Fuzzy-Neuro Model for Brinjal Disease Recognition Using Image Processing

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Abstract

In many applications, image mining is a vital part of the decision-making process. It can help improve the efficiency of the management and information processing in agriculture. Plant diseases can affect the productivity of the nation's farmers, which can lead to social and economic losses. The use of image mining can also help boost the country's agricultural production. A study conducted on the use of image mining to identify and quickly treat brinjal diseases was conducted to improve the efficiency of the process. The images collected from the infected and decontaminated plants were then stored in a database. The database's unique feature descriptors include the color information, spatial-frequency, and texture appearance of the plants. In this research, the digitally acquired four categories of infected and one category of disinfected images stored in JPEG format in the database. Each category defines unique image features. All pre-processed images are segmented using Otsu's method. Fifty-four hybrid features of segmented images were extracted using image analysis which includes entropy, texture, and spatial-frequency components. The extracted features are passed in the decision tree to select only thirteen relevant features. The selected features forwarded in the Fuzzy Inference System summarization into six features. The summarized features used in the MLPNN to design brinjal diseases recognition system. The hybrid model produces 97.5% training and 95.02 % testing efficiency.

Keywords: Classification and Regression Tree, Fuzzy Inference System, Multilayer Perceptron Neural Network, Image Processing.

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1. Introduction

The weather conditions, the regions, and the agronomic factors that affect the production of brinjal are some of the factors that can affect the country's agricultural production. Besides these, diseases such as non-pathogenic and pathogenic strains can also affect the production of the plant. This is why it is important to use an integrated Disease management strategy to reduce production loss. The timely identification and treatment of diseases can help reduce the plant's production loss. The appearance and texture of the leaves, branches, and neck are some of the factors that can be used to identify diseases. The symptoms of brinjal diseases considered in this investigation are discussed in Table 1.

Table 1: Symptoms of Brinjal diseases

S.No.	Disease Name	Types	Features
1	Bacterial Wilt	Bacterial	Leaf surface become wilt, yellow offoliage, stunt and finally collapse the whole plant, First, the lower leaves may droop, Later become brown in color
2	Leaf Spot	Fungal	Pale lesions, irregular and angular in shape, Later become grayish-brown, infected leaf drop off prematurely
3	Late Blight	Fungal	Wilting plants and water soaked, Few secondary roots, Brown discoloration, Water-soaked brown lesions on stem
4	Little Leaf	Virus	Leaves size are small, Leaf appears sticky with step, Stalks are short, Leaves are small, narrow, yellow and smooth, Internodes are also in small size, Newly emerging leaves are shorter

Although the use of visual observation techniques can be used to identify diseases, it is still not the most accurate method due to its low accuracy and time-consuming nature. This is why it is important to use a classification-based visual process instead. Another disadvantage of this method is that it can only be used in certain areas. Due to the increasing interest in plant diseases, the development of automatic and accurate plant disease recognition has been pursued in recent years. This process can be performed with minimal human intervention and with better accuracy. One of the most important factors that can be considered when it comes to developing this technology is the use of soft computing techniques. This method can help automate the prediction and recognition of plant diseases.

A computer-based system for identifying and predicting brinjal diseases is usually composed of various steps, such as segmentation, pre-processing, and recognition. There are various challenges that need to be addressed in order to achieve the high accuracy and detection of plant diseases. The selection of the appropriate feature

Descriptor and the optimal models for each disease are some of the most challenging factors that can be considered when it comes to developing a system for accurate plant disease recognition. The paper proposes an automatic system that can be used to identify and predict the plant diseases that are affecting the species of brinjal. It utilizes soft computing techniques to extract images of the plant diseases.

The paper's remaining pages are divided into five sections: the literature survey in section 2, the theoretical analysis in section 3, the proposed methodology in section 4, the experimental results in section 5, and the research findings discussed in section 6.

2. Literature Review

Early stages of plant condition are studied by Hetzoni et al. [1] in order to identify and classify plant diseases. Several studies [2,3] have been conducted on the use of soft computing and digital image processing techniques to classify and identify plant diseases. Some studies related to plant disease recognition and classification based on machine vision techniques as are follows:

A variety of feature analysis techniques are proposed for the detection and identification of plant diseases. One of these is the use of texture features to identify mineral deficiencies and disease in plant leaves. This method is mainly performed by extracting the color texture features of the plant from the co-occurrence matrix [4,5,6]. The cluster of color pixels derived from the majority of similar color images is used to identify unhealthy and healthy images of chili leaf. The extraction process is performed on

segmented images[7]. The threshold method is used to detect citrus canker lesions[8]. The final feature analysis is carried out using the weighted voting system and the threshold method[9].

In a study conducted by Wang et al., the method was able to identify three different types of wheat diseases, namely, powdery mildew, wheat stripe, and wheat rust, in digital images. The method was mainly performed using an extension of the IRKT feature. The three color space conversion models, namely, YCbCr, HSV, and SFC, are then applied to the captured images. Otsu then divides the infected area into two parts[10]. The IRKT feature extraction method is mainly used to retrieve statistic directions and detect edges from noise image. The method was able to identify early tomato blight using the classification of the color content by Molina et al. Three different descriptors are used in the process, namely, the Color Structure Descriptor, the Scalable Color Descriptor, and the Color Layout Descriptor [11]. The efficient classification and three types of seedling disease are reported on proposed algorithm[12]. The rice crop disease such as rice blast and brown spot are detected and classified in digital images[13].

