pattern recognition. This problem of replication of patterns by machines (computers) involves the original patterns. The pattern recognition is better known as optical pattern recognition. Since, it deals with recognition of optically processed patterns rather than magnetically processed ones. A neural network is a processing device, whose design was inspired by the design and functioning of human brain and their components. There is no idle memory containing to data are programmed, but each neuron is programmed and continuously active. The Image recognition is one of the earliest applications of Artificial Neural Networks. One of the applications of neural networks is in the field of pattern recognition. It can store and recognize correctly. In this paper, recognize the several Images, with the condition that the images should be slightly in differently retrieved.

Keywords: Neural Networks, Perceptron model, pattern recognition, clustering, linear Vector Classifier, Neural Network, Tool Box, Mat Lab.

1. INTRODUCTION

1.1 Elements of Visual Perception:

Image processing is built on a foundation of mathematical and probabilistic formulations, human intuition and analysis play a central role in the choice of one technique versus another. Developing a basic understanding of human visual perception as a first step. Mechanics and parameters related to how images are formed and perceived by humans. The physical limitations of human

vision in terms of factors that also are used in our work with images. Thus, factors such as how human and electronic imaging devices compare in terms of resolution and ability to adapt to changes in illumination.

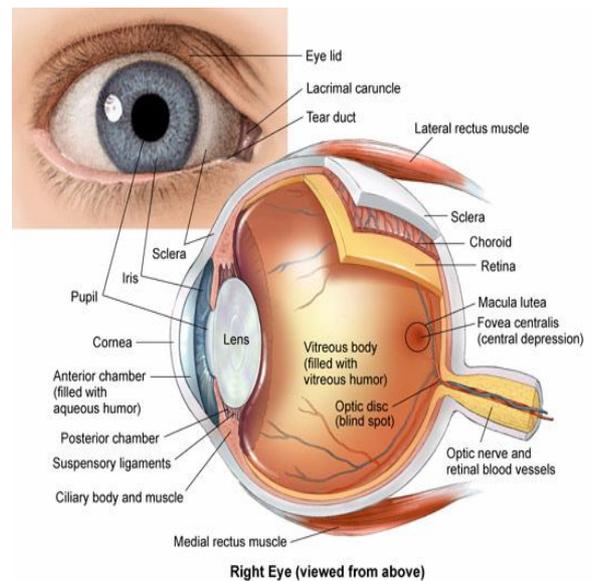


Fig 1: Structure of the Human Eye

The eye (Fig 1) is nearly a sphere, with an average diameter of approximately 20mm. Three membranes enclose the eye: the cornea and sclera outer cover; the choroid; and the retina. The cornea is a tough, transparent tissue that covers the anterior surface of the eye. The sclera is an opaque membrane that encloses the remainder of the optic globe.

The Choroid lies directly below the Sclera. This membrane contains a network of blood vessels that serve as the major source of nutrition to the eye. Even superficial injury to the choroid, often not deemed serious, can lead to severe eye damage as a result of inflammation that restricts blood flow.

The Choroid coat is heavily pigmented and hence to help to reduce the amount of extraneous light entering the eye and the backscatter within the optic globe.

The Choroid is divided into the ciliary body and the iris. The Central opening of the iris varies in diameter from approximately 2 to 8 mm. The front of the iris contains the visible pigment of the eye. Whereas the back contain a black pigment.

The lens is made up of concentric layers of fibrous cells and is suspended by fibers that attach to the ciliary body. It contains 60% to 70% water, 6% fat, and more protein than any other tissue in the eye. The lens is colored by a slightly yellow pigmentation that increases with age. The lens absorbs approximately 8% of the visible light spectrum, with relatively higher absorption at shorter wavelengths. Both infrared and ultraviolet light are absorbed appreciably by proteins within the lens structure and in excessive amounts can damage the eye.

The inner most membrane of the eye is the Retina, which lines the inside of the wall's entire posterior portion. When the eye is properly focused, light from an object outside the eye is imaged on the retina. Pattern vision is afforded by the distribution of discrete light receptors over the surface of the retina. There are two classes of receptors cones and rods. The Cones in each eye numbered between 6 to 7 million. They are located primarily in the central portion of the retina is called the fovea. Fovea is highly sensitive in color. Muscles controlling the eye rotate the eyeball until the image of an object of interest falls on the fovea. Cone vision is called Photopic or bright-light vision.

