Global Pattern Feedforward Neural Network Structure with Bacterial Foraging Optimization towards Medicinal Plant Leaf Identification and Classification

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***Abstract*—Medicinal Plant species help to cure various diseases across the world. The automated identification of medicinal plant species to treat disease based on their structure is much required in pharmaceutical laboratories. Plant Species with a complex background in the field will make the detection and classification more difficult. In this paper, optimization of bacterial foraging technique has been employed towards medicinal plant prediction and classification architecture based on feed-forward neural network. It is capable of identifying both complex structures of medicinal plants. Feed-forward Neural Networks are considered to have good recognition accuracy compared to other machine learning approaches. Further bacterial foraging has been implemented to minimize the feature search space to the classifier and provides optimal features for the plant classification. The experimental outcomes of the proposed approach has been analysed by employing the medley dataset and evaluating the performance of the proposed approach with respect to dice similarity coefficient, Specificity and sensitivity towards medicinal plant classification. The findings are very positive, and further research will focus on using a large dataset and increased computing resources to examine how well deep-learning neural networks function in identifying medicinal plants for use in health care.**

Keywords—Medicinal plant; feed-forward neural networks; linear discriminant analysis; bacterial forging

I. Introduction

Most individuals around the world utilise traditional medicines made from medicinal herbs. India is known as the world's botanical garden as well as the country that produces the most medicinal herbs. Due to their natural origins and lack of side effects, herbal medicines have experienced an exponential surge in popularity during the last several years across both developed and developing nations. Plant species have medicinal value and it is considered as the essential resource for curing various diseases around the world [1]. These medications are more widely used since they aim to treat illnesses devoid of causing any negative effects. Indian traditional medicine is renowned for using Naturopathic remedies, Ayurvedic medicine, Unnani, breathing exercises, meditation techniques, yoga, homoeopathy and many more. There are about 8,000 herbal remedies used in these traditional medicines. As per surveyed findings, approximately 75% of migrants utilize herbal plants for medicinal reasons [2, 3].

Manually identifying medicinal plants is still the most used way. Humans gather information about the entire plant or certain parts like leaves, flowers, fruits, or bark using their eye, nose, fingers, or other human organs [4, 5]. Depending on either individual perspectives or referrals, they will decide which species of medicinal plants to use. It has been demonstrated via practise, nevertheless, that this type of identification strategy is time-consuming, inefficient, and heavily dependent on the expertise and subjective experience of the persons using it.

Mainly to determine the variety of medicinal plants, automated models using image processing approaches [6] has been employed to assist botanists in the early identification of plant by employing machine learning architectures [7]. However, machine learning techniques reveal the structural and texture appearance of the plant along with its discriminative visual symptoms. Further detection and classification of the plant species suffer from the noise and illumination effects of the images [8]. In addition, it is mandatory to discriminate the different growth stages of the plant along the virus and disease involvement which was found to be highly complex in identification.

In order to manage these challenges, various image processing steps such as Image segmentation of the seed region [9], feature extraction on the segmented region [10] and optimal feature selection [11] have to be aggregated to achieve high recognition accuracy in prediction and classification of the medicinal plants from large sizes of input images. In this paper, bacterial foraging optimization has been employed to feed forward neural network towards plant classification on basis of pathological properties.

Among numerous machine learning architecture, feed-forward neural networks produce high recognition accuracy in classifying the image dataset. Initially, region-growing segmentation [12] techniques are applied to group the seed points having similar pixel values as the segmented region. The segmented region is analysed using linear discriminant analysis which is considered as a feature extraction technique. Shape descriptors and Texture features are extracted. That extracted feature is reduced using the bacterial foraging technique to generate the optimal features. Finally, feed-forward neural network classifier is employed to optimise features to classify into linear plant classes.

The balance part of the article is sectioned into the following form; Section II provides the review of literature containing similar mechanisms of machine learning for plant identification. Section III defines the proposed architecture containing the Feed Forward Neural Network and bacterial foraging based optimization. Section IV highlights the experimental solutions of the proposed approach along with performance evaluation and at the last, summary of the article with conclusion and future work is provided.

