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Identification of Medical Plants Using Genetic Algorithm and Recurrent Neural Network

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Abstract: Medicinal leaves widely used in medicine, cosmetic and pharamastic cosmetic industry. Medicinal leaves are verge of extinction. Presently identification of the type of medicinal leaves is still done manually and it will be occur to human error. Leaves are the key components of plants. The leaf extracts of many medicinal plants can cure various diseases and alternating for allopathic medicinal system now a days. In this method an extraction of shape, color, morphology and texture features from leaf image. Next step is using Genetic algorithm to feature selection process. Final step training a Recurrent Neural Network (RNN) classifier and Support Vector Machine (SVM) to display the leaf name and uses. The results of the flavia database leaf achieved an average accuracy is 95.53% from the ACO-based approach. Same method used to find medical leaf using Genetic Algorithm an average accuracy is 91.30%. This research has been implemented using the image processing and neural network toolbox in MATLAB.

Key words: Medicinal leaves, feature extraction, genetic algorithm, recurrent neural network and support vector machine

INTRODUCTION

Since, recent years digital image processing, image analysis and machine vision have been roughly developed and they have become a very important part of artificial intelligence and the interface between human and machine grounded theory applied technology. These technologies have been applied widely in industry and medicine but rarely related to agriculture or natural habitats.

Despite the importance of the subject of identifying plant diseases using digital image processing and although this has been studied for at least 30 year the advances achieved seem to be a little timid. Some facts lead to this conclusion: Methods are too specific. The ideal method would be able to identify any kind of plant. Clearly, this is impractical given the current technological level. However, many of the methods that are being proposed not only are able to deal with only one species of plant but those plants need to be at a certain growth stage in order to the algorithm to be effective.

That is acceptable if the plant is in that specific stage but it is very limiting otherwise. Many of the researchers do not state this kind of information openly but if their training and test sets include only images of a certain growth stage. Operation conditions are too strict. Many images used to develop new methods are collected under very strict conditions of lighting, angle of capture, distance between object and capture device among others. This is a common practice and perfectly acceptable in the early stages of research.

Lack of technical knowledge about more sophisticated technical tools. The simplest solution for a problem is usually the preferable one. In the case of image processing some problems can be solved by using only morphological mathematical operations which are easy to implement and understand. However, more complex problems often demand more sophisticated approaches. Techniques like neural networks, genetic algorithms and support vector machines can be very powerful if properly applied. Unfortunately, that is often not the case. In many cases, it seems that the use of those techniques is more demand in the scientific community than in their technical appropriateness with respect to the problem at hand. As a result, problems like over fitting, overtraining, undersized sample sets, sample sets with low representativeness, bias among others seem to be a common disease.

In recent times, computer vision methodologies and pattern recognition techniques have been applied towards automated procedures of plant recognition. Digital image processing is the use of the algorithms and procedures for operations such as image enhancement, image compression, image analysis, mapping, geo-referencing, etc. The influence and impact of digital images on modern society is wonderful and considered as a critical component in variety of application areas including pattern recognition, computer vision, industrial automation and healthcare industries.

One of the most common methods in leaf feature extraction is based on morphological features of leaf. Some simple geometrical features are aspect ratio, rectangularity, convexity, sphericity, form factor, etc. One can easily transfer the leaf image to a computer and a computer can extract features automatically in image processing techniques. Some systems employ descriptions used by botanists. But it is not easy to extract and transfer those features to a computer automatically.

The aim of the project is to develop a leaf recognition program based on specific characteristics extracted from photography. Hence, this presents an approach where the plant is identified based on its leaf features such as area, histogram equalization and edge detection and classification. The main purpose of this program is to use MATLAB resources. Indeed, there are several advantages of combining MATLAB with the leaf recognition program. The result proves this method to be a simple and an efficient attempt.

Future study will discuss more on image pre-processing and acquisition which includes the image pre-processing and enhancement, histogram equalization, edge detection. Further on sections introduces texture analysis and high frequency feature extraction of a leaf images to classify leaf images i.e., parametric calculations and then followed by results.

Ayurveda is called medicinal plants is important of a system of medicine and useful in the treatment of certain chronic diseases. Ayurveda is considered as a form of alternative to allopathic medicine in the world. Ayurveda definitely brings substantial profits to India by export of Ayurvedic medicines in foreign exchange because of many countries inclining towards this system of medicine. Wang *et al.* (2012), in this study plant diseases has been recognized based on principal component analysis and neural networks.

