Plant Species Recognition Using Custom-Developed Neural Network with Optimized Hyperparameters

S. Anubha Pearline and V. Sathiesh Kumar

1 Introduction

Global Biodiversity is steadily deteriorating as a consequence of direct and indirect human activities. A crucial prerequisite in preserving plant biodiversity is the identification of the presence of plant species around the globe. This warrants the development of an efficient and robust real-time plant species recognition system. Botanists manually examine a wide range of plant characteristics to identify and recognize the plant species. However, this method is incredibly hard for non-professionals such as farmers, gardeners and individuals. As an alternative approach, plant species recognition could be performed by using computer vision and machine learning techniques. Numerous plant species recognition systems employ leaves as an input to identify the plant species owing to the prevalence of the leaves throughout the year. The real-time classification of plant species based on the characteristics (geometry, shape, colour, texture, vein pattern, leaf margin and leaf form–simple or compound) of leaves is more challenging due to the large diversity in plant species [1]. Computer-based plant species recognition methods also encounter challenges due to variation in camera viewpoint, ambient light changes, scale modification and cluttered background [2, 3]. Recently, Neural Networks play a major role in several applications of computer vision. Neural Networks are capable of feature learning and classification.

Numerous research studies have been reported by different research groups across the world to tackle these aforementioned issues. Conventional image processing

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methods [4–6], Neural Networks and deep learning-based architectures are used in the context of plant species recognition.

The main contributions of this research paper are as follows:

- The pre-processed leaf images are utilized as direct input (pixel intensities) to the recognition system. Such processing of leaf images gives access to complete information of the leaf rather than extracting specific feature information.
- Investigated the performance of a custom-developed neural network (four layers–one input and output layer, two hidden layers) with different activation functions (ReLU, PReLU, ELU and L-ReLU).
- Hyperparameters such as optimizer, learning rate, activation function, alpha in PReLU and number of epochs are tuned to achieve the best performance metrics.
- Extensive experiments are performed on two standard (Flavia and Swedish leaf) and one real-time (Leaf 12) dataset.
- The proposed method (Neural Network with PReLU activation function) has lower model complexity as well as lower computational time compared to deep neural networks.

The rest of the paper is organized as follows. A short review of the existing literature is presented in the next section. Section 3 discusses the proposed methodology. Section 4 describes the experimental results and discussion. Also, Sect. 4 contains the comparison between the proposed method and other existing methods. Section 5 concludes this research article.

2 Related Works

Kumar et al. [5] proposed a method to perform a plant species recognition process using a Multi-layer Perceptron with Adaboosting technique. Flavia dataset is used in the evaluation of the architecture. The images from the dataset are pre-processed and the morphological features are extracted. The extracted features are classified using machine learning classifiers such as K-Nearest Neighbour (K-NN), Decision Tree and Multi-layer Perceptron with Adaboosting technique.

Another method for plant species recognition is described by Saleem et al. [6]. The authors utilized the handcrafted features with machine learning classifiers. The images from the dataset are pre-processed, colour converted (RGB to Lab colour space) and thresholded (Otsu method) to form a binary image. From which, the shape features (11), statistical features (7) and venation features (5) are extracted. Principal Component Analysis (PCA) is used to reduce the number of features before it is classified using machine learning classifiers such as K-NN, Decision Tree, Naive Bayesian and Multi-Support Vector Machine. Two datasets namely, Flavia and self-collected are used to evaluate the method. This method exhibited better performance when compared to AlexNet Convolutional Neural Network.

Plant species recognition based on the GIST texture feature extraction method is demonstrated by Kheirkhah et al. [7]. The dimensionality reduction of features is performed using PCA followed by classification using Patternnet Neural Network, SVM and Cosine-based K-NN classifiers. The method is evaluated using the leaf datasets, namely Flavia, ImageCLEF and LeafSnap. The authors observed that the utilization of Cosine-based K-NN classifier resulted in achieving higher performance metrics compared to other methods. The reported accuracies are 98.7, 88.8 and 74.5% on Flavia, ImageCLEF and LeafSnap datasets, respectively.

Yousefi et al. [8] proposed a neural network approach to carry out a plant species recognition. The shape, morphological and textural features are extracted from the images of Flavia dataset. The shape feature (leaf contour) is extracted by Rotation Invariant Wavelet Descriptor (RIWD). The extracted features are then classified using a Multi-layer Perceptron (MLP) with 6 layers (inclusive of 4 hidden layers). The authors reported that the utilization of the RIWD feature along with morphological and texture features resulted in achieving higher accuracy (97.5%) compared to Invariant Elliptic Fourier Descriptor (IEFD).

