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# Quality Grading of a Pea Using Artificial Intelligence

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**Abstract:** In the recent years, computer vision has emerged as a prospective field, related to the recognition of the object by a computer or machine. In the presented work, the application of computer vision to extract the features of a pea is explored. Feature related to pea are shape, texture, and color. The present work analyzes the object, on the basis of surface areas of the pea, computed from different angle. The quality assigning system based on artificial intelligence is developed. The input to back propagation neural network (BPNN) is range data, consisting of surface areas from different views of object. Surface based analysis technique has advantage that the recognition of object becomes simpler and faster. BPNN uses mean square error as a performance index. The selected network models are simulated with available test data, to evaluate the performance. The result shows the effectiveness of the proposed approach to classify the pea on basis of quality.

**Key word:** Image segmentation, edge detection, back propagation neural network, classifier design.

## 1. Introduction

Computer vision is a field related to identification of object by computer or robots automatically and analyzes them [1], [2]. Earlier work in the direction of recognition is based on visual ability by processing intensity or range image. Intensity based images are usually degraded by noise or shadow of the image so range image is used in 3-D recognition model [3]. The three dimensional (3-D) object recognition using computer vision identifies objects in an input image using the structured modelbase. Range image is composed of a finite number of elements, each of which has a particular location and values, called pixel. It directly gives information about the 3-D object and is not affected by the illumination and reflection.

Computer vision mainly consists of two component, first object recognition and second classification. By finding the structure, the range images are classified according to similar patterns, attributes, features and other characteristics are known as classification [4]. Modelbase approach recognize an object using the geometric features like edge, normal vector, surface patch, relationship of surface patches and so on. The geometric features are extracted from the 3-D object [3].

An object and a model could be represented in terms of graphs, containing nodes and links. The surface of an object is described by segmenting it into surface patches. The surface patches with no shape distortion are selected [3]. Such description can be viewed as an attributed graph, a node denotes features of patches such as area, curvature, texture, moment and so on and link shows relation and distance between two nearby surfaces. The segmentation and description of surface is based on measure of curvature of an object [5]. The conventional method for object recognition is based on kernel surface which is the largest area selected from surface patch and relationship with the other surface is considered [6]. In another method object is recognized in term of volume instead of surface [7]. Recognition of an object by shape has advantage that no needs of learning and easier to describe an object. Pattern recognition can be defined as a process of identifying structure in data by comparison to known structure; the known structure is developed through methods of classification [4]. But this technique having disadvantage if orientation (distance between neighboring) of surface of an object is change then it may lead wrong recognition.

In object recognition another main part is classification. Classifier or model base can make by the previous information of the object. Some artificial techniques are implemented for classifier making. Selection of perfect or appropriate model is difficult. Some old neural network models are perceptron model, mean field annealing neural network (MFA NN), Hopefield model and Back propagation neural network (BPNN). MFA NN is biased on the Hopefield model [8]. Some modern classifications are support vector machine (SVM), particle swarm optimization and some hybrid classification techniques. Some reviewer gave their ideas for model construction. Horn *et al* uses multi view extended Gaussian image (EGI) to recognize 3-D object [9], [19], [20]. This method has the advantages that EGI can be computed directly. The main disadvantage is that EGI is sensitive to occlusion and is unique for convex object only.

Horaud and Bolles and Bolleset al. developed the three dimensional part orientation (3DPO) system recognizing and locating 3-D parts in range data [10], [11]. This system is able to recognize objects in highly complex scene, but uses are limited to very few model. Grimson and Lozano – Perez proposed a model that an object can be recognized and locates among a set of unknown objects, by knowledge of its 3-D position and surface normal [12]. The model consists of polyhedral objects represented by planner faces. Only polyhedral objects or objects with a sufficient number of planer surfaces can be used in this system. Oshima and Shirai developed a model based recognition system for planer and curved objects. In this model object is represented by augmented graph [13], [14]. A node denotes planer or curved surface and link connecting the node give information about the neighbor surface patch. Matching can be achieved by a combination of data driven and model driven searching process. At first a kernel node, which have largest surface area with no occlusion and distortion is pointed then similar surface in model base is considered as matching candidates.

Yang-Lyul Lee, Rae-Hong Park proposed a model-based 3-D object recognition system [3]. In this recognition system object is represented by graph. Each surface of object is represented by node (known as surface patch). These patches are connected by the link. They use different technique to extract the feature (surface area) of the object like 3D invariant moment, 3-D area of image and area calculation by the knowledge of information about the neighboring pixel. The distance between the patches are minimized by the technique known as mean field annealing (MFA) neural network. MFA neural network minimize the energy function between an input object and a model. This network is based on solving the traveling salesman problem.