There is considerable depletion in the population of certain species of medicinal plants. Hence, we need to grow more plant species in India. This upgrading work requires easy recognition of medicinal plants. In society all the people not well know the medical plants and their medical uses (Anami *et al.*, 2010).

India has 15 Agro climatic zones and 17000-18000 flowering plants species of which 6000-7000 are estimated to have medicinal usage in folk and documented systems of medicine, siddha, unani and homoeopathy.

In this study leaf recognition has been done by using shape analysis and feature extraction (Chaki and Parekh, 2011). The features are given as input to the neural network which is based on supervised learning algorithm having multilayer preceptor with feed forward backward back propagation architecture. The result of this are tabulated for each feature category and are of the range from 90-94 having mean square error in the range of 0-0.7. In certain test folds foe classifying the leaf types the classification rate even goes as high as 100 but in his conclusion he is mentioning an accuracy of 94%.

In this study they have used wavelet based analysis of fruit/leaf images for doing classification (Anami *et al.*, 2010). The fruit/leaf images consist of the fruit and the insect which is damaging it; therefore it is a classification problem which tries to identify fruit/leaf having particular pests damaging it. The objective of this thesis have been to take advantage of taking images of the fruit leaf without doing manual labor in terms of inspection and climbing trees and manually checking the pest infected areas. This person is also using neural network based classifier for identifying different types of pests on particular set of fruits/leafs and the accuracy result is >90%.

In this study they are used to classify leaf using shape, color and texture Features (Abdul *et al.*, 2011). Baraldi and Parmiggiani (1995). In this study, they investigate the textural characteristics associated with gray level co occurrence matrix statistical parameters.

In this study, Artificial neural networks has been used for mosquito species Classification and identification (Banerjee *et al.*, 2008).

Kulkarni *et al.* (2013) in this study low level features (texture features)are used to classify different types of grass weeds leaves The image is subjected to gabor wavelet transformation and its features are extracted and given to multilayer preceptor neural network. The weeds are classified into two major categories-broad leaves and grass category. The results of study for each type of broad leaf and grass weed ranges from 88-92%.

In this study, they combined color, Texture and edge feature based approach for identification and classification of indian medicinal plants (Wu *et al.*, 2006). In this study, PNN (Probabilistic Neural Network) has been used for plant species classification based on leaf architecture They have extracted 12 features of the leaf which are further orthogonal into five principle variables which consist of the input vectors. PNN has been trained on very large number of leaves and has classified 32 species of plants. These studys also give an accuracy which is >90% for most of the classification.

In this study, the researcher is discussing the importance of discovering new plants to mankind and purposes leaf recognition and classification based on hybrid image segmentation algorithm (Choras, 2007). He develops a histogram of each leaf image segmented. In the end his results include calculation of energy mean square error and PSNR (Peak to Signal Ratio). These results basically give the quality of segmentation. Chaki and Parekh (2011), in this study they are used shape based features and neural network classifiers for plant leaf recognition.

In this study, they are used Shape recognition based on radial basis probabilistic neural network and application to plant species identification (Du *et al*., 2005). In this study, they are used edge detection matching GLCM for texture-Based image retrieval (Zhang *et al*., 2008).

In this study, they are used texture element feature characterizations for CBIR (Jalja *et al*., 2005). In this study, they are used to find image correlogram in image database indexing and retrieval. In this study they are used to classify leaf using shape, color and texture features. In this study, they are used feature decision-making ant colony optimization system for an automated recognition of plant species (Ghasab *et al*., 2015).

In this study, they are analysed Medicinal Plants Importance and uses. In this study, they are used support vector machine for recognition of plant leaves (Man *et al*., 2008). In this study, they are used artificial neural network for feature extraction and automatic recognition of plant leaf (Wu *et al*., 2006). In this study they are used textural feature based image retrieval algorithm (Song and Chen, 2008). In this study they are used fault diagnosis based on support vector machines with parameter optimization by an ant colony algorithm (Zhang *et al*., 2010).

MATERIALS AND METHODS

Initially plants leaves images are acquired by a scanner. First step is all the coloured images after rescaling are converted to gray-scale and pre-processing method gray-scale image converted to binary. Next process is extract the feature for constructing the feature search space some techniques are automatically applied on the leaf images to extract shape, morphology, texture and colour features (Fig. 1).