II. Background Study

A. Literature Work

This part of the work describes the problem statement of the research, a review of literature related to the current problem and various deep learning models applied to plant identification using various image datasets has been detailed as follows. The medicinal plant identification model which performs similarly with respect to the proposed architecture has been discussed below.

The Artificial Neural Network Model [ANN] segments the leaf into subfields on different growth stages of the plant. The affinity propagation model computes the variation of the leaf on pixel parameters with reference to plant pathologies and produces the affinity set containing similar leaf properties. Sparse Principle component analysis considered as a feature extraction technique is employed to affinity set to gather the sparse feature and its associations are represented as covariance and correlation matrix [13]. Further Artificial Neural Network is projected to produce the class labels for the sparse features in the feature set. ANN [14, 15] uses a normalization technique to smoothen the edges of the class labels in order to separate plant types.

A Random Forest classifier is implemented to classify the plant on basis of the specified medicinal properties. A classified plant can be employed for disease treatment purposes. Initially, feature extraction methods such as SIFT technique have been employed towards shape extraction, color extraction and texture feature extraction from the plant images. Further genetic algorithm has been applied as a feature selection technique to select effective features towards classification purposes using a Random forest classifier [16].

Convolution Neural Networks (CNN) can be used for the classification of medicinal plant species and they contain built in feature extraction functionality. The shape and texture characteristics are contained in the feature. It classifies the features with respect to the activation function and multiple layers to obtain the effective classes [17]. CNN is also used in various identifications and analysis of images like spatial data, eye tracking data, networks attack and many more [18, 19, 20, 21].

B. Problem Statement

As a critical problem for the preservation, authenticity, and production of herbal medicines, the automatic classification of medicinal plants needs further study [22]. Owing to the difficulties due to illumination effects, shadow effects, nonlinear seed points, overfitting issues and accumulation of reconstruction error in the processing of medicinal plant datasets, the identification and classification of plant leaves will face significant challenges in employing machine learning algorithms. These necessitate a better approach to be developed for identifying and classifying medicinal plants.

III. Proposed Model

This section defines the design procedure towards optimization of Feed-Forward Neural Networks using the bacterial foraging technique to classify the medicinal plant in the Mendeley dataset. In addition, the design procedure of the region growing segmentation approach is to segment the medical plant and linear discriminant Analysis to feature extract is also provided in detail. It is as follows:

A. Image Pre-processing

Image preprocessing is used to increase the image pixel properties on the normalization approach and contrast enhancement approach. A further large number of learning parameters of the modelled have been managed for dataset processing. Image Normalization is employed using histogram stretching. Further to eliminate the image noise and image blur, Contrast enhancement [23] is used in addition to the image thresholding approach [24] to improve the image details which contains an important factor for image classification.

B. Region Growing Segmentation

In this part, seed points illustrating the discriminate image parts of the medicinal plant have been analysed and it is grouped into vectors representing the similar seed points to the entire image. Similar points of the medicinal plant are computed with respect to the homogeneity pixel. Vector represents the segmentation results as a growth process on verification of the homogeneity rule among the pixels. The growth process for the selected regions at every stage S is defined as in (1).

$$G_p i(s) \text{ where } i=1, 2 \tag{1}$$

Homogeneity of the pixel is computed for the seed pixel to verify the presence of unfermented pixels in the neighborhood of the remaining pixel in the particular region. The computation rule is as follows in (2).

$$\text{If } (H\,(G_p i(s)) \text{ for each pixel} = \text{True}) \tag{2}$$

Then compute the Mean M and Standard deviation of each pixel in region R_i is as follows as in (3) and (4).

$$\text{Mean } M = \frac{1}{n}\sum_{i=0}^{n} R(i) \tag{3}$$

$$\text{Standard deviation SD} = \frac{\sqrt{(1\backslash n)R(i)}}{\mathrm{Gpi(s)}} \tag{4}$$

Employ strategy to group two regions $G_p(1)$ and $G_p(2)$ on conditions as in (5) and in (6)

If ((Mean of region 1- Mean of Region 2) < Standard Deviation of Region 1) (5)

Verification of the homogeneity of seed points

Else if (pixel intensity of the region 1 is close to mean value of the threshold Ti) (6)

Where Threshold is as in (7)

$$Ti = \{1- \frac{SD_i}{M_i}\} \tag{7}$$

Threshold T_i depends on the variation of the region R_n and the pixel intensity P_i.