The recognition method proposed in this paper detailed as follows. In this paper 3-D object is a pea. Firstly an object is divided into number of segments. Each segment is similar to surface patch. Feathers are extracted from the surface patches and neighbor of patches. Each patch is kernel surface. If properties of modelbase are matched with the input range data then no occlusion in the image. If not match then there is matching error. If image is proper matched with the range data then energy level determined by proper energy function is converges to the stable state as temperature decreases trough mean field annealing (MFA) process [8]. At optimal matching condition energy has its minimum value. The main problem with MFA, if matching error has some significant valve then convergence time may increase. Sometimes optimal valve does not find. So here another neural network model known as BPNN (BPNN) is selected. BPNN minimizes mean square error between target and output. As mean square error goes to zero output tends to target vector. Back propagation NN is fast as compare to other neural network.

## 2. Model Construction

Some technique explained in the previous section for the model construction are based on (1) the kernel surface (2) or by a number of models described in multiple directions. If this kernel is selected properly among several object surfaces, the object recognition process is simple and fast.

On the other hand selected surface is incorrect or distorted either due to occlusion or different viewing angle, the matching process become difficult.

In this paper model base is developed by obtaining various feature of surface of subject. The features of all surfaces are obtained from multiple images from different angles and the information obtained from features is combined to from a model. So that the recognition should be independent of specific viewing direction. The process of model construction is illustrated in Fig. 1.

### 2.1 Feature extraction

The main objective in image processing application is to extract some important features from range image data, from which a machine can provide a description, interpretation or understanding of the scene [15]. Features can be extracted using either of the 2 approaches. The first is the 3-D invariant approach and second is calculating area by neighboring pixel in the image.

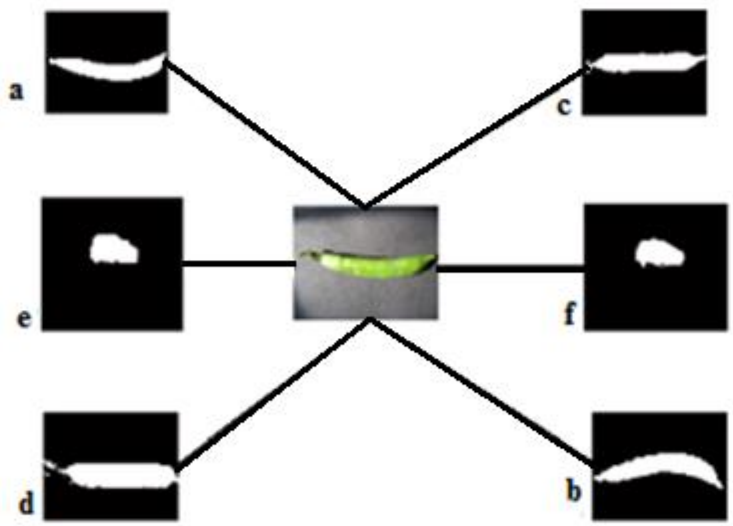


Fig.1: Model construction by taking images from different angles

(a) Top view (b) bottom view (c) side view

(d) Other side view (e) front view (f) rear view

#### 2.1.1 3-D Invariant moments

Invariant method is used to obtain the 3-D area of the image after range image segmentation. The moments provide some useful alternative to series expansions for representing shape of object [13]. 2-D invariant moments are used in object recognition and character reorganization. Invariant moments independent of translation, rotation, scale changing, and mirroring [16]. Their application to 3-D object reorganization does not yield good result when direction of observation changes. The distribution of pixel over a surface could be denoted by the moments.

The $(m+n+q)^{th}$ order moment $\mu_{mnq}$ is defined by

$$\mu_{mnq} = \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} \sum_{q=0}^{q-1} x^m \, y^n z^q \; g(x,y,z) \tag{1}$$

g(x,y,z) = 1if pixel lie in the surface and 0 otherwise. The central moment s given by

$$\xi_{mnq} = \frac{1}{\mu_{000}} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} \sum_{q=0}^{q-1} (x-\mu_{100})^m (y-\mu_{010})^n (z-\mu_{001})^q \tag{2}$$

Two moments invariant to rotation and translation

$$I_1 = \frac{J_1^2}{J_2} \qquad\qquad I_2 = \frac{\Delta_2}{J_1^3} \tag{3}$$

are used as features for matching the surfaces, where the relative invariant moments $J_1$&$J_2$ and $\Delta_2$ are defined in terms of the second order central moments,

$$J_1 = \xi_{200} + \xi_{020} + \xi_{002} \tag{4}$$

$$J_2 = \xi_{020}\xi_{002} - \xi_{011}^2 + \xi_{200}\xi_{002} - \xi_{101}^2 + \xi_{200}\xi_{020} - \xi_{110}^2 \tag{5}$$

$$\Delta_2 = \begin{matrix} \xi_{200} & \xi_{110} & \xi_{101} \\ \xi_{110} & \xi_{020} & \xi_{011} \\ \xi_{101} & \xi_{011} & \xi_{002} \end{matrix} \tag{6}$$

where values are related to area and the shape of surface respectively.