Following this step the Ant Colony Optimization algorithm (ACO) based on a feature decision making algorithm is apply to the feature search space to select a different subset of features while the repeated process measures the quality of selected features. Based on the evaluation of subsets in each iteration the amount of pheromones is reorganized for the best local features as a positive feedback. This technique of feedback is called wrapper in which the classifier is engaged with the search algorithm to measure the interaction of all possible features and determines the distinguish features as the local best features in each iteration (Fig. 2).

Finally, a global best subset is generate when the stopping criteria are satisfied and support vector machine and recurrent neural network trains the dataset based on the selected features as the global best and display the leaf name and their uses.

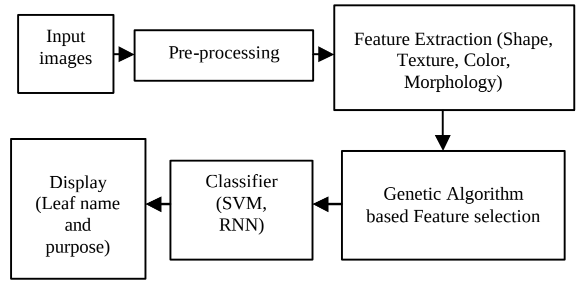

Fig. 1: Overall flow diagram

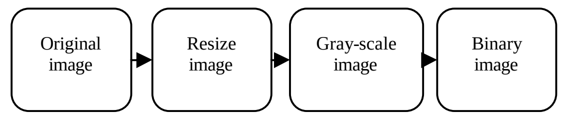

Fig. 2: Detailed block diagram of pre-processing

Pre-processing

Original image: The original image is obtained from the flavia dataset. Original image size is 1600X1200 pixels. Processing of the original images is very difficult because it is too big.

Resized image: Resize the image into 250X250 pixels to fit into Matlab (Fig. 3).

Gray-scale image: A gray-scale image is combination of different shades of grey color. Preserving the brightness of the image a RGB color image can be converted to a gray scale image. Some early grayscale monitors can only show up to sixteen different shades but in recent days grayscale images are commonly stored with 8 bits per sampled pixel which allows 256 different intensities.

Binary image: From a grayscale image, thresholding can be used to create binary images. A digital image is a binary image that has only two possible values for each pixel. Normally the two colors used to a binary image that is black and white. The color used for the object in the image is the foreground color while the rest of the color is the background color. Binary images are also called bi-level or two-level. This means that each pixel is stored as a single bit in 0 or 1.

Feature extraction: In this step the features were extracted from shape, colour, vein and texture of the leaf.

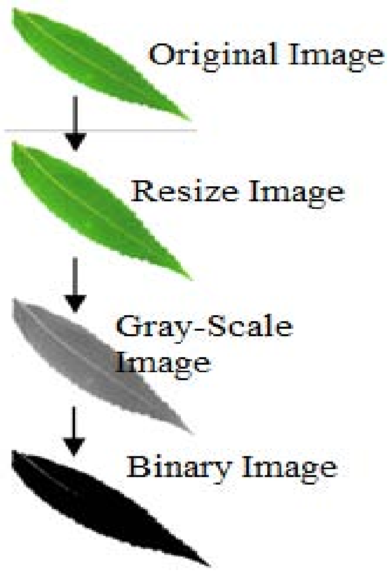

Fig. 3: Example of pre-processing step

Feature extraction involves reducing the amount of resources required to describe a large set of data.

Color features: Color features are important for colour based image analysis. The information of colour distribution is an image captured by the low order moments.

Moment 1: It is called Mean. It provides average colour value in the image:

$$\mu = \frac{1}{MN}\sum_{i=j}^{M}\sum_{j=1}^{N} Pij \quad (1)$$

where, M and N represents the total number of pixels in the image.

Moment 2: It is called Standard Deviation (SD). The standard deviation is defined as square root of the variance of the distribution:

$$\sigma = \sqrt{\frac{[1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(P_{ij}-\mu)^2]} \quad (2)$$

Moment 3: It is called Skewness. It measure the degree of asymmetry in the distribution:

$$\partial = \sqrt[3]{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(Pij-\mu)^3} \quad (3)$$

Moment 4: It is called Kurtosis. It measure the peakness in the distribution:

$$\gamma = \sqrt[4]{\left[\frac{1}{MN}\right.\sum_{i=1}^{M}\sum_{j=1}^{N}(P_{ij}-\mu^4)} \quad (4)$$

Shape features

Aspect ratio: The ratio of maximum width to major axis length.

Roundness: The roundness ratio is defined as roundness = A/P^2 where, A and P represented area and perimeter of the leaf.

Perimeter: Perimeter is the distance around a two dimensional shape or measurement the distance around something the length of the boundary.