Resultant segmentation outcomes are represented as image vectors containing the seed points which are further processed for feature extraction and classification process.

C. Linear Discriminant Analysis

Linear Discriminant Analysis (LDA) has been employed to exploit a feature from the image projection using the fisher criterion function [25]. The feature extraction projection in a specific direction extracts properties of homogeneous seeded points in the segmented region vector. Properties of the seed points are represented as a feature. Initially, the homogenous seed point is transformed into scatter matrix to reduce the feature space. Scatter Matrix SM of the vector undergoes the following computation.

Mean of the Vector is as in (8)

$$Mi = =\frac{1}{n} \sum_{x\varepsilon C}^{n} x, n\text{I} \tag{8}$$

Total Mean of the Vector is as in (9)

$$TM =\frac{1}{n} \sum_{x\varepsilon C}^{1} x, N \tag{9}$$

$$\text{Scatter Matrix Sw} =\sum_{i=1}^{c} si\frac{ni}{n} \tag{10}$$

$$\text{Scatter Matrix Sb} = \frac{1}{2}\sum_{i=1}^{c} P\text{iPj(fvi –fvj) (fvi –fvj)T} \tag{11}$$

where (vfi –vfj) is vector feature variation.

The covariance of Mean is as in (12)

$$Si= \frac{1}{n} \sum_{x\varepsilon C}^{1}(x - m\text{i}) \text{(x-mi)T} \tag{12}$$

Aggregate Covariance of Scatter matrixes is to produce an optimal feature set is as in (13).

$$\mathbf{S_T} = \frac{1}{n}\sum ((fv_i - fv_j) (fv_i - fv_j)^T \tag{13}$$

Reducing the Feature space is a vital part of the LDA. It can be generated by improving the scatter ratio $|S_b| / |S_w|$. Further, scatter ratio weight will improve on eigenvectors of S_bS_w producing the projection matrix with column matrix W as in (14).

$$W= [W_1, W_2 \ldots\ldots\ldots W_{c-1}] \tag{14}$$

Where W_i are the Eigen Vector of the Scatter matrix S_b and S_w and its value corresponds to reducing Eigen values λ_i

The linear discriminant analysis produces the feature of processing the scatter matrix of the seed points. It is further treated as a reduced feature set on the fusion of two or more vectors. However, this reduced feature set has been employed for feature selection to obtain the optimal feature for classification.

D. Feed-Forward Neural Networks

Feed Forward Neural Network (FFNN) is to determine the plant classes of the image. FFNN is employed to process the spatial and temporal features obtained from the segmented region of the image. An FFNN model is composed of many processing states. FFNN produces the plant classes by representing the feature vector in Direct Acyclic Graph (DAG) structure. In FFNN, seed point features of the segmented region are contained in each layer of the graph network. Table I shows the FFNN parameter components. Extracted spatial and temporal features undergo various computations in a graph structure.

TABLE I. HYPER PARAMETER OF FEED-FORWARD NEURAL NETWORKS

Tuning of Hyper Parameter	Values
Class Batch Size	200
Feature Learning Rate	0.09
Attribute Size	85
Maximum No of pixels to each layer	1000
Length of the pixel in sublayers	250
Loss function	Cross entropy

- Abstraction layer

In this layer, the Abstraction layer is used to collect high-level features in the plant. Vector structure contains the feature. Vector is processed in the activation function. It generates a new state from the old state using epoch functions and a few parameter functions. Matrix Feature weight and Vector feature bias are computed by aggregating the input vectors with output vectors extracted hidden layer. The feature weight of the matrix is computed as in (15).

$$A_t = Sigmoid\ (W(c(t))+h(t-1)) \tag{15}$$

Where A_t represents the feature weight of the Input vector c(t) and hidden vector h(t-1) of the seed points of the plant region.