The number of rods is much larger 75 to 150 million are distributed over the retinal surface, several rods are connected to a single nerve end reduce the amount of detail discernible by these receptors. They are not involved in color vision and are sensitively to low-levels of illumination. This phenomenon is known as a scotopic or dim -light vision. The fovea itself is a circular indentation in the retina of about 1.5 mm in diameter. In a square sensor array of size 1.5 mm * 1.5 mm. cones in that area of the retina is approximately 1,50,000 elements per mm². Based on these approximation, the number of cones in the region of highest acuity in the eye is about 3,37,000 elements. Whereas Black image element has a value of 1 and White image element has a value of 0.

In an ordinary photographic camera, the lens has fixed focal length, and focusing at various distances is achieved by varying the distance between the lens and the imaging plane where the film is located. In the human eye, the converse is true, the distance between the lens and the imaging region is fixed, and the focal length needed to

achieve proper focus is obtained by varying the shape of the lens. The fibers in the ciliary body accomplish this, flattening or thickening the lens for distant or near objects, respectively. The distance between the center of the lens and the retina is along the visual axis is approximately 17 mm. The range of focal lengths is approximately 14 mm to 17 mm. when the eye is relaxed and focused at distances greater than about 3 m.

At the earliest Adult nerve system every human trained about the character in two ways. One is voice oriented training, second is Pattern oriented training. Some people know only voice oriented data because they never read and Write that data for ever. Today also many people try to speak more languages but they may be trained or not about the Pattern oriented data's. In this world every human try to learn to speak other language but without knowing their Characters completely. Most of things every language have a character set. But at the earlier stage are trained our own mother tongue character set. After that try to learn English Character set because English is the world most people understanding language character sets it contained.

2. LITERATURE REVIEW:

1973(Duda and Hart) defined the pattern recognition is a field concerned with machine recognition of meaning regularities in noisy of complex environments. [1].

1977(Pavlidis) defined pattern recognition in his book: "the word pattern is derived from the same root as the word patron and, in his original use, means something which is set up as a perfect example to be imitated. Thus pattern recognition means the identification of the ideal which a given object was made after." [2].

1978(Gonzalez,Thomas) defined pattern recognition as a classification of input data via extraction important features from a lot of noisy data. [3].

1985(Watanabe) said that pattern recognition can be looked as categorization problem, as inductive process, as structure analysis, as discrimination method and so on. [4].

1990(Fukunaga) defined pattern recognition as" A problem of estimating density functions in a high-dimensional space and dividing the space into the regions of categories of classes." [5].

1992(Schalkoff) defined PR as"The science that concerns the description or classification (recognition) of measurements" [6].

1993(Srihari,Govindaraju) defined pattern recognition as a discipline which learn some theories and methods to design machines that can recognize patterns in noisy data or complex environment. [7].

1996(Ripley) outlined pattern recognition in his book: "Given some examples of complex signals and the correct decisions for them, make decisions automatically for a stream of future examples" [8].

2002 (Robert P.W. Duin) described the nature of pattern recognition is engineering; the final aim of Pattern recognition is to design machines to solve the gap between application and theory. [9].

2003(Sergios Theodoridis,) Pattern recognition is a scientific discipline whose aim is the classification of the objects into a lot of categories or classes. Pattern recognition is also a integral part in most machine intelligence system built for decision making. [10].

2.1 Knowledge-based pattern recognition

This approach to PR [12] is evolved from advances in rule-based system in artificial intelligence (AI).Each rule is in form of a clause that reflects evidence about the presence of a particular class. The sub-problems spawned by the methodology are:

1. How the rule-based may be constructed, and
2. What mechanism might be used to integrate the evidence yielded by the invoked rules?

2.2 Neural Pattern Recognition

Artificial Neural Network (ANN) provides an emerging paradigm in pattern recognition. The field of ANN encompasses a large variety of models [13], all of which have two important characteristics:

1. They are composed of a large number of structurally and functionally similar units called neurons usually connected various configurations by weighted links.
2. The Ann's model parameters are derived from supplied I/O paired data sets by an estimation process called training

3. METHODOLOGY

There are many neural network algorithms for the pattern recognition. The Various algorithms differ in their learning mechanism and Learning can be either supervised or unsupervised. In supervised learning, the training set contains both inputs and required responses. After training the network, and get the result of response that is equal to target response. Unsupervised classification learning is based on clustering of input data. There is no prior information about input's membership in a particular class. The Image as the patterns and a history of training is used to assist the network in defining

classes. This unsupervised classification is called clustering.