Vein features: Vein features are features analysis from vein of the leaf. There are four kinds of vein features defined as follows:

$$V1 = A1/A,\ V2 = A2/A,\ V3 = A3/A,\ V4 = A4/A$$

Where: A1, A2, A3 and A 4 are pixel number that define the vein and A is area of the leaf.

The vein of the leaf is find by using morphological operation called opening. Then the operation is performed on the gray scale image by flat and disk-shaped structuring element of radius 1-4 and from the margin remaining image subtracted remaining. As a result, a structure like vein is obtained. RGB image is converted to gray scale image is done by using following equation:

$$Gray = 0.2989R + 0.5870\,G + 0.1140\,B \quad (5)$$

Texure features: An image texture is a position of standard of measurements computed an image processing future to detail the clear texture of a leaf image. Leaf image texture gives information about spatial arrangement of colour or intensities in a leaf image or selected region of a leaf image. Gray Level Co-occurrence Matrices (GLCMs) used to extracted texture features. GLCM is very useful to obtain the relative position of the neighbouring pixels in an image. The co-occurrence matrix GLCM (i,j) counts the co-occurrence with gray value of pixels i and j at given distance d. Texture features are:

- Energy
- Entropy
- Cntrast
- orrelation
- Homogeneity

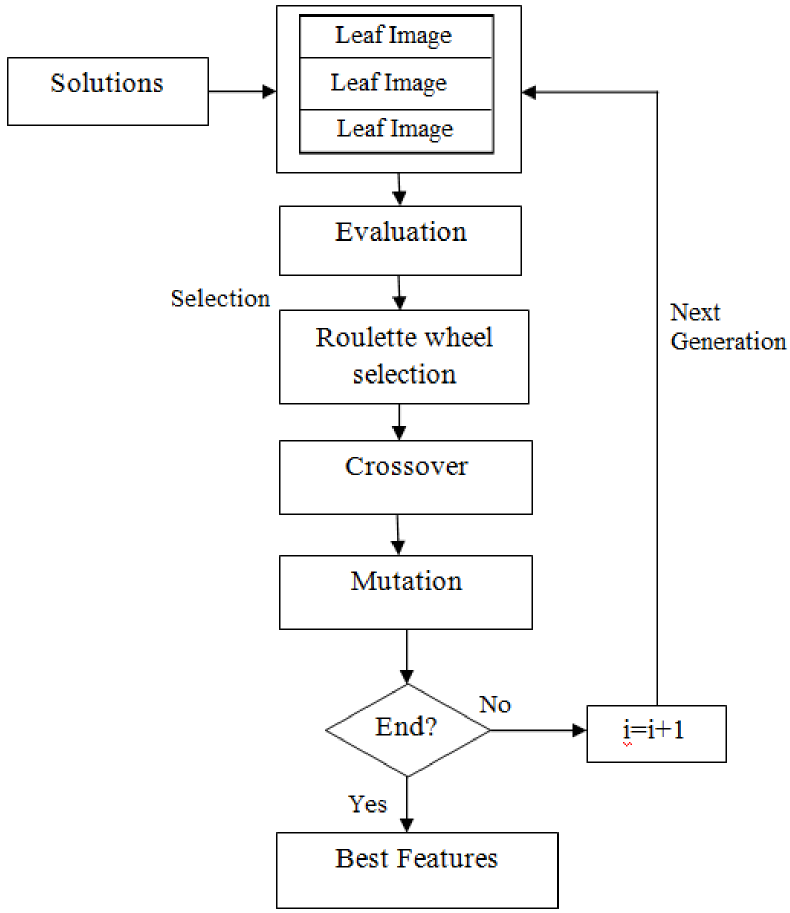

Fig. 4: Genetic algorithm flow chart

Table 1: Comparison of classification rate on flavia database

References	Method	Feature extraction technique	No. of features	Classification rate (%)
Wu *et al.* (2006)	PNN	Shape, morphology	12	90.312
Singh	SVM-BDT	Shape, morphology	12	81.580
Singh	PNN-PCNN	Shape, morphology	12	91.250
Singh	Fourier moments	Shape, morphology	12	46.300
Wang *et al.* (2012)	FCA-PNN	Shape, morphology,Texture, color	25	95.000
Mohammad	ACO algorithm	Shape, morphology,Texture, color	11	96.250
Proposed method (2016)	Genetic algorithm	Shape, morphology,Texture, color	13	91.300

Genetic algorithm: The Genetic Algorithm (GA) is an optimization and search technique based on the principles of genetics and natural selection. GAs operates on a population of potential solutions applying the principle of survival of the fittest to produce successively better approximations to a solution. At each generation of a GA, a new set of approximations is created by the process of selecting individuals according to their level of fitness in the problem domain and reproducing them using operators borrowed from natural genetics. This process lead to the evolution of populations of individuals that is better suited to their environment than the individuals from which they were created just as in natural adjustment (Table 1 and Fig. 4).