The captured images are transformed into the HIS color space for segmentation. A boundary detection algorithm is then used to perform segmentation. The green components are then extracted from the images to separate the various diseases from the rest. A self-organizing map is then used to classify the images [14]. These features further fed to multi-layer perceptron (MLP) neural network for final classification.

In a study conducted by Wang et al., they proposed a method that can classify four types of fungal diseases of grapes. The method utilizes a median filter to remove the noise from the images, and k-means clustering is then used to perform segmentation. The various features of the images, such as the textures, colors, and shapes, are then analyzed to reduce the feature size. The authors proposed a method that can classify four types of fungal diseases of grapes. The method utilizes a median filter to remove the noise from the images, and k-means clustering is then used to perform segmentation. The various features of the images, such as the textures, colors, and shapes, are then analyzed to reduce the feature size [15,16]. The researchers then proposed a method that can identify two types of fungal diseases on the plant: downey mildew and powdery mildew. After removing the background pixel information, the k-means clustering algorithm is then used to perform segmentation. According to the researchers, the images were then divided into six different clusters. The researchers then proposed a method that can identify two types of fungal diseases on the plant: downey and powdery mildew. After performing a color co-occurrence analysis, the GLCM is then used to compute the various textures in the infected regions. The authors noted that the proposed algorithm performed well in its testing [17].

The various approaches used in the development of image recognition models for diseases identification include the digital image acquisition, feature extraction, and pre-processing. The difference between these approaches is the selection of the appropriate ROI, as well as the implementation of the model. The following gaps have found in the literature survey.

- The models that are implemented according to the extracted features of the input images do not consider the redundancy and relevance of the input attributes. This issue led to the model's performance being reduced.
- The performance of the model depends on the number of classes it is designed to identify. Increasing the number of classes can cause the model's performance to degrade dramatically.
- The implementation of neural networks is often complex due to the noisy data collected during the training phase. This issue can cause the training to take longer than expected. The implementation of neural networks is often complex due to the noisy data collected during the training phase. This issue can cause the training to take longer than expected.
- Although deep learning techniques are commonly used in the development of image recognition models, they cannot be generalized to all types of images. For instance, they are very good for capturing

images with distinct ROI objects. However, they need specific hardware requirements to perform well in images with large image data sets.

This paper proposes a methodology that can overcome the various issues related to the development of image recognition models for diseases identification. It involves the creation of a unique feature descriptor, the selection of relevant features, and the implementation of a hybrid model.

3 Methodology

The proposed methodology divided into four sub-sections. The components of the proposed system depicted in Fig.1. The color images of four diseases infected and one disinfected image of brinjal crop obtained utilizing a digital camera in JPEG compressed format. The images extracted in the RGB model for cropping and resizing. The cropping performed to get the region of interest (ROI) manually. The cropped images were segmented into three different segments using Otsu's threshold. Textures, and color entropy features of each segment were extracted individually. The spatial-frequency features of each segment were extracted using the wavelet transform and two-way ANOVA analysis. The extracted features were then combined and aggregated into different categories for use in the development of various applications. The feature sets were forwarded to the decision tree for an appropriate feature selection.The relevant features with the desired category further filtered using a fuzzy inference system. The filtered features applied in the MLPNN for automatic brinjal diseases categorization.

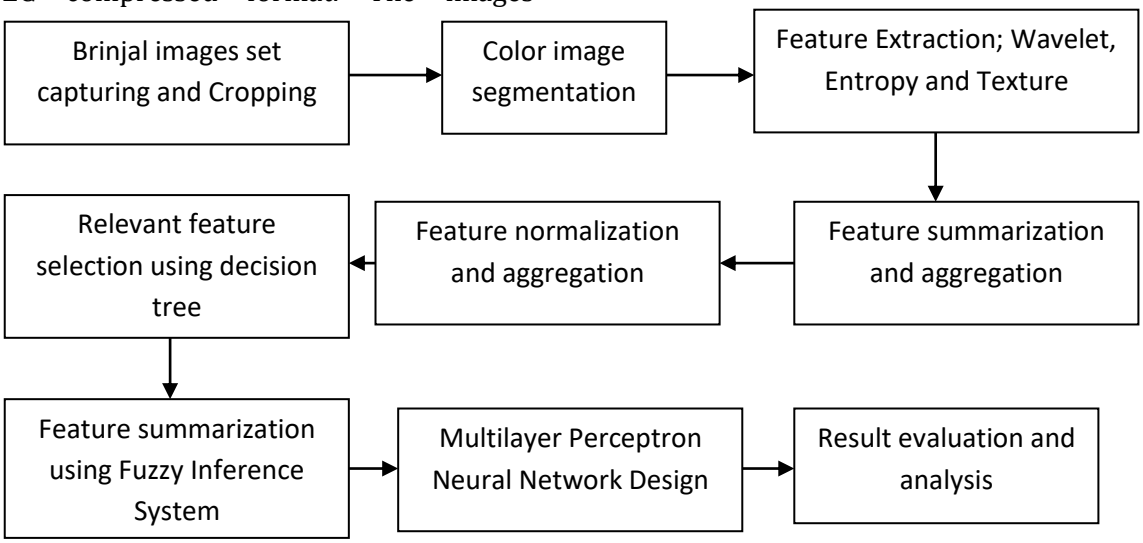


Fig. 1: Components of automated brinjal diseases recognition model

Same segmentation method applied of the earlier work [38]. The all three segmented RGB images of five categories of brinjal images were transformed in L*a*b* color model and forwarded to extract spatial- frequency wavelet F-ratio, color entropy, and texture features. The feature extraction steps are as follows;

1. Read JPEG segmented images in the RGB color model.
2. Color transform from the RGB to the L*a*b* to extract a* and b* components.
3. Segment images using Otsu's method [18].
4. Extract spatial-frequency [19,20] F-ratio features using Two-way ANOVA [21,22] using Haar structure.
5. Evaluate entropy [23] features based on a* and b* components.
6. Extract Contrast, Correlation, Energy, and Homogeneity texture features [24] based on a* and b* components.