The Image as a pattern of neurons and initial weights are specified based upon the training method of the network. The pattern sets is applied to the network during the training [7]. The pattern is to be recognized in the form of vector, whose elements is obtained from a pattern grid. The elements are either binary values 0 and 1 or bipolar values -1 and 1. In some of the algorithms, weights are calculated from the pattern presented to the network and in some algorithms weights are initialized. The network acquires the knowledge from the environment. The network stores the patterns presented during the training in another way it extracts the features of pattern. Neural networks have demonstrated its capability for solving complex pattern recognition problems [9].

Commonly solved problems of pattern have limited scope. Single neural network architecture can recognize only few patterns. Various neural network algorithms with their implementation details for solving pattern recognition problems. The relative performance evaluation of these algorithms has been carried out.

4. PROPOSED MODEL

The objective of this paper is Relative performance of various neural network algorithms have not been reported in the literature. This paper extract the issues on various neural network algorithms with their implementation details for solving pattern recognition problems. The relative performance evaluation of these algorithms has been carried out.

4.1 Rosenblatt's Perceptron

The perceptron occupies a special place in the historical development of neural networks, and it is the first algorithmically described neural network, invented by Rosenblatt, a psychologist, who inspired engineers, physicists, and mathematicians like to devote their research effort to different aspects of neural networks in the 1960s and the 1970s. Now, recently computer science developers also devote their research effort to different aspects of neural networks. Moreover, it is truly remarkable to find that the perceptron is as valid today as it was in 1958 when Rosenblatt's paper on the perceptron was first published [8].

The perceptron is the simplest form of a neural network used for the classification of patterns. The perceptron is a computational model of the retina of the eye and hence, is named Perceptron. Basically, it consists of a single neuron with adjustable synaptic weights and bias. The algorithm used to adjust the free parameters of this neural network first appeared in a learning procedure developed by Rosenblatt (1958, 1962) for his perceptron brain model [8]. Rosenblatt proved that if the patterns (vectors) used to

train the perceptron. The perceptron built around a single neuron is limited to performing pattern classification with only two classes (hypotheses). By expanding the output (computation) layer of the perceptron to include more than one neuron, may correspondingly perform classifications. The perceptron network comprises three units (Fig. 2)

- Sensory Unit S,
- Association Unit A,
- Response Unit R.

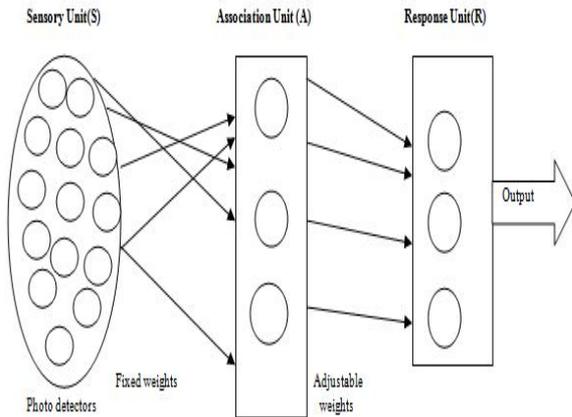


Fig. 2: Rosenblatt's original Perceptron model

The Sensory Unit(S) Comprising 400 photodetectors receives input of images. and they provides a 0/1 electric signal as an output. If the input signals exceed a threshold, then the photodetectors outputs 1 else 0.

The photodetectors are randomly connected to the Association unit (A). The Association unit Comprises

feature demons or predicates. The predicates examine the output of the Sensory unit(S) for the specific features of the image.

The third unit Response unit(R) Comprises **pattern recognizers or perceptron**, which receives the results of the predicates, also in binary form. While the weights of the Sensory unit(S) and Association Unit (A) are Fixed, and the Response unit(R) weights are adjustable.

The output of the Response unit (R) could be such that, if the weighted sum of its inputs is less than or equal to 0 and then the output is 0 otherwise it is weighted sum itself. It could also be determined by a step function with binary values (0/1) or bipolar values (-1/1). Thus, in the case of a step function yielding 0/1 output values, it is defined as

$$Y_j = f(\text{net}_j) = 1, \text{net}_j > 0$$

$$= 0, \text{otherwise.}$$

Where,

$$\text{net}_j = \sum_{i=1}^n x_i w_{ij}$$

Here, x_i is the input, is the weight on the connection leading to the output units (R unit), and Y_j is the output.