A method to classify the medicinal plant species is suggested by Naresh et al. [9] wherein the feature extraction process is implemented using a Modified Local Binary Pattern (M-LBP). The M-LBP method uses the mean and standard deviation values instead of threshold values to generate the binary pattern. The Nearest Neighbour classifier is used to classify the medicinal plant species. Five datasets (UoM medicinal plant dataset, Flavia, Foliage, Swedish Leaf and Outex) are used. Anubha et al. proposed several ensemble techniques such as bilateral Convolutional Neural Network (CNN) [10], dual deep learning architecture [11] and Bi-channel Convolutional Network [12] for plant species recognition.

In a study by Lu et al. [13], a method is proposed to classify five different species of Camelia Genus plant. The total number of images/classes in the dataset is about 93. The considered features are comprised of architectural and morphological characteristics. The classification is performed by different methods such as Learning Vector Quantization Artificial Neural Network (LVQ-ANN), Dynamic Architecture for Artificial Neural Network (DAN2) and SVM. It is found that the classification using the DAN2 method resulted in achieving higher accuracy compared to other methods.

Pandolfi et al. [14] used a back-propagation neural network (BPNN) to classify 17 different species of tea plants from Vietnam. The Neural Network contains three layers inclusive of a hidden layer. The hidden layer has 50 optimal hidden neurons which use the Logistic Sigmoid activation function. Fourteen morphological features are extracted. In addition to it, the BPNN outputs are investigated through a cluster analysis (Unweighted Pair Group Method Analysis–UPGMA) to form a dendrogram.

Plant species recognition system employing a Probabilistic Neural Network (PNN) model is proposed by Wu et al. [15]. PNN includes an input layer, a radial basis layer and a competitive layer. Flavia dataset is used to determine the performance analysis of the PNN. Among twelve morphological features extracted, five important features are selected using PCA and fed as an input to the PNN (classification). The authors reported a classification accuracy of 90%.

Fu et al. [16] utilized the leaf vein pattern to perform the classification of plant species. The segmentation and threshold process are carried out using the Sobel and

Laplacian operators. The extracted features (4 gradient features from Sobel operator, local pixel contrast and 5 statistical features) are fed as an input to the Artificial Neural Network (classification).

Based on the extensive literature survey, it has been identified that most of the reported literature utilize a feature extraction method (to extract the features) and classifier or Neural Network (classification). Further, the considered dataset images are heavily pre-processed even before the methodology is tested. Also, most of the Neural Networks reported in the literature consist of three layers (inclusive of one hidden layer) with a lesser number of neurons per layer. On the other hand, studies that involve feeding raw pixel intensities to the Neural Network are sparse.

Hence, in this paper, a custom-developed Neural Network with Parametric Rectified Linear Unit (PReLU) activation function is proposed and evaluated for plant species recognition. Three datasets (Flavia (D1), Swedish Leaf (D2) and custom-developed Leaf 12 (D3)) are considered in the process of model evaluation. The model hyperparameter (Optimizers, Learning Rate, Activation Function and Epochs) are tuned to achieve higher classification accuracy. Since the raw pixel intensities are used in the process of classification, the proposed architecture is better suited to perform a real-time plant species recognition.

3 Methodology

The proposed plant species recognition methodology consists of a Neural Network comprising of four layers inclusive of two hidden layers with the back-propagation algorithm. The schematic representation of the proposed methodology is shown in Fig. 1. The first hidden layer has 500 neurons while the second one has about 250 neurons. The transfer of information from one layer to the other is performed by the activation function in the hidden layer neuron. The hidden layers are tested with different activation function such as Rectified Linear Unit (ReLU) [17], Parametric Rectified Linear Unit (PReLU) [18], Exponential Linear Unit (ELU) [19] and Leaky Rectified Linear Unit (L-ReLU) [20].

Three datasets namely, Flavia (D1) [15], Swedish Leaf (D2) [21] and custom-developed Leaf 12 (D3) [22] are considered. The total number of images and number of images/class for the above-specified datasets are listed in Table 1. A few sample images of the plant species from each of the datasets are shown in Fig. 2. The images in the dataset are resized to 32×32 pixels using the Nearest Interpolation method. Resizing is performed by maintaining the aspect ratio of the images. The normalized pixel intensities of the image are provided as an input ($32 \times 32 \times 3 = 3072$–pixel intensities) to the input layer neuron of the network. The number of output layer neurons depends on the number of output classes. A softmax activation function is used in the output layer neurons.