The decision tree is used to select the relevant features after feature extraction. The extracted features forwarded in the decision tree for relevant feature selection. The approaches for

relevant feature selection using the decision tree [25] are as follows:

1. Apply the extracted features in the previous step.
2. Calculate Gini Index of root node.
3. Evaluate split point according to maximum reduction in impurity.
4. Divide root node in two subsets according to maximum reduction in impurity.
5. Repeat step (2) and step (3) for all subsets till stopping criteria reached to form decision tree.
6. Extract relevant features appeared on the interior node of the binary decision tree.

The selected relevant features were filtered using fuzzy filtering. The Sugeno FIS [26] used for fuzzy filtering in this research. The approaches used for fuzzy filtering are as follows:

1. Apply subtractive clustering in the selected features defined by the decision with desired outcomes to create the cluster and calculate cluster center and spread.
2. Design Sugeno FIS by defining fuzzy rules of each cluster using least square estimator (LSE).
3. Reapply training input in the designed Sugeno FIS without desired response generates filtered outcome using linear weighted average.

The fuzzy filtered outcome of all five categories of brinjal datasets with desired response applied in the multilayer perceptron neural network (MLPNN) using SCG back-propagation (BP) [27] algorithm for brinjal plant disease recognition.

Steps are as follows:

1. Create MLPNN architecture input, hidden, and output neuron with softmax activation function in hidden and output neuron.
2. Divide input datasets in training, validation and testing data.
3. Initialize the synaptic weights of MLPNN and present training data in batch mode.
4. Perform forward and backward computation update synaptic weights using SCG back-propagation (BP) algorithm.
5. Validate trained MLPNN using validation data.
6. Evaluate the performance of MLPNN using test data.

The brinjal plant diseaserecognition efficiency (E) of ANOVA-NARX-KNN based model defined as (2).

$$E = \frac{CPC}{N} \times 100 \qquad (2)$$

where CPC is the total number of correctly predicted class of test pattern, and N is the total number of the test pattern.

4 Result and Discussion

The following brinjal images were taken from the plant's field during day-lighting under two categories; infected and disinfected using a digital camera. The entire experiment conducted in MATLAB Version: 8. The stored images were accessed in RGB color space, cropped, and resized at 205×410. The resized images carrying most diseased parts, manually selected for segmentation. In this research, five categories of brinjal plant images with 30 images with each category had considered. The four categories belonged to diseased brinjal plant, and one category was a disinfected image. The considered infected brinjal plants were the Bacterial Wilt, Leaf Spot, Late Blight, and Little Leaf. The snapshot of the sample images is depicted in **Fig. 2**.

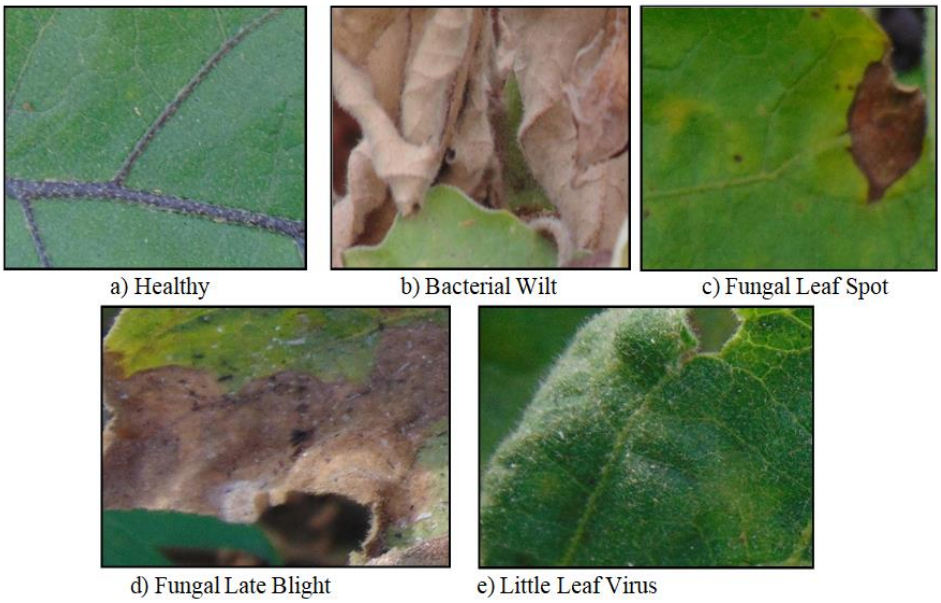
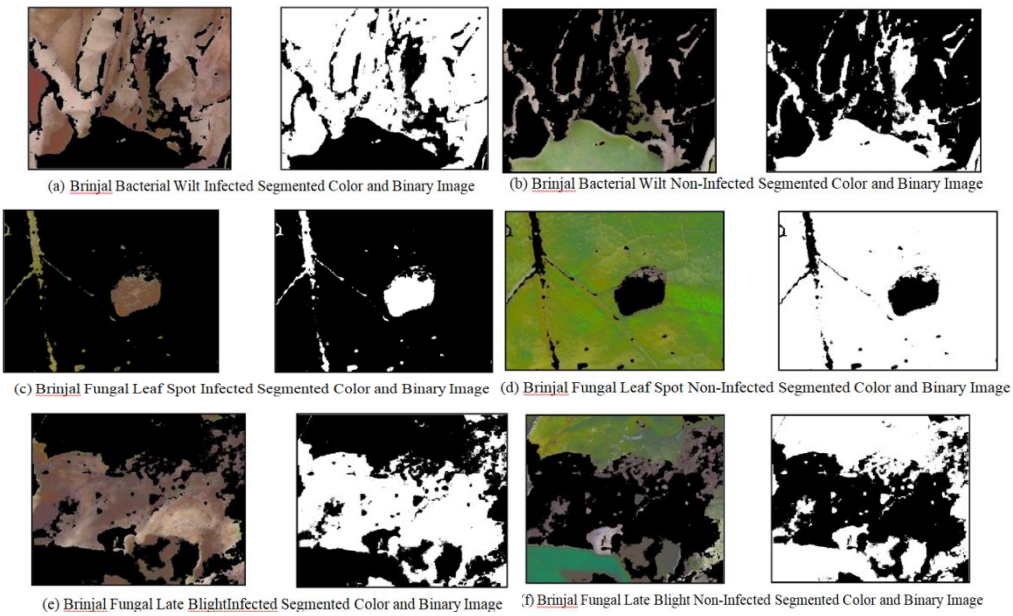