The training algorithm of the perceptron is a supervised learning algorithm where the weights are adjusted to minimize error whenever the output does not match the target output.

4.1 a) Single Layer perceptron Network Model:

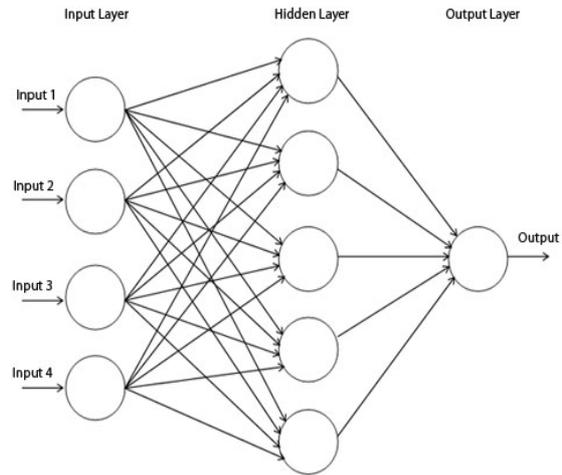


Fig.3: Single Layer feed forward Network

4.1 b) Multilayer feed forward Perceptron Network Model:

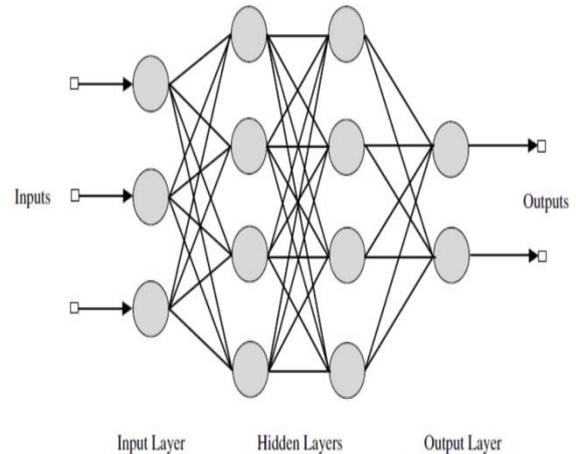


Fig.4: Multilayer feed forward Network

A basic learning algorithm for training the perceptron is as follows:

- If the output is correct then no adjustment of weights is done (i.e) $w_{ij}^{(k+1)} = w_{ij}^{(k)}$
- If the output is 1 but should have been 0 then the weights are decreased on the active input links.
- (i.e) $w_{ij}^{(k+1)} = w_{ij}^{(k)} - \alpha \cdot x_i$ If the output is 0 but should have been 1 then the weights are increased on the active input links. (i.e) $w_{ij}^{(k+1)} = w_{ij}^{(k)} + \alpha \cdot x_i$

Here, $w_{ij}^{(k+1)}$ is the new adjusted weight, $w_{ij}^{(k)}$ are the old weights, x_i is the input and α is the learning rate parameter. Also small α leads to slow learning and Large α leads to fast learning.

However, large α also runs the risk of allowing weights to oscillate about values which would result in the correct outputs. For a constant α , the learning algorithm is termed **fixed increment algorithm**.

4.2 PERCEPTRON ALGORITHM

Fixed increment perceptron learning algorithm for classification problem with n input features (x1, x2, x3.....xn)

Fixed-Incre-Percept-Lrng ($\bar{X}_j, \bar{Y}_j, \bar{W}$)

Step 1: Create a Perceptron with (n+1) input neurons $x_0, x_1, x_2, \dots, x_n$, where $x_0=1$ is the bias input. Let 0 be the output neuron.

Step 2: Initialize $\bar{W} = (w_0, w_1, \dots, w_n)$ to random weights.

Step 3: Iterate through the input patterns \bar{X}_j of the training set using the weight set, That is Computes the weighted sum of $net_j = \sum_{i=0}^n x_i w_i$ for each input pattern j.

Step 4: Compute the output Y_j using the step function $Y_j = f(net_j) = 1, net_j > 0$
 $= 0, otherwise.$

Step 5: Compare the Computed output Y_j with the target output Y_j for each input pattern j. if all the input patterns have been classified correctly, output the weights and exit.

Step 6: Otherwise, update the weights as given below:
 If the computed output Y_j is 1 but should have been 0, $w_i = w_i - \alpha x_i \quad i=0,1,\dots,n.$
 If the computed output Y_j is 0 but should have been 1, $w_i = w_i + \alpha x_i \quad i=0,1,\dots,n.$

Step7: goto step 3.