- Hidden Layer

In this layer, hidden feature information is extracted from the input layer vector seeded point and it is represented as the hidden vector H. The FFNN model uses the hidden layer to compute the feature to be represented in the output layer for a period of data availability. Stored Seeded region will be forgotten in the subsequent process. The FFNN model includes the sigmoid function as an activation function to compute the feature weight to eliminate the less-weighted features. Fig. 1 illustrates the proposed research architecture.

The FFNN hidden layer is concealed with the output information of the output layer illustrated in (16).

$$O(f(t)) = \sigma(G_p\,[A(t)\,C^{n-k} + h(t-1)] + W_f) + \sum_{k=1}^{n} \binom{n}{k} m^k \quad (16)$$

The Hidden layer information of the FFNN is identified as an important process to analyse the structural changes and temporal changes of the plant on various growths stage and disease stages. This information is helpful to classify the medicinal plant. The hidden layer of FFNN identifies which input accommodating the plant features and its concealing is provided by (17).

$$H_f = \sigma\, B_V\,(WmG_i(s);\, Wmd_i(s)) + \sigma\, B_V\,(WmG_i(t);\, Wmd_i(t)) \quad (17)$$

Where H_f represents the model outcome containing features of growth stage and disease stages along the matrix feature weight W_m and bias of feature vector B_V It is further interpreted with pathological information. Ϭ is considered as a sigmoid activation function to extract the disease and growth stages features.

- Activation function

The activation function set the decision point of the learning rate of the proposed model to manage and change the feature weights of the growth and disease feature of the plant of various stages from the hidden layer on employing the sigmoid function [26]. FFNN model activation function is illustrated in form of a tree structure which has a high ability in parsing the feature using the sigmoid function. The activation function is optimized using a hyperparameter to improve the output layer representing the plant classes. The activation function is as follows in (18).

$$A_f = \text{Sigmoid}\,(F_s) * \sum_{n=1}^{\infty} \left(a_n \cos\frac{n\pi w}{B} + b_n \sin\frac{n\pi w}{B}\right) \quad (18)$$

Activation functions of the hidden layer process the feature set to identify the plant classes on basis of distance measures on feature weight.

- Output Layer

The output layer generates the plant classes. The output layer interprets the feature set of the hidden layer with reference to the pathological information to discriminate the plant classes with high recognition accuracy. Plant classes of the output layer are discriminated using the output function. Function Z(t) uses the feature vector on various stages to classify effectively with the activation function. Output Function is given by (19).

$$\text{Output Function } Z(T) = \text{Sigmoid}\,(G(f) * D(f)) \quad (19)$$

The output function of the FFNN contains the sigmoid function to differentiate the growth and disease stage features of the plant. These outcomes are stored as classes with reference to the output function.

- Loss Layer

The loss layer is employed to assure the classification accuracy of plant classes. It is assured on the processing the image data with various folds using the cross entropy function. On identification of irregularity or reconstruction error on the processing layer of the model, hyperparameter tuning is carried out on each layer of the network to reduce the error in the hidden layer, input layer and output layer. The loss function for hidden and output layers are given by (20) and (21) respectively.

$$\text{Loss function Lf for hidden layer} = \text{Softmax}\,(At*Er*Ht) \quad (20)$$

$$\text{Loss function Lf for output layer} = \text{Softmax}\,(At*Er*Zt) \quad (21)$$