Fig. 2: Snapshot of cropped brinjal images

The sample outcomes of color segmented and binarized image are shown in Fig. 3. The spatial-frequency F-ratio using 2D ANOVA, entropy, and texture features of the segmented image of five categories of brinjal images extracted. The extracted features of bacterial wilt infected brinjal crop depicts in Fig. 4. The features of the remaining four categories extracted in the same way. The features were aggregated and associated with distinct desired class for five categories before processing. Each category name considered as desired classes in the decision tree. The hybrid features with desired category applied in the decision tree to extract relevant features. The decision tree selected thirteen features out of fifty-four features as relevant.

The decision tree selected features with desired response were applied in Sugeno Fuzzy Inference model. The assumed desired response for five categories were [1 0 0 0 0], [0 1 0 0 0], [0 0 1 0 0], [0 0 0 1 0], and [0 0 0 0 1]. The simulated result of Sugeno Fuzzy Inference model with thirteen inputs and five outputs depicts in Fig. 5.



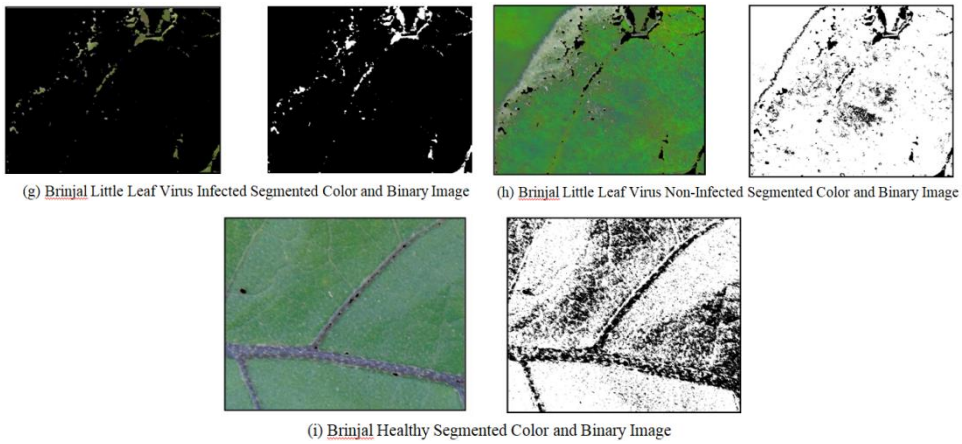


Fig.3 : Segmented outcomes of brinjal images