5. RESULT AND DISCUSSION

Here, demonstrated the application of this model to the image based on pattern recognition application in this work. Specifically, tested its performance on Pattern recognition. As a general perceptron sequential memory organization, The Acceptance to this model can also be generalized to many real-world applications that require complex sequence learning or sequential behaviors. The network which is stabilized with the parameters is tested within new data files for clustering.

Every day, people encounter a large amount of information and store or represent it as a data, for further analysis and management. In computers every data should

be represented by using binary numbers (0,1).At the same way our human brain receiving images, that images represented as a binary manner in the neuron. An image may be received by the standard Perceptron network is intended for work with a binary input vector [1] and this fact greatly reduce a contribution of Perceptron structures in image recognition because real images represented in color format and conversion to gray scale image and then converted to black and white form of images in neuron. Assign the value of 0 and 1 as black and white respectively. A value may be 0 that means an image fully in black. So never see an image. A value may be 1 that means an image fully in white. So we never see a image. An image contained value 0 to1. The mid value is 0.5.The range of value 0.1 to 0.5 black occupied mostly when they increased about the value. The range of value 0.6 to 1 white occupied mostly when they increased about the value. The results of this work are carried out in several phases.

The following procedure has been put in use in getting the results.

5.1 Result:

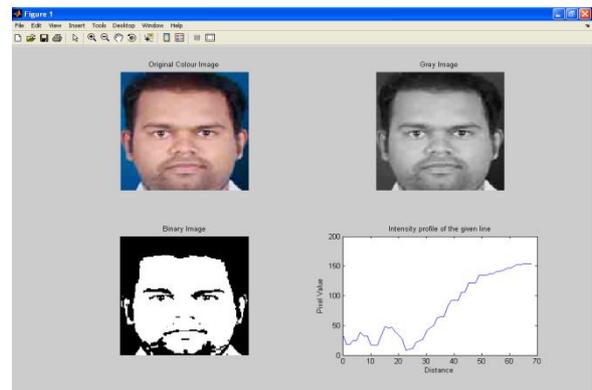


Fig 5: Original Image converted to gray scale & binary image, and retrieves the intensity value of a pixel.

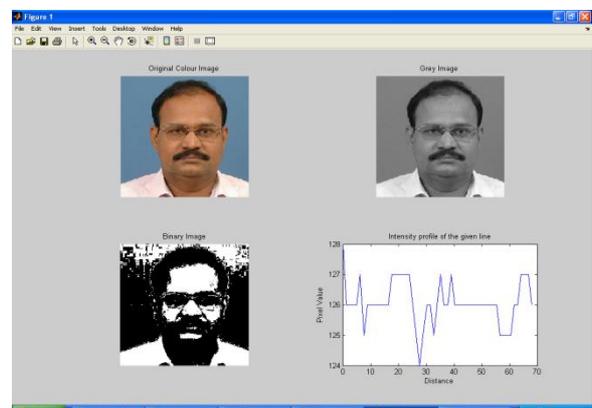


Fig 6: Original Image converted to gray scale & binary image, and retrieves the intensity value of a pixel.

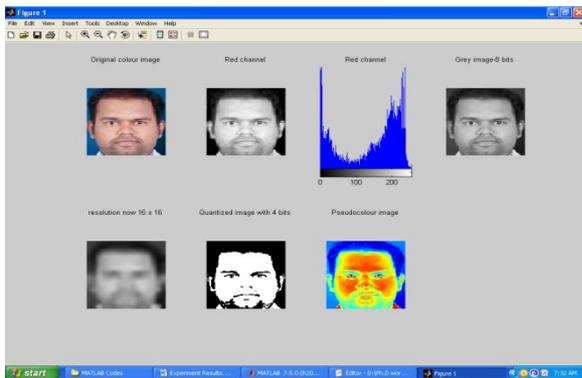


Fig 7: Original Image converted to gray scale & binary image before removed the Red channel of an original image, and retrieves the intensity value of a Red Channel, Change the Resolution of a gray scale Image, and recognition of Pseudocolour Image.