**2.3 Calculating area by neighboring pixel in image**

The area of a gray image can be getting by counting on pixels in an image by summing the areas of each pixel in the image. The area of an individual pixel is determined by looking at its 2-by-neighbourhood. There are six different patterns, each representing different area. This technique is used for the surface area calculation of the image. In this area calculation process brighter pixels are counted and darker pixels are left.

Patterns with zero on pixel (area=0)
Patterns with one on pixel (area=1/4)
Patterns with two adjacent on pixels (area=1/2)
Patterns with two adjacent on pixels (area=3/4)
Patterns with three on pixels (area=7/8)
Patterns with all four on pixels (area=1)

## 3. Back propagation Neural Network

Back propagation neural network is a form of supervised learning. As explained by Hagan [18] the performance index of the network is expressed as mean square error. For multilayer neural network, the transfer function may be nonlinear, so calculation of error for the network becomes more complex. The BPNN algorithm was used for training the network for image compression/decompression [17].

3.1 Back propagation Algorithm

In multilayer network, the output of the previous layer becomes the input to the following layer. The mathematical expression elaborate this statement

$$a^{m+1} = f^{m+1}(w^{m+1}a^{m+1} + b^{m+1}); \ \ (\forall\, m \in 0,1,2,\ldots,M-1) \tag{7}$$

where *M* is the number of layer in the network, *a* neuron output, *f* transfer function, w weight matrix and *b* bias. The initial layer accepts input as a neuron externally [18]. BPNN use mean square error as performance index.

This algorithm tries to minimize the mean square error

$$F(x) = E[e^T e] = E[(t-a)^T (t-a)] \tag{8}$$

$a$ vector having network weight and biases. In generalized way, the output of the network of multiple output networks is expressed as

Mean square error is given by

$$\hat{F}(x) = \big(t(k) - a(k)\big)^T \big(t(k) - a(k)\big) \tag{9}$$

$$= e(k)^T e(k) \tag{10}$$

Where the expression squared error has been replaced by the squared error at iteration k.

In much generalized way the mean square error is given as

$$w_{i,j}^m(k+1) = w_{i,j}^m(k) - \alpha \frac{\partial \hat{F}}{\partial w_{i,j}^m} \tag{11}$$

$$b_i^m(k+1) = b_i^m(k) - \alpha \frac{\partial \hat{F}}{\partial b_i^m} \tag{12}$$

where α is learning rate. Fig. 2 shows a multilayer neural network that input layer hidden layer an output layer.