Initialization: Create an initial population. This population is usually randomly generated and can be any desired size.

Evaluation: Each member of the population is then evaluated and calculates a ‘fitness’ for that individual. The fitness value is calculated by how well it fits with our desired requirements:

$$C = \{c1...cq\ ,\ c1...c2q,...,c(d-1)q+1,..,cdq\} \quad (6)$$

Selection: Constantly improving our populations overall fitness. Selection helps us to do this by discarding the

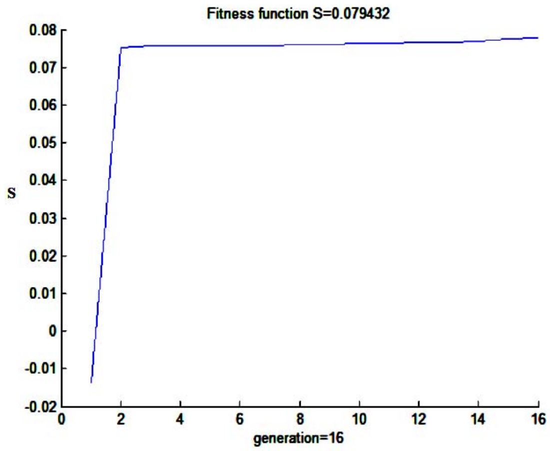

Fig. 5: Calculation of fitness function

Selected Class
7
6
2
4
3
5

Fig. 6: Feature selected using genetic algorithm

bad designs and only keeping the best individuals in the population. There are a few different selection methods but the basic idea is the same make it more likely that fitter individuals will be selected for our next generation. Here roulette wheel selection technique is used. Actually, the probability of selecting an individual is calculated as:

$$P(C_i) = f(C_i)/\sum_{k-1}^{M}(C_k) \tag{7}$$

Where:

C_i = The number of leaf image of ith extracted feature (f)
(C_i) = The fitness value corresponding to C_i and
M = The number of individuals in the population

The value of the fitness function is calculated from the Fig. 5. It is used for feature selection.

Crossover: The crossover operator is used to create new individuals by recombining the features of the leaf. Considering that there are different types of features for selection and at least one feature in each type should be selected, the multi-point crossover is performed. Features are selected using fitness function which is shown in Fig. 5. Actually, we divide the leaf of an individual into several parts, each of which is corresponding with a type of features.

Let it is denoted as P_c. Initially, a large Pc is used to strengthen the search ability. As the evolution goes on, P_c is decreased to improve the convergence speed gradually. Formally, let P_{c0} be the initial crossover probability, g be the number of generation; C_i and C_j is the leaf features, then P_c is adjusted by:

$$p = \begin{Bmatrix} \dfrac{p_{co}}{\log_{10}(g+1)}, \dfrac{f_{max}\bar{f}}{f_{max}\bar{f}} \\ p_{co} \end{Bmatrix} \tag{8}$$

Where:

$$F_{max} = \max(f(C_i).f(C_j)) \tag{9}$$

And:

$$\bar{f} = \frac{1}{M}\sum_{i=1}^{M} f(C_i) \tag{10}$$

Mutation: Need to add a little bit randomness into our population's genetics otherwise every combination of solutions we can create would be in our initial population. Mutation typically works by making very small changes at random to an individual's genome. Total length of generation = No. of gen in leaf×No. of population.

Final process: Now next generation start again from step two until reach a termination condition (Fig. 6).

Recurrent neural network architecture: The fundamental feature of a Recurrent Neural Network (RNN) is that the network contains at least one feed-back connection, so the activations can flow round in a loop. That enables the networks to do temporal processing and learn sequences, e.g., perform sequence recognition/reproduction or temporal association/ prediction.

Recurrent neural network architecture is shown in Fig. 7. It consists of a standard Multi-Layer Preceptor (MLP) plus added loops. These can exploit the powerful non-linear mapping capabilities of the MLP and also have some form of memory. Others have more uniform structures, potentially with every neuron connected to all the others and may also have stochastic activation functions (Fig. 8).