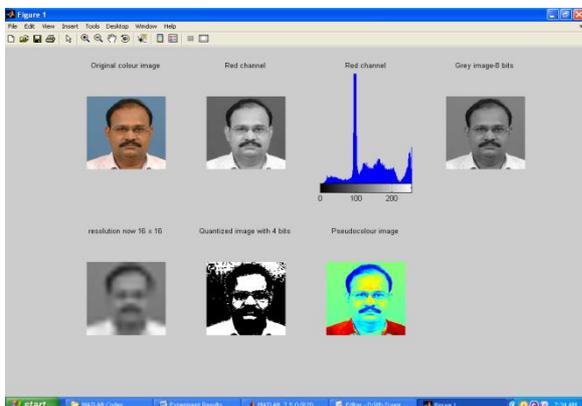


Fig 8: Original Image converted to gray scale & binary image before removed the Red channel of an original image, and retrieves the intensity value of a Red Channel, Change the Resolution of a gray scale Image, and recognition of Pseudocolour Image.

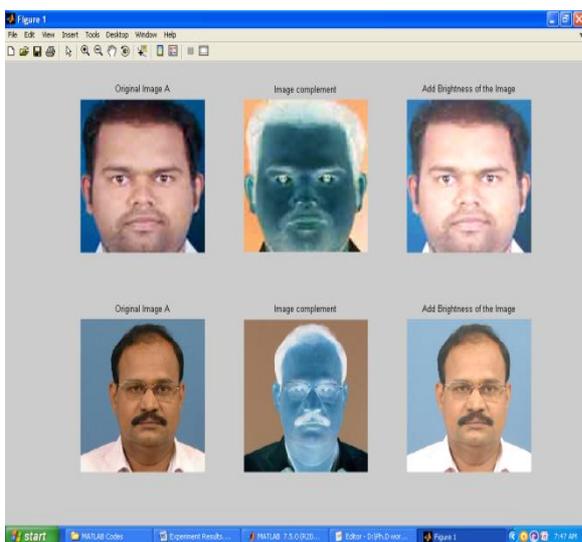


Fig 9: Recognize an original image after Complement an image and add brightness to image.

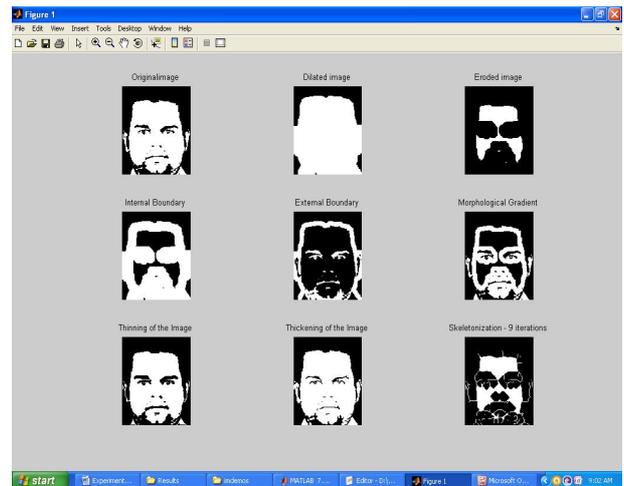


Fig 10: Recognize the binary image, Dilated Image, Eroded image, internal & external boundary of an Image, Morphological gradient & skeletonization of an image, Thinning & Thickening of an Image.

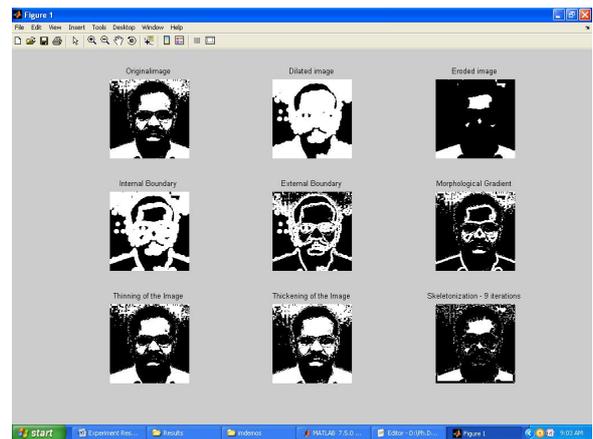


Fig 11: Recognize the binary image, Dilated Image, Eroded image, internal & external boundary of an Image, Morphological gradient & skeletonization of an image, Thinning & Thickening of an Image.