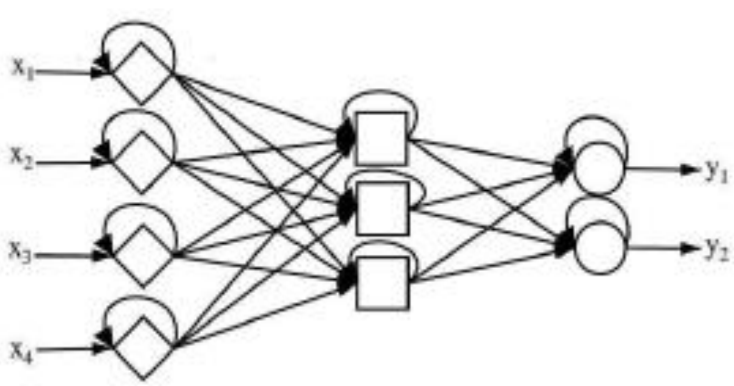


Fig. 2 Multilayer feedback neural network

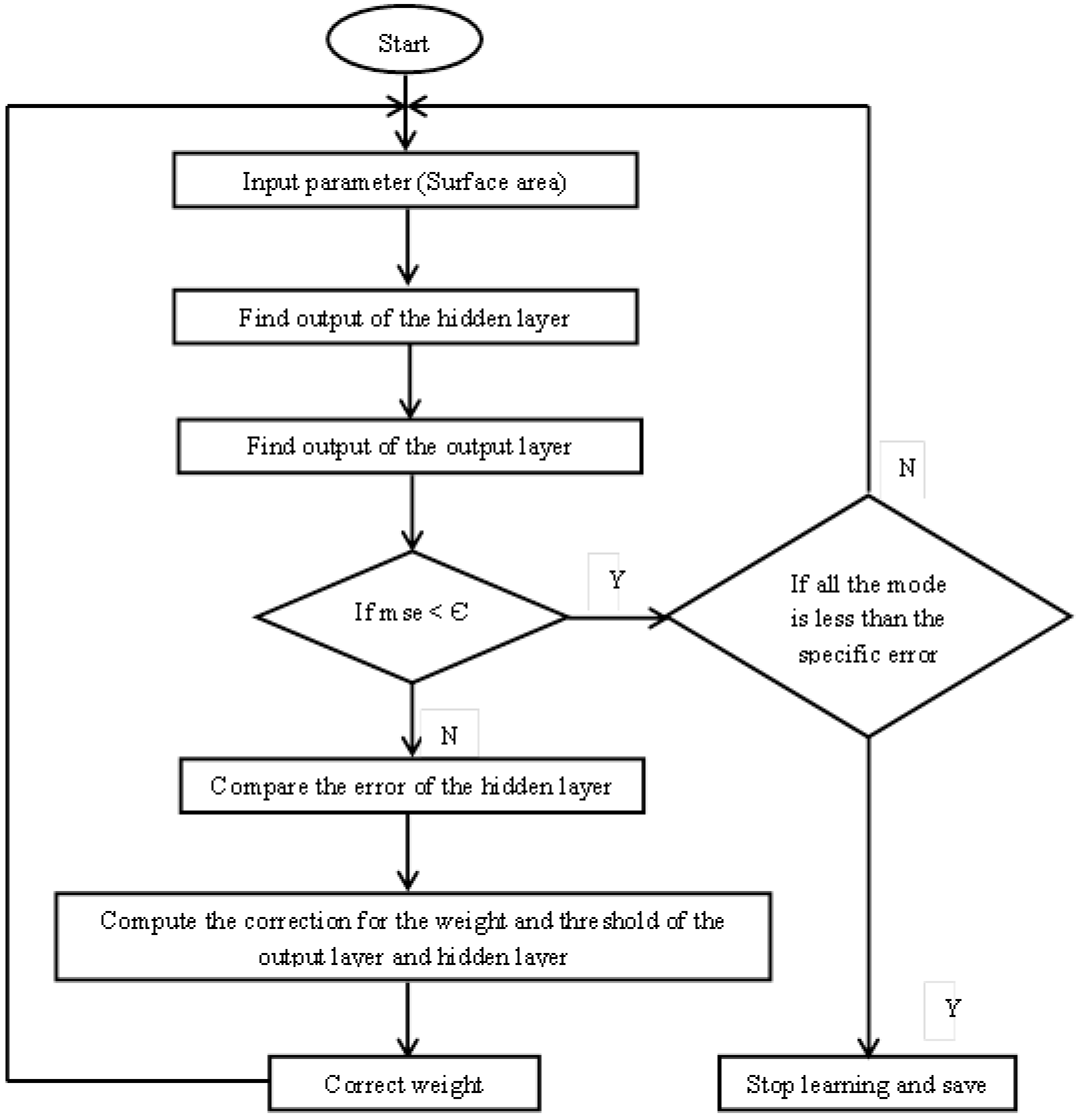


Fig. 3 Proposed Back propagation Flow Chat for Object Recognition

3.2 Model construction and classification using Back propagation Neural Network (BPNN)

In this paper feature extracted is the surface area of pea of all six possible faces, work as the input for the BPNN. Six faces are top view, bottom view, side view, other side view, front view and rear view. BPNN is used as the classifier. Here *X* is the input vector, which is applied at BPNN's input. Input *X* contains the information about the all vision of pea.

$$X = \begin{cases} x_1 & top\ view \\ x_2 & bottom\ view \\ x_3 & front\ view \\ x_4 & rear\ view \\ x_5 & side\ view \\ x_6 & other\ side\ view \end{cases} \tag{13}$$

$$T = [t1, t2, \ldots ti] \forall\ i = 1,2 \ldots 15 \tag{14}$$

where T is the target vector.

Since more than one subjects are to be investigated. Let $X_j$ represent a particular subject such that

$$X_j = \{x_{1j}, x_{2j}, \dots, x_{ij}\} \; \forall \; i \in [1, 15] \tag{15}$$

where $i$ is the view and $j$ is the subject.