For simple architectures and deterministic activation functions, learning can be achieved using similar gradient descent procedures to those leading to the

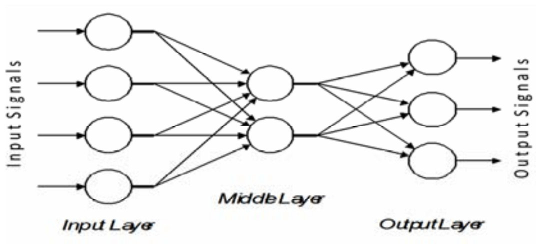

Fig. 7: Neural neatwork architecture

Fig. 8: Input images

back-propagation algorithm for feed-forward networks. When the activations are stochastic, simulated annealing approaches may be more appropriate. The following will look at a few of the most important types and features of recurrent networks.

SVM classifier: Support Vector Machine (SVM) is machine learning tool that based on the idea of large border data classification. The tools have strong theoretical foundation and the classification algorithms based on it gives good generalization performance. Standard implementations provides good classification accuracy is slow and do not scale well. Hence, they do not applied to large-scale data mining applications. Hence, the training as well as the classification times is high.

First part of the research is developing a new learning algorithm which is used to solve the dual problem add the support vectors incrementally. These algorithm selects a new support vectors from a random sample based on simplification ability. In the second part of the research, we developed a classification algorithm problem instead of the dual problem they solving the primal. This algorithm performs better in terms of resulting classifier difficulty comparable with generalization error when compared to the first phase algorithm.

In both phases we reduced the resultant classifier complexity which is compared with existing works. Experimental results is done on real-world large datasets show these methods help to reduce the storage cost produce comparable classification accuracy by existing works and result in reduction of support vectors thereby reducing the inference time.

RESULTS AND DISCUSSION

SVM Classifier and recurrent neural network used to display leaf name and then command window display that plant uses. Classification rate is compared with flavia database and is given in the Table 2.

Performance measurement between mean square error and 1000 epochs in Fig. 9. The property tr.best-epoch indicates the iteration at which the validation performance reached a minimum. The training continued for 1000 iterations before the training stopped.

This Fig. 10 does not indicate any major problems with the training. The validation and test curves are very similar. If the test curve had increased significantly before the validation curve increased, then it is possible that some over fitting might have occurred. The three plots represent the training, validation and testing data. The dashed line in each plot represents the perfect result-outputs = targets.