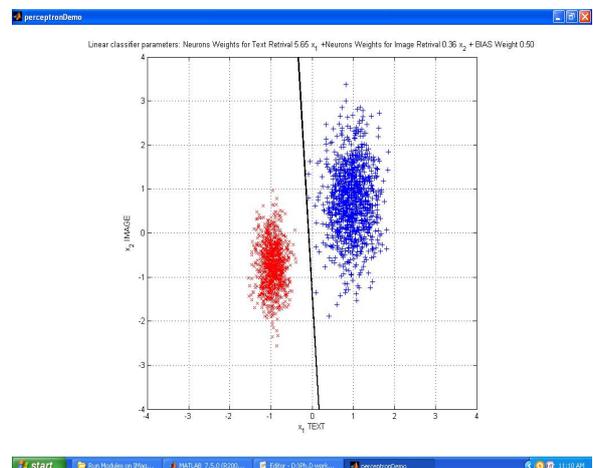


Fig 12: Linear vector Classifier Parameter

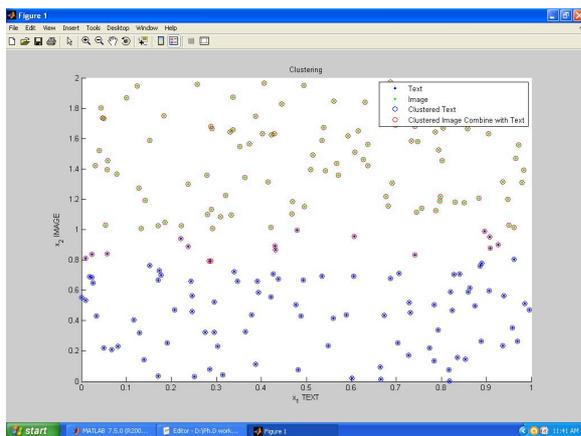


Fig 13:Cluster

6. CONCLUSION

Actually, it is the most primitive activities of human beings classification play an important and indispensable role in the long history of human development. In order to learn a new object or to understand a new phenomenon, people always try to seek the features that can describe it, and further compare it with other known objects or phenomena, based on the similarity or dissimilarity, generalized as proximity, according to some certain standards or rules. Basically, classification systems are either supervised or unsupervised, depending on whether they assign new inputs to one of a finite number of discrete supervised classes or unsupervised categories. Binary inputs caused information loss. We have shown that by bit slicing method is possible to represent a color pixel as the set of binary numbers and use this binary sequence as input of neural network. For three bits color encoding, Perceptron neural network has interpolation ability that allow interpolating any input color to the nearest base color. We have tested ability of the network for recognition of color images that gave co-efficient of sensitivity approximately equal one in case of recognition of the objects with different forms and colors. The work stands to gain a lot of advantages namely no time delay in calculating the presence of recognizing pattern and faster computerized report generation and also helpful in data records.

REFERENCES

- [1]. B. Rypma, V. Prabhakaran, J. Desmond, G. H. Glover, and J. D. Gabrieli, "Load-dependent roles of frontal brain regions in the maintenance of working memory," *Neuroimage*, vol. 9, pp. 216–226, 1999.
- [2]. J. J. Todd and R. Marois, "Capacity limit of visual short-term memory in human posterior parietal cortex," *Nature*, vol. 428, pp. 751–754, 2004.
- [3]. D. Talmi, C. L. Grady, Y. Goshen-Gottstein, and M. Moscovitch, "Neuroimaging the serial position curve—A test of single-store versus dual-store