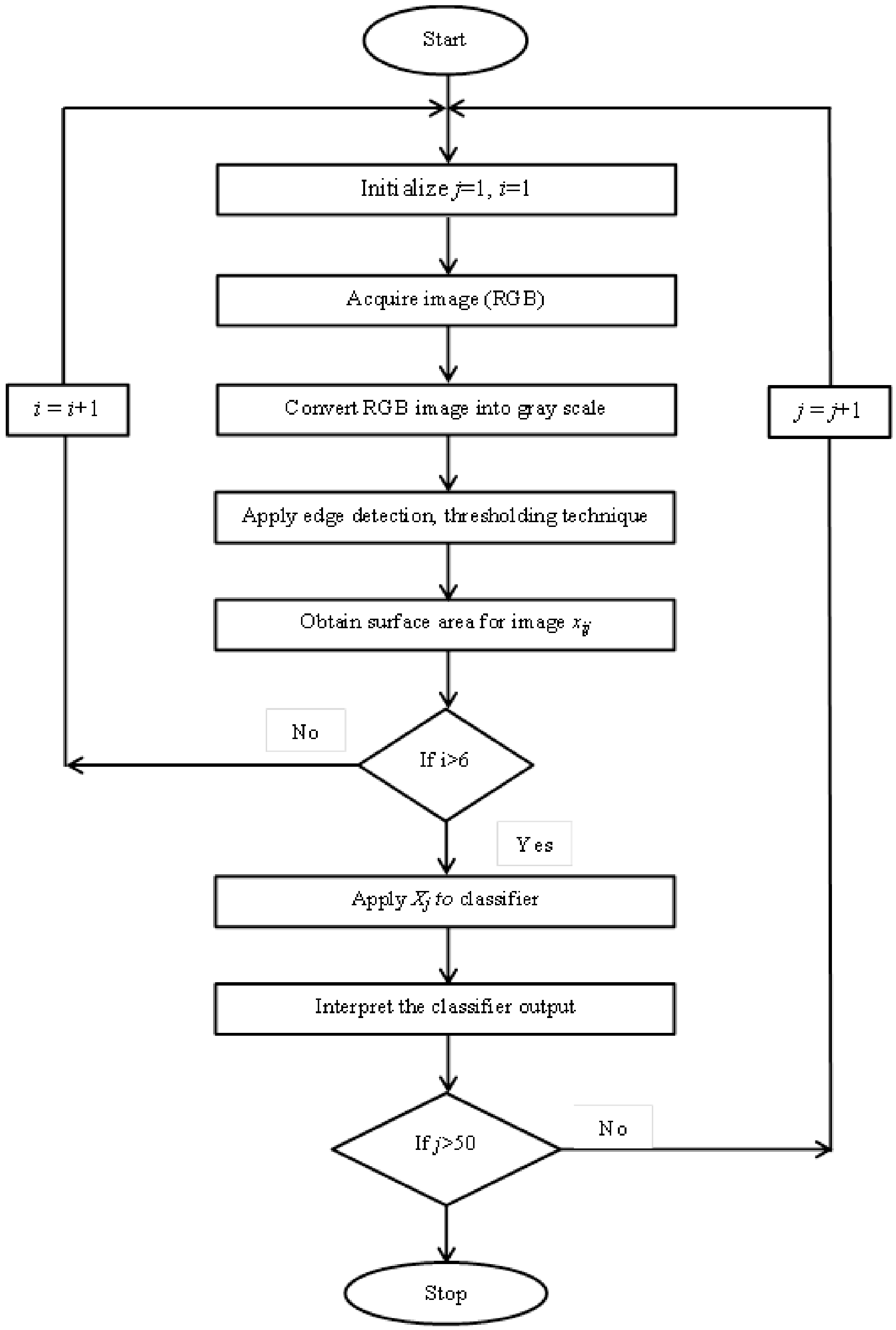

Fig. 4 Flow chart for feature extraction and classification

Weight and bias values are change according to the BPNN such that mean square error can be minimized. Number of hidden layers is selected on the basis of hit and trail. In my experiment number hidden layers are four. Here transfer function log sigmoid is used because problem is non-linear. Output transfer function is hard limit because object is selected or rejected on the basis of quality or on the basis of surface area.

## 4. Experimental result and discussion

In this experiment, all possible surfaces of pea are analyzed separately. Area of each surface is calculated by the proposed 3-D area calculation technique Object used in this experiment has 6 surfaces. Area of the object is input for the neural network. BPNN gives best result because it minimizes mean square error. Main drawback with this NN, iteration time increases with the increase in number of input. If nonlinearity is involved with the input data then output of the system, some time, may not be satisfactory. Boundary separates the input data according to output or target nonlinear. In feature some other technique can be used to classify the nonlinear data. In the presiding section some experimental result is given. Area of the surface is calculated it is assumed that the surfaces are not occulted mean they are exactly matched.

Table1 Network training input vector and target vector

| Object no.($j$) | $x_{j1}$ | $x_{j2}$ | $x_{j3}$ | $x_{j4}$ | $x_{j5}$ | $x_{j6}$ | Target (T) | Output (a) |
|---|---|---|---|---|---|---|---|---|
| 1 | 0.80 | 0.63 | 0.90 | 1.0 | 0.87 | 0.83 | 1. | 0.96 |
| 2 | 0.98 | 0.83 | 0.81 | 0.53 | 0.91 | 0.60 | 1 | 0.97 |
| 3 | 0.72 | 0.18 | 0.40 | 0.37 | 1.0 | 0.61 | 1 | 0.97 |
| 4 | 0.85 | 0.83 | 0.55 | 0.24 | 0.12 | 0.33 | 1 | 0.95 |
| 5 | 0.86 | 0.84 | 0.24 | 0.21 | 0.19 | 0.58 | 1 | 0.87 |
| 6 | 1.0 | 0.98 | 0.26 | 0.24 | 0.05 | 0.22 | 0 | 0.91 |
| 7 | 0.97 | 1.0 | 0.85 | 0.22 | 0.07 | 0.23 | 0 | 0.97 |
| 8 | 0.21 | 0.93 | 1.0 | 0.29 | 0.40 | 0.64 | 1 | 0.95 |
| 9 | 0.81 | 0.77 | 0.25 | 0.28 | 0.10 | 0.52 | 1 | 0.97 |
| 10 | 0.23 | 0.69 | 0.28 | 0.37 | 0.09 | 0.34 | 0 | 0.93 |
| 11 | 0.91 | 0.84 | 0.32 | 0.27 | 0.11 | 0.45 | 1 | 0.94 |
| 12 | 0.76 | 0.85 | 0.28 | 0.10 | 0.01 | 1.0 | 0 | 0.93 |
| 13 | 0.91 | 0.78 | 0.31 | 0.32 | 0.10 | 0.51 | 1 | 0.94 |
| 14 | 0.86 | 0.79 | 0.22 | 0.22 | 0.12 | 0.35 | 1 | 0.94 |
| 15 | 0.18 | 0.76 | 0.10 | 0.10 | 0.05 | 0.73 | 0 | 0.96 |