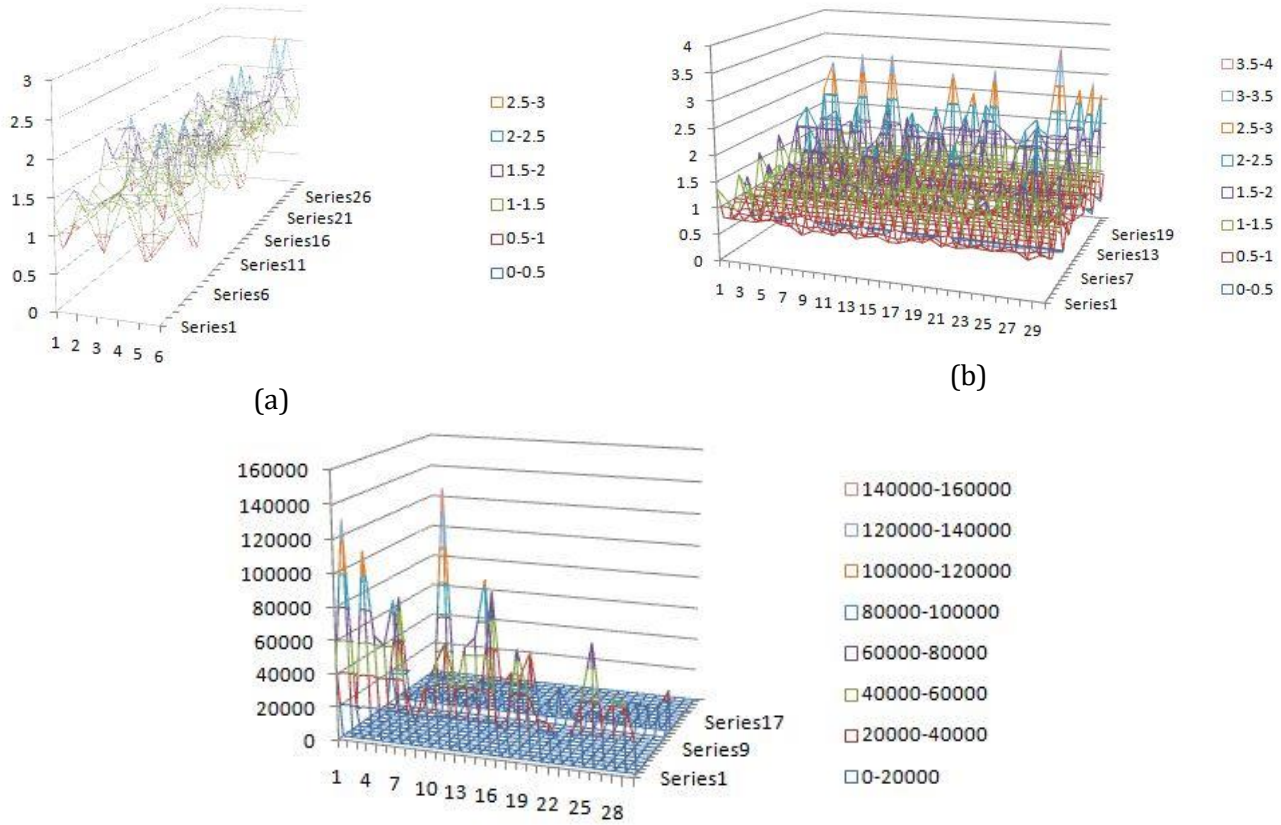


Fig. 4: bacterial wilt infected brinjal crop (a) Entropy (b) Texture (d) Spatial-frequency F-ratio

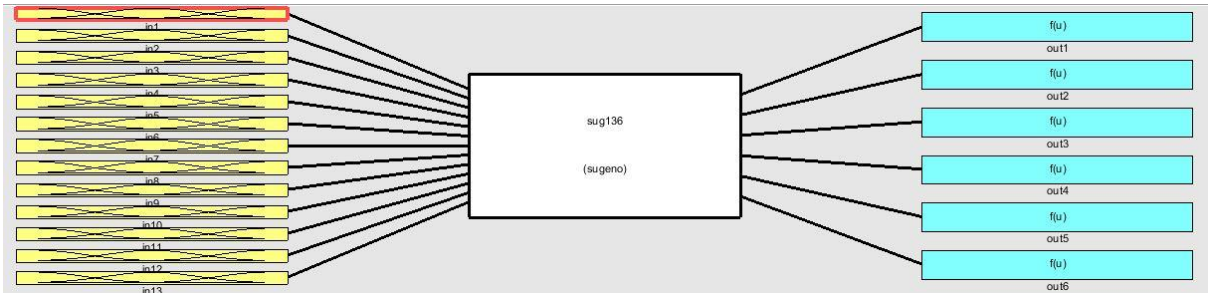


Fig. 5: Sugeno Fuzzy Inference Model

The simulated result of fuzzy if-then rules of inference system for filtering features depict in Fig. 6. Thirteen features reduced to six features by the fuzzy inference system.

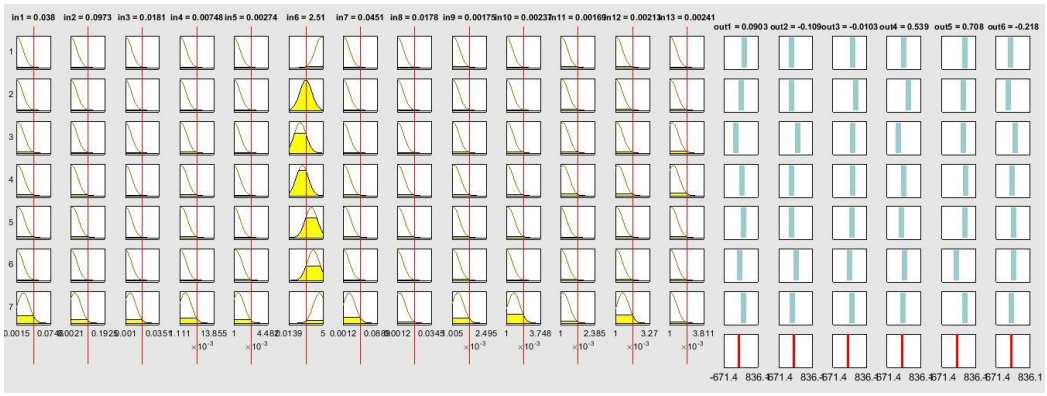


Fig. 6: Seven fuzzy if-then rules for filtering

The filtered feature set is composed of the five categories that were used to design the MLPNN model. The training and testing sets are split into multiple sets. The model was tested ten times with varying weights. The one sample instance using MATLAB is shown in Fig. 7, Fig. 8, Fig. 9, Fig. 10, Fig. 11, and Fig. 12. The simulated outcomes of the MLPNN architecture with five input, ten hidden and five output neurons depicts in Fig. 7. The five inputs were the filtered outcomes of the Fuzzy inference system. The five output neurons were considered according to five categories of brinjal images with desired responses [1 0 0 0 0], [0 1 0 0 0], [0 0 1 0 0], [0 0 0 1 0], and [0 0 0 0 1] respectively.