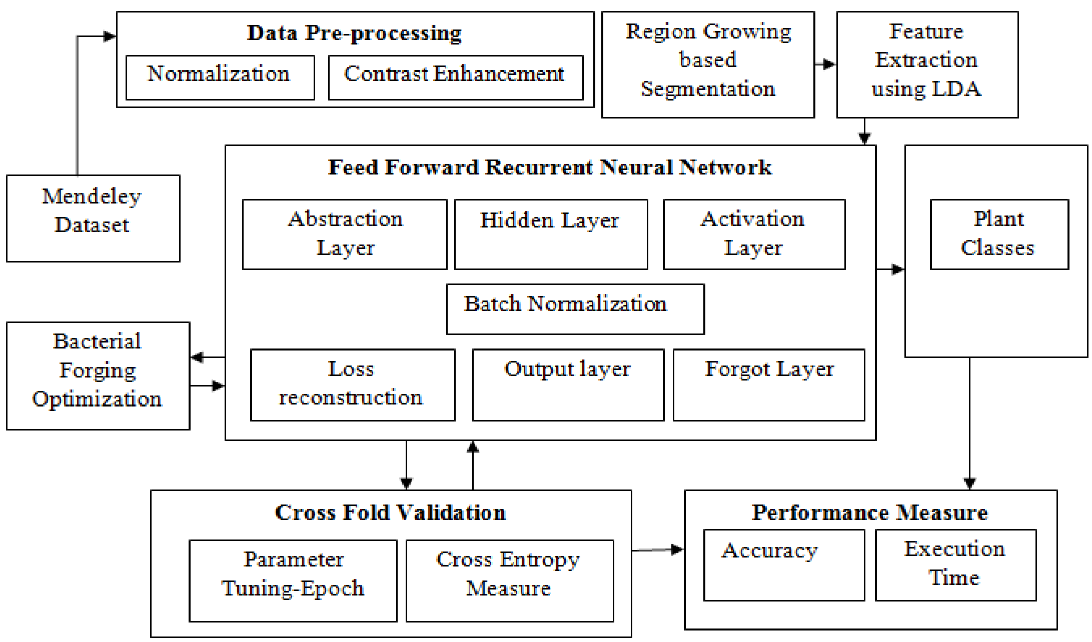

Fig. 1. Proposed architecture.

An accurate neural network model for classification is obtained with the inclusion of the loss function in the layer.

Algorithm 1: Plant Identification

Input: Mendeley Dataset

Output: Plant class

Process

Image Pre-Process ()

Image Thresholding ()

Contrast Stretching ()

Region Segmentation ()

Identify the seed Point

Compute Mean M and Standard deviation SD for Seed point()

Homogeneity Rule ()

$F(s)^n = 1 + \frac{Rx}{2n} + \frac{R(n-1)x^2}{2(n-1)} + \cdots \frac{R(n-1)x^n}{2(n-y)}$

If (Pixel intensity of Region 1 == Pixel Intensity of Neighbour Region of Seeded point 2)

Merge the two pixels into the seed point of the Region as Vector V
Linear Discriminant Analysis ()

Compute Scatter matrix S_m[] of seed region= $\frac{1}{2}\sum_{i=1}^{c} P_i P_j (fv_i - fv_j)(fv_i - fv_j)^T$
FFNN Learning ()
Input layer ( )

Determine the Spatial Feature of Seed Points ()

$F(S) = S_m \sum_{n=1}^{\infty} D(x,y)$

Compute Temporal Features of seed points ()

$F(T) = S_m \sum_{n=1}^{\infty} C(x,y)$

Hidden Layer ()

Identify the hidden feature of the various growth stage

$O(f(t)) = \sigma(G_p [A(t) C^{n-k} + h(t-1)] + W_f) + \sum_{k=1}^{n} \binom{n}{k} m^k$

Activation Layer ()

Use the Sigmoid Function

Output Layer ()

Cross Entropy Layer ()

Loss FunctionL_f Softmax ()

$\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}}$

Identify and display the Plant Class

Algorithm Description:

The classification algorithm initiates with image pre-processing approaches with histogram normalization and contrast stretching for noise removal and image normalization in the Medley dataset. Region-growing segmentation is employed for the preprocessed image. Linear Discriminant Analysis (LDA) has been employed as a Feature extraction approach. Obtained features are processed to classify the feature into classes using Feed Forward Neural Network on the computation of the features in the activation layer of the network using the sigmoid function.