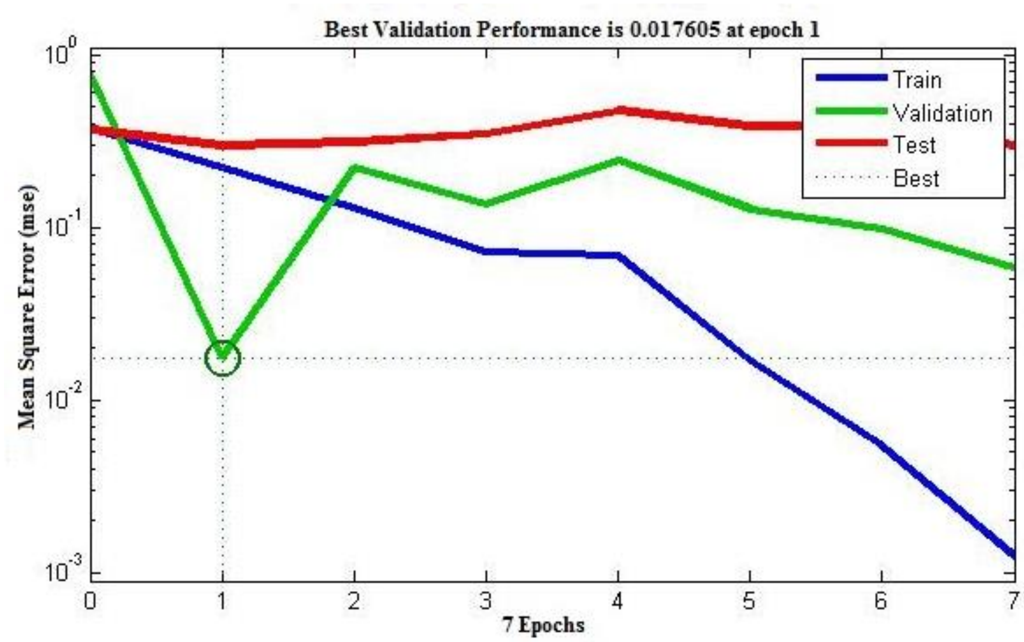


Fig. 5 Best validation performance

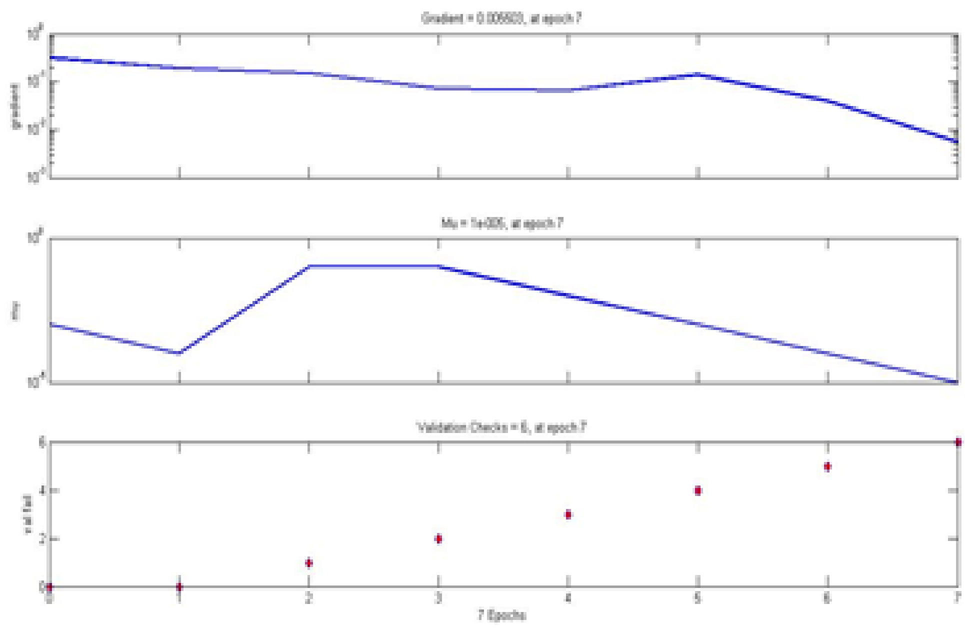

Fig.6 Trainng states of the network

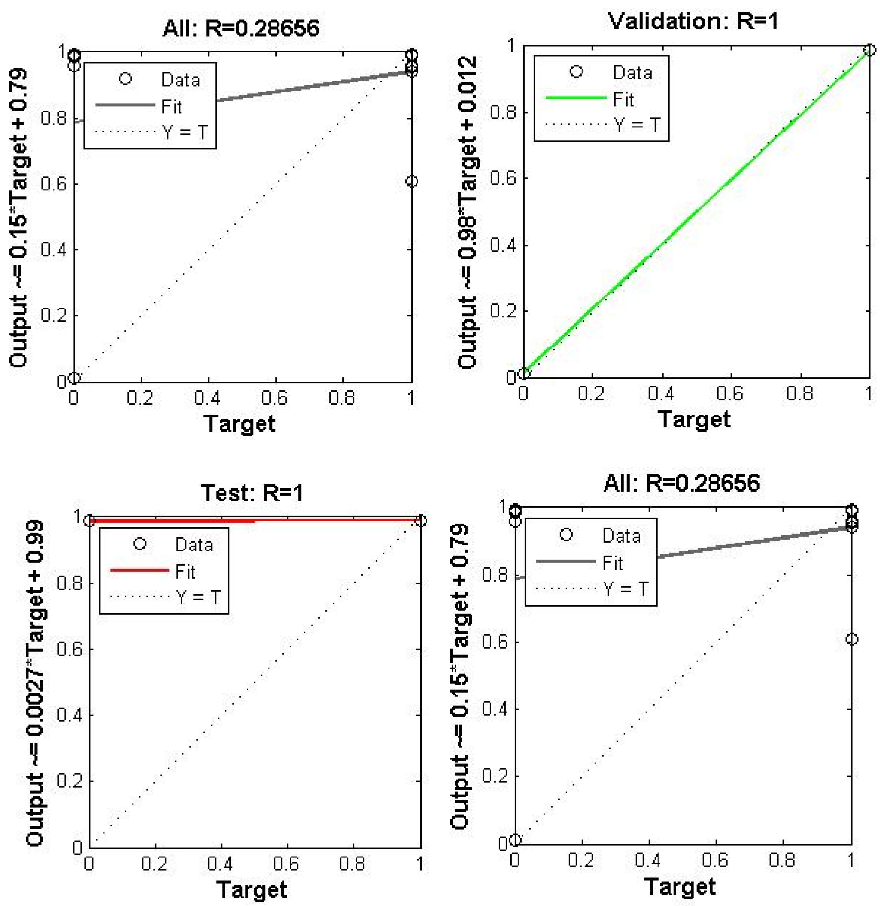


Fig. 7 Training regration of the network

Model base is tested with the input vector and target vector. On the basis of success rate of the network six neurons and four hidden layers are selected.