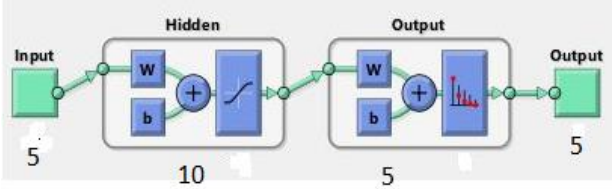


Fig. 7: MLPNN Architecture with size 5 × 10 × 5

The performance based on cross-entropy validation represented in Fig. 8, and the validation parameters of training depicts in Fig. 9. The error histogram, and the region of the curve depicts in Fig. 10, and Fig. 11 consecutively. The overall performances are displayed by the confusion matrix in Fig. 12. The error histogram, region of curve and confusion matrix shows minimal training and validation error, and it can accurately test random pattern.

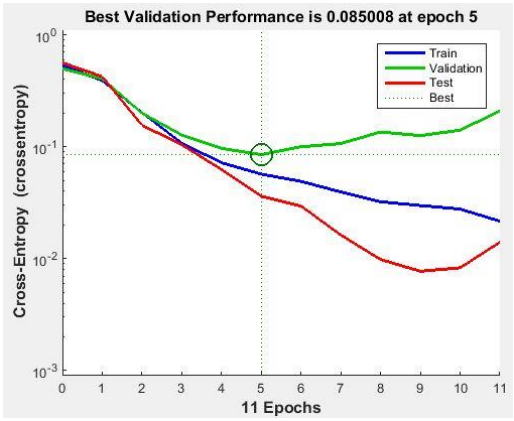


Fig. 8: Cross-Entropy validation graph

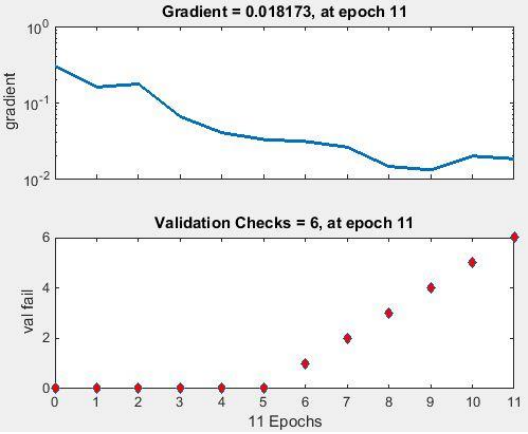


Fig. 9: Validation parameters for training

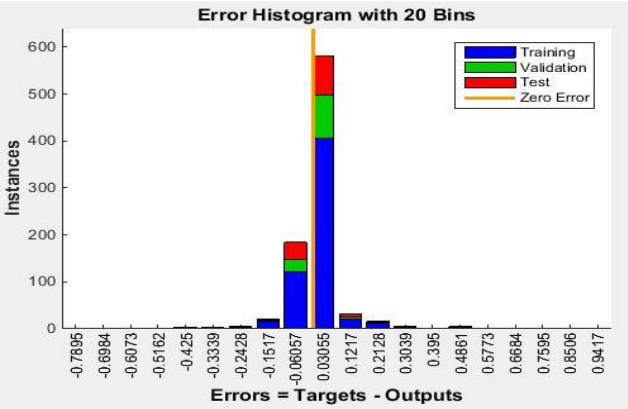


Fig. 10: Error histogram

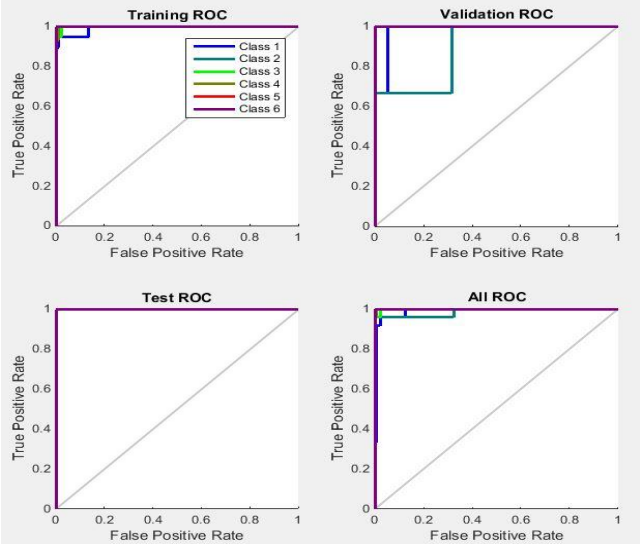


Fig. 11: Region of curve

The BPNN algorithm was executed 10 times to check the robustness of the method. The proposed method; decision tree features selected and fuzzy filtered output applied in 5 × 10 × 5 MLPNN and the result depicted in **Table 2**. The average training performance is 97.5%, validation performance is 94.7%, and testing performance is 95.2% to recognize brinjal diseased and disinfected plant.