E. Bacterial Foraging Optimization

In this section, bacterial foraging optimization is employed to the hidden layer to obtain the optimal feature space from the hidden layer to enhance plant classification accuracy in processing the features of various plants. The bacterial foraging uses the fitness criteria on the feature space from the hidden layer of the FFNN model [27]. Bacterial Optimization computes the optimal features to classify the plant into categories, especially it is found effective to classify various patterns. The optimal feature set has to be determined using the following fitness function (22).

$$\text{Fitness Function} = \sum_{m=k}^{n-1} \text{Correlation}(\boldsymbol{\delta}_i^j(f_k) - \boldsymbol{\delta}_i^j(f_{m+1})) + O(f_n) \quad (22)$$

Feature set given by fitness function is F(s)

IV. Experimental Results

Experimental analysis has been carried out in the Mendeley plant dataset [28]. The proposed architecture is simulated in Matlab (version 2017). In processing of the model, training data and validating data have been partitioned. In that, 60% of the image has been utilized for model training and 20 % of the image has been fixed for validation and rest 20% of the image has been fixed for model testing. In 10-fold cross-validation of the learning model, the performance of the classification and segmentation of the leaf region has been enhanced.

In this work, the proposed neural network model achieves high recognition accuracy on the identification of plant classes. The model provides excellent outcomes in computing the leaf region with different image sizes and image characteristics evaluated against conventional methods. Model performance has been evaluated with Dice coefficient, sensitivity and specificity against the conventional approaches for medicinal plant detection with volumetric changes of the plant at various stages of the plant growth.

- Dice similarity Coefficient

It is accessed on basis of the variation of classified results against the pathological classes. This difference computation is carried out using a confusion matrix. The confusion matrix yields True Positive (TP), False Positive (FP) and False Negative (FN) values on the class results. It is denoted as in (23).

Dice Similarity Coefficient

$$=\frac{\text{2True Positive}}{\text{2True Positiv}+\textit{False positve}+\textit{False Negative}} \quad (23)$$

- Sensitivity

It is considered as the ability of a test to correctly classify the plant in terms of various features. It is denoted as in (24).

$$\text{Sensitivity} = \frac{\text{True Positive}}{\text{True Positive}+\textit{False Negative}} \quad (24)$$

- Specificity

It is considered as the ability of a test to correctly classify the plant without various features. It is denoted as in (25).

$$\text{Specificity} = \frac{\text{True Positive}}{\text{True negatives}+\textit{False Negatives}} \quad (25)$$

The Mendeley medicinal plant leaves dataset containing image samples has been analysed to determine the medicinal plant class using machine learning approaches. The learning model has been assessed using the Dice coefficient measure, Sensitivity and Specificity measures. Its performance value is represented in Table II.

The proposed model exhibits good performance in segmenting the plant regions. Optimization of Feed Forward neural Network has been carried out with bacterial foraging illustrating the excellent outcomes on relating with conventional approaches such as Artificial Neural Networks and Convolution Neural Networks.

The Dice Coefficient generates the best outcomes on accessing with a classification accuracy of plant classes, generated using the machine learning model has been illustrated in Fig 2.

TABLE II. PERFORMANCE EVALUATION OF MEDICINAL PLANT CLASSIFICATION TECHNIQUES

Samples	Technique	Dice Coefficient	Sensitivity	Specificity
1^{St} Fold Validation Set	Bacterial foraging optimized Feed-Forward Neural Network– Proposed model	0.9788	0.9485	0.9792
	Artificial Neural Network - Existing Model	0.9578	0.9122	0.9689
2rd Fold Validation set	Bacterial foraging optimized Feed-Forward Neural Network l – Proposed model	0.9777	0.9194	0.9798
	Artificial Neural Network - Existing Model	0.9665	0.9014	0.9271
3^{rd} Fold Validation set	Bacterial foraging optimized Feed-forward Neural Network – Proposed model	0.9771	0.9115	0.9785
	Artificial Neural Network - Existing Model	0.9656	0.9015	0.9365

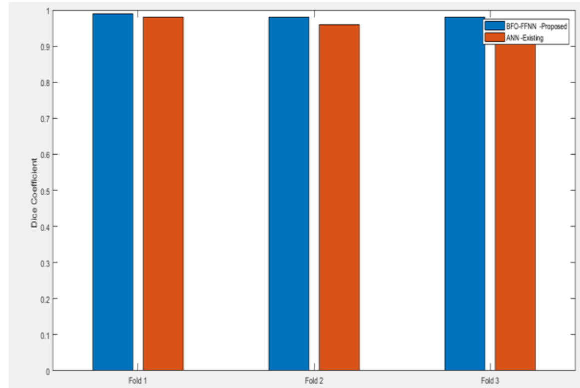

Fig. 2. Performance comparison of the learning model with respect to the dice coefficient.