Table 2 Validation of network using test data

| Object no.($j$) | $x_{j1}$ | $x_{j2}$ | $x_{j3}$ | $x_{j4}$ | $x_{j5}$ | $x_{j6}$ | Target | Output |
|---|---|---|---|---|---|---|---|---|
| 1 | 0.95 | 0.94 | 0.78 | 0.79 | 0.89 | 0.88 | 1 | 0.999 |
| 2 | 0.21 | 0.20 | 0.82 | 0.89 | 0.74 | 0.79 | 1 | 0.999 |
| 3 | 0.85 | 0.75 | 0.21 | 0.20 | 0.10 | 0.01 | 0 | 0.002 |
| 4 | 0.40 | 0.12 | 0.92 | 0.85 | 0.72 | 0.78 | 1 | 0.999 |
| 5 | 0.53 | 0.45 | 0.71 | 0.60 | 0.45 | 0.51 | 0 | 0.990 |
| 6 | 0.31 | 0.21 | 0.11 | 0.10 | 0.15 | 0.19 | 0 | 0.000 |
| 7 | 0.87 | 0.79 | 0.11 | 0.19 | 0.25 | 0.29 | 0 | 0.001 |
| 8 | 0.80 | 0.91 | 0.69 | 0.62 | 0.80 | 0.76 | 1 | 0.982 |
| 9 | 0.42 | 0.40 | 0.87 | 0.80 | 0.95 | 0.83 | 1 | 0.999 |
| 10 | 0.98 | 0.91 | 0.89 | 0.79 | 0.89 | 0.92 | 1 | 1 |
| 11 | 0.31 | 0.26 | 0.83 | 0.95 | 0.96 | 0.89 | 1 | 0.989 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 12 | 1.0 | 0.86 | 0.46 | 0.49 | 0.90 | 0.93 | 1 | 0.999 |
| 13 | 0.71 | 0.74 | 0.60 | 0.69 | 1.0 | 0.93 | 1 | 0.990 |
| 14 | 0.23 | 0.25 | 0.31 | 0.9 | 0.87 | 0.89 | 1 | 0.987 |
| 15 | 0.19 | 0.21 | 0.76 | 0.89 | 0.87 | 0.83 | 1 | 0.999 |
| 16 | 0.36 | 0.31 | 0.54 | 058. | 0.43 | 0.52 | 0 | 0.009 |
| 17 | 0.55 | 0.59 | 0.71 | 0.78 | 0.83 | 0.88 | 1 | 0.824 |
| 18 | 0.98 | 0.98 | 0.83 | 0.89 | 0.98 | 0.95 | 1 | 1 |
| 19 | 0.48 | 0.42 | 0.73 | 0.75 | 0.89 | 0.85 | 1 | 0.999 |
| 20 | 0.20 | 0.21 | 0.41 | 0.43 | 0.82 | 0.89 | 1 | 0.999 |
| 21 | 0.32 | 0.36 | 0.89 | 0.86 | 0.90 | 0.92 | 1 | 0.999 |
| 22 | 0.89 | 0.86 | 0.89 | 0.93 | 0.86 | 0.89 | 1 | 0.999 |
| 23 | 1.0 | 0.98 | 0.36 | 0.36 | 0.23 | 0.30 | 0 | 0.129 |
| 24 | 0.45 | 0.46 | 056 | .52 | .49 | .51 | 0 | 0.345 |
| 25 | 0.95 | 0.95 | 0.89 | 0.88 | 0.96 | 0.96 | 1 | 1 |
| 26 | 0.87 | 0.80 | 0.83 | 089 | 0.80 | 0.79 | 1 | 0.999 |
| 27 | 0.32 | 0.32 | 0.24 | 0.25 | 0.89 | 0.90 | 1 | 0.983 |
| 28 | 0.13 | 0.12 | 0.35 | 0.36 | 0.99 | 0.98 | 1 | 0.991 |