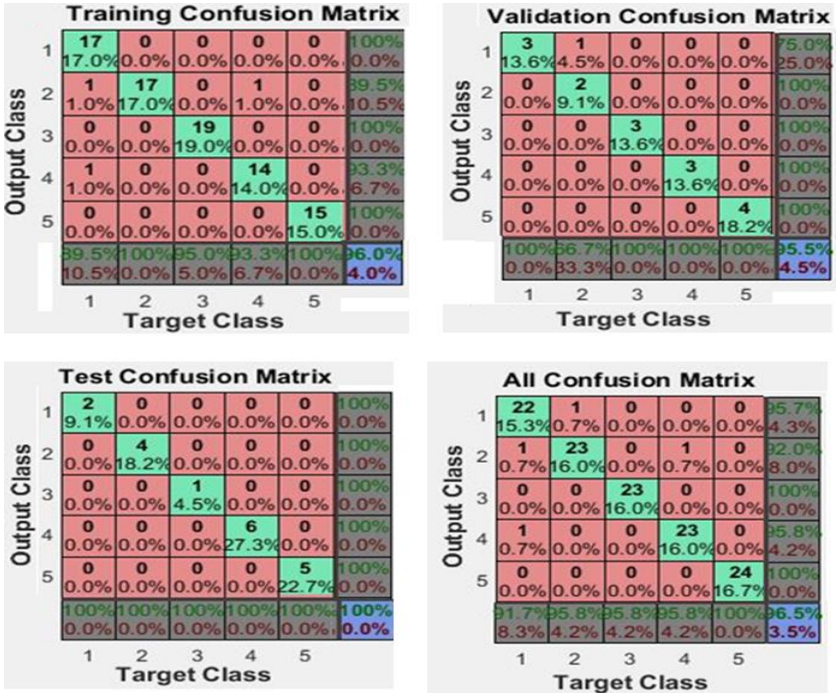


Fig. 12:Confusion matrix

Table 2**:** MLPNN average performance (%) for training, validation, and testing

MLPNN Model-Ten times tested and validated	Training	Validation	Testing
1	98	90.9	95.5
2	98	95.5	95.5
3	97	90.9	90.9
4	96	95.5	100
5	98	95.5	95.5
6	98	100	100
7	96	95.5	90.9
8	98	95.5	90.9
9	96	95.5	95.5
10	100	90.9	95.5
Average Performance	**97.5**	**94.57**	**95.02**

The experimental results compared with four other similar work. The images captured with the help of the high-resolution camera. Since the captured images are large, some of the authors [28] [29] [30] [31] reduce the size of the images by cropping. The result of the proposed method also compared with CNN based model, where images compressed instead of cropping and low-level variance features extracted for CNN model implementation[36]. The comparative results depicted in **Table 3** according to brinjal diseases detection accuracy.

Table 3: Performance Comparison

Author name and Year	Method	Number of diseased class and disinfected class	Features	Average Accuracy
Santanu Phadikar et al. [28]	SVM	2 (diseased)	Vegetation indices-based texture features	84%
Amrita A. Joshi et al.[29]	K-nearest neighbor	4 (diseased)	Color and shape features	K-NN: 87.02%
Xiaochun Mai et al.[30]	Random forest Classifier	1(diseased)	Color, shape and texture features	88.50%
T. Gayathri Devi et al. [31]	Multiclass SVM	5 (diseased), 1 (disinfected)	DWT, scale invariant feature transform and Texture	98.63%
Proposed Method	**Fuzzy Filtered MLPNN**	**4 (diseased),1 (disinfected)**	**Spatial-Frequency F-ration, Entropy, Texture**	**95.02%**

The comparative results depict that proposed method give better performance to recognize brinjal plant diseases comparison to [28][29][30]. Hence, the proposed method and hybrid feature descriptor legitimate the desired objective.

5. Conclusion

The timely diagnosis of crop diseases is essential to reduce production loss and pest management. Therefore the image processing based intelligent system is designed to perform brinjal crop disease recognition. The decision tree is used to select relevant features from extracted hybrid fifty-four features. The decision tree generates thirteen relevant features. Fuzzy filtering process removes redundant data from the dataset and performs data summarization and reduced it into six features. The summarized features reduces the design complexity of

MLPNN architecture into 5×10×5 size. It also enhances the disease pattern recognition efficiency of MLPNN with 95.02% test results.

The proposed process can be further improved by implementing a hybrid model that combines the genetic algorithm and nature-inspired features. This will automatically improve the performance of the model.

References

[1] A. Hetzroni, G. E. Miles, B. A. Engel, P. A. Hammer, and R. X. Latin, "Machine vision monitoring of plant health",Adv Space Res, vol. 14, no. 11, pp. 203-212, 1994.

[2] J. G. A.Barbedo, "Digital image processing techniques for detecting, quantifying and classifying plant diseases",SpingerPlus, vol. 2 no. 660, pp. 1-12, 2013.

[3] H. Sabrol and S. Kumar, "Recent Studies of Image and Soft Computing Techniques for Plant Disease Recognition and Classification", International Journal of Computer Applications, vol. 126, no. 1, 44-55, Published by Foundation of Computer Science (FCS), NY, USA, 2015.

[4] R. Pydipati, T.F. Burks, and W.S. Lee, "Identification of citrus disease using color texture features and discriminant analysis",Computers and Electronics in Agriculture,vol. 52, pp.49-59, 2006.

[5] M.Wiwart, G.Fordonski, K.Zuk-Golaszewska, and E. Suchowilska, "Early diagnostics of macronutrient deficiencies in three legume species by color image analysis", Computers and Electronics in Agriculture,vol.65, pp. 125-132, 2010.

[6] O.M.Opstad Kruse, J.M. Prats-Montalbán, U.G. Indahl, K. Kvaal, A. Ferrer, and C.M. Futsaether, "Pixel classification methods for identifying and quantifying leaf surface injury from digital images", Computers and Electronics in Agriculture, vol. 108, pp. 155-165, 2014.