- models," *Psychol. Sci.*, vol. 16, no. 9, pp. 716–723, 2005.
- [4]. L. G. Ungerleider, S. M. Courtney, and J. V. Haxby, "A neural system for human visual working memory," *Proc. Nat. Acad. Sci.*, vol. 95, pp. 883–890, 1998.
- [5]. G. E. Muller and A. Pilzecker, "A. Experimentelle Beitrage zur Lehre vom Gedächtniss," *Z Psychol.*, vol. 1, pp. 1–288, 1900.
- [6]. H. A. Lechner, L. R. Squire, and J. H. Byrne, "100 years of consolidation—remembering Müller and Pilzecker," *Learn. Memory*, vol. 6, no. 2, pp. 77–87, 1999.
- [7]. R. W. Gerard, "Physiology and psychiatry," *Amer. J. Psychiatry*, vol. 106, pp. 161–173, 1949.
- [8]. D. O. Hebb, *The Organization of Behavior*. New York: Wiley, 1949.
- [9]. K. Touzani, S. V. Puthanveetil, and E. R. Kandel, "Consolidation of learning strategies during spatial working memory task requires protein synthesis in the prefrontal cortex," *Proc. Nat. Acad. Sci.*, vol. 104, no. 13, pp. 5632–5637, 2007.
- [10]. J. L. McGaugh, "Memory—A century of consolidation," *Science*, vol. 287, pp. 248–251, 2000.
- [11]. J. L. McGaugh, "Emotional arousal and enhanced amygdala activity: New evidence for the old perseveration-consolidation hypothesis," *Learn. Memory*, vol. 12, pp. 77–79, 2005.
- [12]. J. G. Pelletier, E. Likhtik, M. Filali, and D. Pare, "Lasting increases in basolateral amygdala activity after emotional arousal: Implications for facilitated consolidation of emotional memories," *Learn. Memory*, vol. 12, pp. 96–102, 2005.
- [13]. N. Burgess and G. Hitch, "Computational models of working memory: putting long-term memory into context," *Trends Cogn. Sciences.*, vol. 9, no. 11, pp. 535–541, 2005.
- [14]. R. Sun and C. L. Giles, "Sequence learning: from recognition and prediction to sequential decision making," *IEEE Intell. Syst.*, vol. 16, no. 4, pp. 67–70, Jul.-Aug. 2001.
- [15]. Janusz A. Starzyk, "Spatio-Temporal Memories for Machine Learning: A Long-Term Memory Organization," *IEEE Transactions on Neural Networks*, Vol. 20, No. 5, May 2009.
- [16]. M. I. Jordan, "Attractor dynamics and parallelism in a connectionist sequential machine," in *Proc. Conf. Cogn. Sci. Soc.*, 1986, pp. 531–546.
- [17]. J. B. Pollack, "The induction of dynamical recognizers," *Mach. Learn.*, vol. 7, pp. 227–252, 1991.
- [18]. J. Tani, "Learning to generate articulated behavior through the bottom-up and the top-down interaction process," *Neural Netw.*, vol. 16, pp. 11–23, 2003.

- [19].J. Tani and S. Nolfi, "Learning to perceive the world as articulated: an approach for hierarchical learning in sensory-motor systems," *Neural Netw.*, vol. 12, pp. 1131–1141, 1999.
- [20].L. Wang, "Learning and retrieving spatio-temporal sequences with any static associative neural network," *IEEE Trans. Circuits Syst. II, Analog Digit. Signal process.*, vol. 45, no. 6, pp. 729–739, Jun. 1998.
- [21].L. Wang, "Multi-associative neural networks and their applications to learning and retrieving complex spatio-temporal sequences," *IEEE Trans. Syst. Man Cybern. B, Cybern.*, vol. 29, no. 1, pp. 73–82, Feb. 1999.
- [22].D. Wang and M. A. Arbib, "Complex temporal sequence learning based on short-term memory," *Proc. IEEE*, vol. 78, no. 9, pp. 1536–1543, Sep. 1990.
- [23].D. Wang and M. A. Arbib, "Timing and chunking in processing temporal order," *IEEE Trans. Syst. Man Cybern.*, vol. 23, no. 4, pp. 993–1009, Jul./Aug. 1993.
- [24].D. Wang and B. Yuwono, "Anticipation-based temporal pattern generation," *IEEE Trans. Syst. Man Cybern.*, vol. 25, no. 4, pp. 615–628, Apr. 1995.
- [25].D. Wang and B. Yuwono, "Incremental learning of complex temporal patterns," *IEEE Trans. Neural Netw.*, vol. 7, no. 6, pp. 1465–1481, Nov. 1996.
- [26].J. Hawkins and D. George, "Hierarchical temporal memory-concepts, theory, and terminology," Numenta, Inc., Menlo Park, CA [Online]. Available: <http://www.numenta.com/>
- [27].J. Hawkins and S. Blakeslee, *On Intelligence*. New York: Times Books, 2004.
- [28].J. Hawkins and S. Blakeslee, "Why can't a computer be more like a brain," *IEEE Spectrum*, vol. 44, no. 4, pp. 20–26, Apr. 2007.
- [29].O. A. S. Carpinteiro, "A hierarchical self-organizing map model for sequence recognition," *Pattern Anal. Appl.*, vol. 3, no. 3, pp. 279–287, 2000.
- [30].J. A. Starzyk and H. He, "Anticipation-Based temporal sequences learning in hierarchical structure," *IEEE Trans. Neural Netw.*, vol. 18, no. 2, pp. 344–358, Mar. 2007.
- [31].G. E. Rawlinson, "The significance of letter position in word recognition," Ph.D. dissertation, Psychology Dept., Univ. Nottingham, Nottingham, U.K., 1976.

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