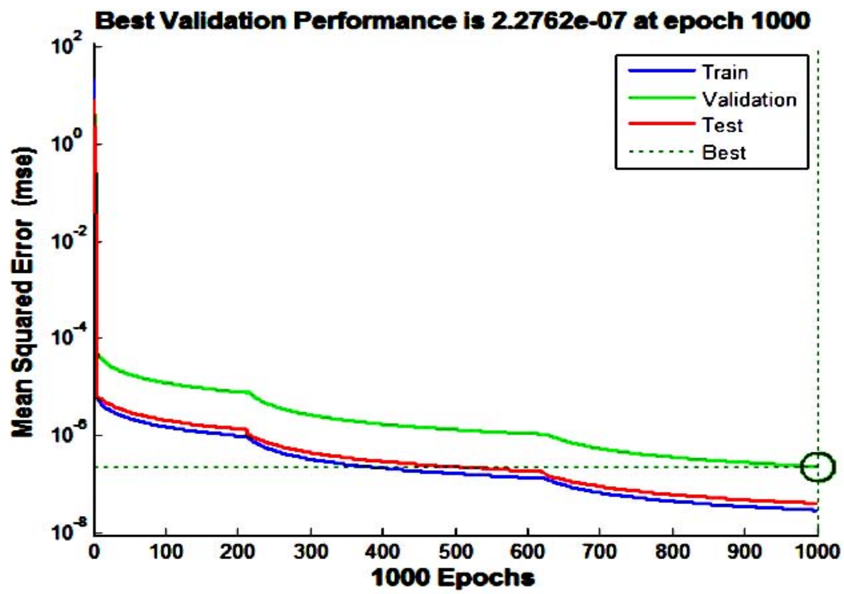

Fig. 9: Graph represents performance measurement

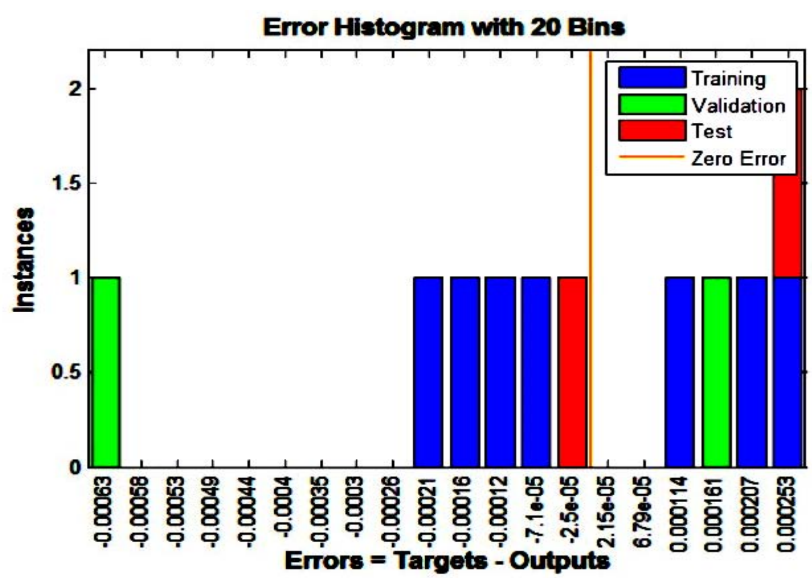

Fig. 10: Error histogram with 20 bins

Table 2: Classifier parameter measurements

Classifier	Accuracy	Spesificity	Sensitivity
Support vector machine	77.2727	66.6667	84.6154
Recurrent neural network	91.3043	90.9091	91.6667

Accuracy, specificity and sensitivity are calculated for SVM and RNN classifier. The values are given in Table 2 and Fig. 11. The next step in validating the network is to create a regression plot which shows the relationship between the outputs of the network and the targets.

If the training were perfect, the network outputs and the targets would be exactly equal but the relationship is rarely perfect in practice. For the housing example, we can create a regression plot with the following commands. The first command calculates the trained network response to all of the inputs in the data set. The following six commands extract the outputs and targets that belong to the training, validation and test subsets. The final command creates three regression plots for training, test and validation (Fig. 12).