Regarding the measure of sensitivity, it measures the excellent results in the optimization of the learning model through bacterial foraging to produce optimal features. Fig. 3 shows the performance outcome of the sensitivity measure on the plant classification.

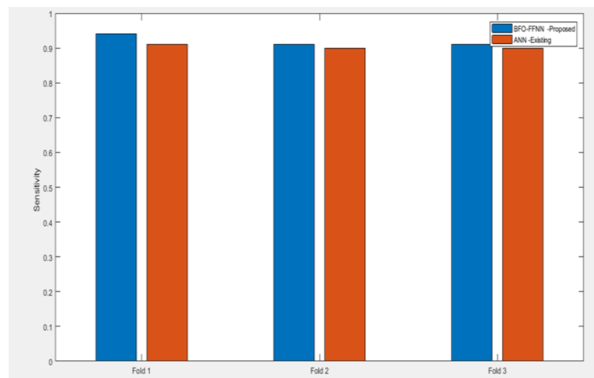

Fig. 3. Performance comparison of the learning model with respect to sensitivity.

The performance of the trained network is adapted to the target domain on producing better outcomes. Fig. 4 illustrates the performance outcome of the specificity. The proposed model is capable of classifying five medicinal plants effectively such as Basella Alba (Basale), Carissa Carandas (Karanda), Citrus Limon (lemon), Ficus Auriculata (Roxburgh Fig) and Rosa-Sinensis (Hibiscus).

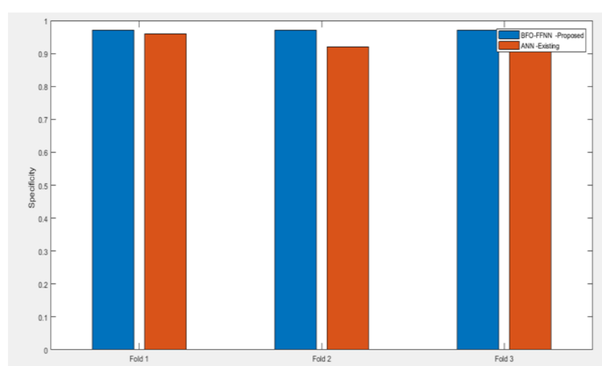

Fig. 4. Performance comparison of the proposed model in terms of specificity.

V. Conclusion

In this work, an optimized framework of Feed Forward Neural Network using bacterial foraging has been designed and implemented to classify the medicinal plant from the medley dataset. The model initiates the segmentation operation to the pre-processed image dataset in order to obtain the segmented region containing seed points in the image. The segment images are further processed using the linear discriminant to extract the spatial and temporal features. The extracted feature set is applied to the feed-forward neural network classifier. The classifier composed of the input layer, hidden layer, output layer and loss layer has fine-tuned with objective and activation function to discriminate the results with high recognition accuracy. The proposed model produces excellent outcomes even presence of image artifacts and volumetric changes in images. Further it is capable of handling the variability in anatomical properties and contrast variations of the dataset in analyzing the modalities and pathologically changed tissues. Further, different posing and structural changes have to be computed to minimize the interpretation issues and enhance the classification accuracy using Gaussian and quantum models on the features of the images to discriminating the medicinal plant classes of leaf images.

The results are very encouraging, and future studies will concentrate on using a huge dataset and more computational power using Quantum Computing to assess how effectively deep learning neural networks work in identifying medicinal plants for use in healthcare [29]. Whilst deep learning is a paradigm for analysis, linked data can be selected as the optimal practice for data representation [30]. The confluence of linked data with the proposed work can further take this study towards more accuracy.

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