[7] Z.B Husin, A. H. B. Abdul Aziz, A. YB MdShakaff, R. YS Mohamed Farook R, "Feasibility Study on Plant Chili Disease Detection Using Image Processing Techniques", In proceeding of 2012 Third International Conference onIntelligentSystem Modelling and Simulation. IEEE, Kota Kinabalu, 2012, pp. 291- 296.

[8] M. Zhang, "Citrus canker detection based on leaf images analysis", In proceeding of 2nd InternationalConference on information science and engineering, IEEE, Hangzhou, 2010,pp. 3584-3587..

[9] M. Zhang and Q. Meng, "Automatic citrus canker detection from leaf images captured in field", Pattern RecognitLett, vol. 32, no. 15, pp. 2036-2046, 2011

[10] L. Wang, F. Dong, Q. Guo, C. Nie, and S. Sun, "Improved Rotational Kernel Transformation Directional Feature for Recognition of Wheat Stripe Rust and Powdery Mildew", In proceeding of Seventh International Conference on Image and Signal Processing, IEEE, Dalian, 2014, pp. 286-291.

[11] J.F. Molina, R. Gil, C. Bojacá, F. Gómez, and H. Franco, "Automatic Detection of Early Blight on tomato Crops using a Colo Based Classification Strategy", In proceeding of 2014 19th International Symposium on Image, signal processing and Artificial Vision, IEEE, Armenia, 2014, pp. 1-5.

[12] K.Y. Huang, "Application of artificial neural network for detecting Phalaenopsis seedling diseases using color and texture features", Computers and Electronics in Agriculture, vol. 57, pp. 3-11, 2007.

[13] S. Phadikar and J. Sil, "Rice disease identification using pattern recognition techniques", In proceedings of 11th International Conference on Computer and Information Technology (ICCIT 2008), IEEE,Khulna, 2008, pp. 420–423.

[14] D. Al Bashish D, M. Braik, and S. Bani-Ahmad, "A framework for detection and classification of plant leaf and stem diseases", In proceeding of 2010 International conference on signal and image processing. IEEE, Chennai, 2010, pp. 113-118.

[15] H. Wang, G. Li, Z. Ma, and X. Li, "Application of neural networks to image recognition of plant diseases", In Proceedings of the 2012 International Conference on Systems and Informatics (ICSAI), IEEE, Yantai, 2012, pp. 2159-2164.

[16] H. Wang H, G. Li, Z. Ma Z, and X. Li, "Image recognition of plant disease based on principal component analysis and neural networks", In Proceedings of the 2012 8th International Conference on Natural Computation (ICNC 2012), IEEE, Chongqing, 2012, pp. 246-252.

[17] S.S. Sannakki, V.S. Rajpurohit, V.B. Nargund, and P. Kulkarni, "Diagnosis and Classification of Grape Leaf Diseases using Neural Networks", Inproceeding of 4th International Conference (ICCCNT), IEEE, Tiruchengode, 2013, pp. 1-5.

[18] Verma, T., Dubey, S. and Sabrol, H., 2017, October. Color image segmentation of disease infected plant images captured in an uncontrolled environment. In International Conference on Next Generation Computing Technologies (pp. 790-804). Springer, Singapore.

[19] Gonzalez, R.C., Eddins, S.L. and Woods, R.E., 2004. Digital Image Processing Using MATLAB. Prentice Hall.

[20] Balamurugan, V. and Anandhakumar, P., 2009. Neuro-fuzzy based clustering approach for content based image retrieval using 2D-wavelet transform. International Journal of Recent Trends in Engineering, 1(1), pp.418-424.

[21] Spiegel, M.R., Schiller, J.J., Srinivasan, R.A. and LeVan, M., 2009. Probability and statistics (Vol. 2). New York: Mcgraw-hill.

[22] Kothari, C.R., 2004. Research methodology: Methods and techniques. New Age International.

[23] Haykin, S., 1994. Neural networks: a comprehensive foundation. Prentice Hall PTR.

[24] Gao, R., Liu, G. and Si, Y., 2010, September. A recognition method of apples based on texture features and em algorithm. In World Automation Congress (WAC), 2010 (pp. 225-229). IEEE.

[25] Han, J., Pei, J. and Kamber, M., 2011. Data mining: concepts and techniques. Elsevier.

[26] Jang,J.S.R., Sun, C.T., Mizutani, E.,1997. A Computational Approach to Learning and Machine Intelligence.–Upper Saddle River, NJ: Prentice Hall, Inc.

[27] Moller, M.F., 1993. A scaled conjugate gradient algorithm for fast supervised learning. Neural networks, 6(4), pp.525-533.

[28] Joshi, A.A. and Jadhav, B.D., 2016, December. Monitoring and controlling brinjal diseases using image processing techniques. In Computing, Analytics and Security Trends (CAST), International Conference on (pp. 471-476). IEEE.

[29] Mai, X. and Meng, M.Q.H., 2016, June. Automatic lesion segmentation from brinjal leaf blast field images based on random forest. In Real-time Computing and Robotics (RCAR), IEEE International Conference on (pp. 255-259). IEEE.

[30] Devi, T.G. and Neelamegam, P., 2018.Image processing based brinjal plant leaves diseases in Thanjavur, Tamilnadu. Cluster Computing, pp.1-14.

[31] Lu, Y., Yi, S., Zeng, N., Liu, Y. and Zhang, Y., 2017. Identification of brinjal diseases using deep convolutional neural networks. Neurocomputing, 267, pp.378-384.