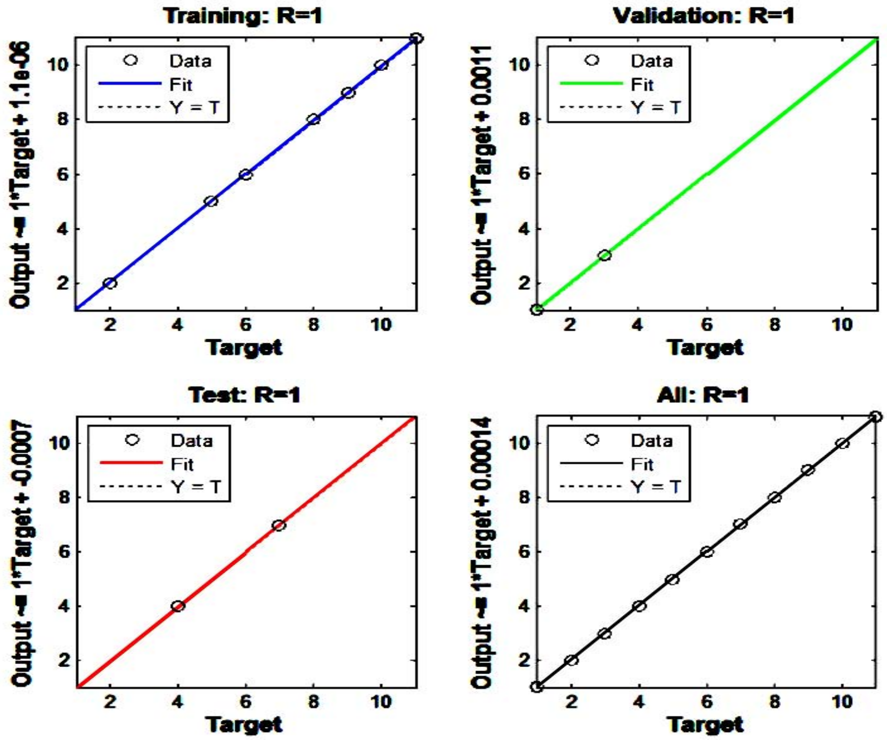

Fig. 11: Response of output element

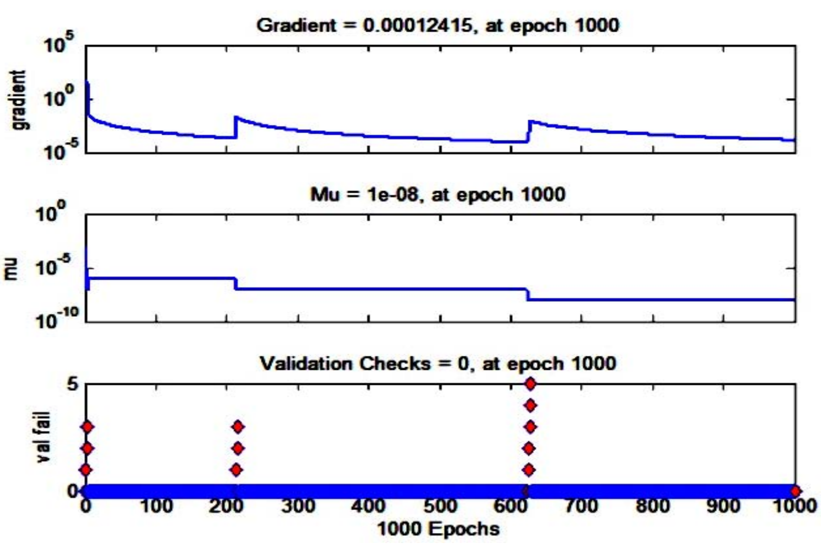

Fig. 12: Gradient, mutation and validation at 1000 epochs

Error calculated to using target value subtracted by outputs. Gradient, mutation and validation at 1000 epochs Fig. 13. The three plots represent the training, validation and testing data. The dashed line in each plot represents the perfect result-outputs = targets.

The solid line represents the best fit linear regression line between outputs and targets. The R value is an indication of the relationship between the outputs and targets. If R = 1, this indicates that there is an exact linear relationship between outputs and targets. If R

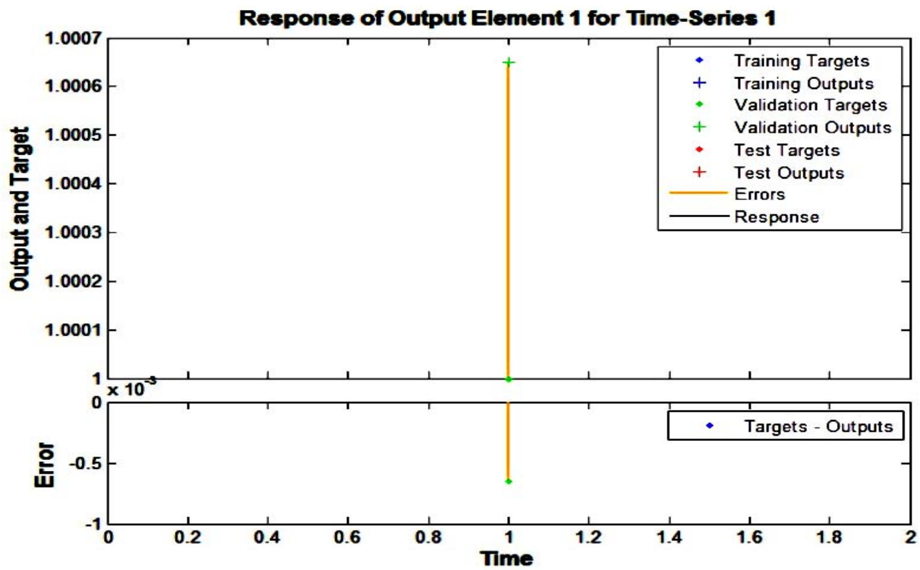

Fig. 13: Training, validation and testing data

is close to zero then there is no linear relationship between outputs and targets. For this example, the training set indicates a good fit. The validation and test results also shows R values>0.9. The scatter plot is helpful in showing that certain data points have poor fits. For example, there is a data point in the test set whose network output is close to 10 while the corresponding target value is about 10. The next step would be to investigate this data point to determine if it represents extrapolation. If so, then it should be included in the training set and additional data should be collected to be used in the test set.

CONCLUSION

An automated technique for identification of various medical plants and displays their uses in which genetic algorithm is used. In Genetic algorithm purpose is selecting best separation of discriminate features from related plants and compares them. In this method, first process from the input image feature will be extracted then feature selection process. Compared to the other methods Genetic algorithm main advantage is feature selection process. Finally RNN and SVM classifier is used to display the plant name. The results of the flavia database leaf achieved an average accuracy is 90.53% from the ACO-based approach. Genetic method used to find medical leaf an average accuracy is 91.30%. Compared to the SVM classifier ANN classifier is best.

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