| 29 | 0.36 | 0.32 | 0.92 | 0.96 | 0.89 | 0.83 | 1 | 0.999 |
| 30 | 0.78 | 0.73 | 0.89 | 0.85 | 0.90 | 0.93 | 1 | 0.992 |
| 31 | 0.10 | 0.12 | 0.25 | 0.23 | 0.12 | 0.12 | 0 | 0.001 |
| 32 | 0.89 | 0.83 | 0.75 | 0.79 | 0.80 | 0.83 | 1 | 0.999 |
| 33 | 0.93 | 0.90 | 0.13 | 0.15 | 0.20 | 0.30 | 0 | .009 |
| 34 | 0.63 | 0.64 | 0.59 | 0.61 | 0.82 | 0.83 | 1 | 0.786 |
| 35 | 0.37 | 0.38 | 0.65 | 0.67 | 0.86 | 0.82 | 1 | 0.999 |
| 36 | 0.76 | 0.69 | 0.78 | 0.78 | 0.84 | 0.81 | 1 | 0.993 |
| 37 | 0.53 | 0.51 | 0.65 | 0.68 | 0.75 | 0.73 | 1 | 0.999 |
| 38 | 0.34 | 0.32 | 0.68 | 0.69 | 0.86 | 0.89 | 1 | 0.999 |
| 39 | 0.96 | 0.97 | 0.82 | 0.81 | 0.86 | 0.89 | 1 | 0.999 |
| 40 | 0.23 | 0.30 | 0.64 | 0.65 | 0.90 | .89 | 1 | 0.999 |
| 41 | 0.80 | 0.81 | 0.86 | 0.89 | 0.81 | 0.91 | 1 | 0.998 |
| 42 | 0.21 | 0.12 | 0.31 | 0.29 | 0.24 | 0.21 | 0 | 0.012 |
| 43 | 0.29 | 0.28 | 0.65 | 0.69 | 1.0 | 0.98 | 1 | 0.999 |
| 44 | 0.13 | 0.15 | 0.31 | 0.29 | 0.30 | 0.31 | 0 | 0.145 |
| 45 | 0.89 | 0.84 | 1.0 | 0.99 | 0.89 | 0.85 | 1 | 0.999 |
| 46 | 0.31 | 0.33 | 0.46 | 0.42 | 0.83 | 0.84 | 1 | 0.989 |
| 47 | 0.51 | 0.52 | 0.76 | 0.81 | 0.79 | 0.80 | 1 | 0.910 |
| 48 | 0.21 | 0.23 | 0.53 | .50 | 0.74 | 0.79 | 1 | 0.810 |
| 49 | 0.41 | 0.42 | 0.59 | 0.60 | 1 | 0.92 | 1 | 0.999 |
| 50 | 0.31 | 0.32 | 0.43 | 0.44 | 0.84 | 0.84 | 1 | 0.841 |

From the Table 2 it is evident that the % success rate for five hidden layers and three neurons network is 0.72 and for six layers and four neurons network is 0.92.

## 5. Conclusion

A 3-D object recognition approach using surface based recognition is proposed. This proposed model based object recognition technique is based on Back propagation NN. The object recognition is based on shape. Nonlinearity involved with input, may fail the system. In feature some nonlinear recognition system can give satisfactory result.

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