The output prediction (y_i) is carried out in the output layer, resulting in the determination of the Categorical Cross-Entropy Loss function [23] as given in Eq. (1).

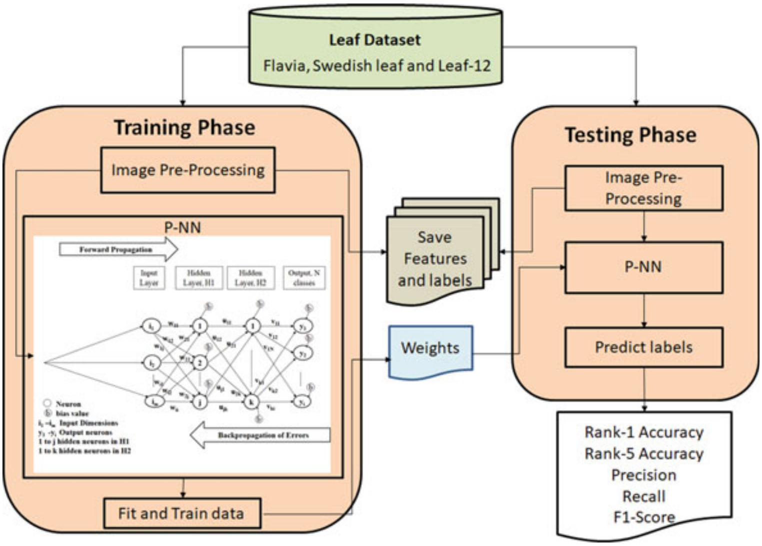

Fig. 1 Schematic methodology representation to perform real-time plant species recognition

Table 1 Dataset description

Dataset	Number of images/class	Number of classes	Total number of images	Image size
D1–Flavia	50	32	1600	1600 × 1200
D2–Swedish Leaf	75	15	1125	799 × 1554
D3–Leaf 12	320	12	3840	1920 × 1080

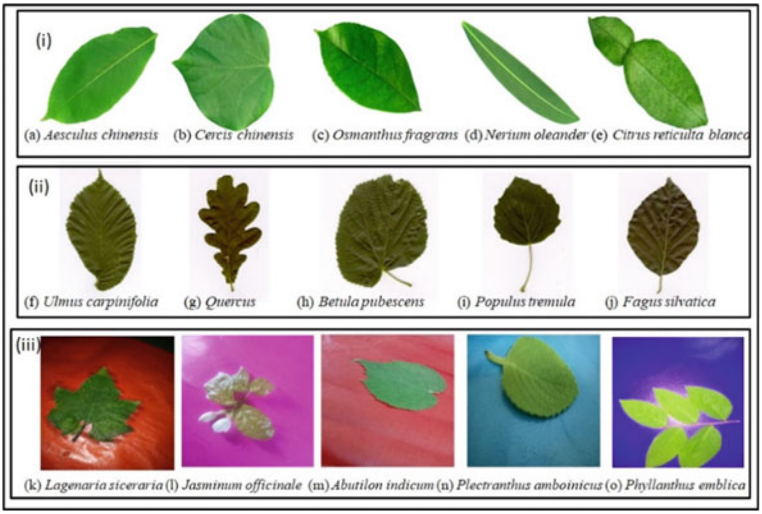

Fig. 2 Sample leaf images: (i) D1–Flavia, (ii) D2–Swedish Leaf and (iii) D3–Leaf 12

$$E_{CC} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} p_{ic}(\log(y_{ic})) \quad (1)$$

where N is the number of pairs $((x_1, t_1)$ to $(x_N, t_N))$ in the training data, $c = 1$ to C is the number of classes, x_i is the input vector, t_i is the target vector, $p_{ic} \in c$ denotes the indicator function for the ith training pattern, $y_{ic} \in c$ represents the predicted probability for the ith observation. Based on the loss values, the interconnection weight and bias terms of the Neural Network are updated in the back-propagation phase [24] resulting in the minimization of loss values, thereby improving the performance of the system. The total number of trainable network parameters are 1,664,762.

Algorithm 1 Inputs: Image, I; pixel intensity, $I(p)$; Weights, w_i; bias, b; net input, y_{in}

Output: Class labels, 0 to N number of classes

1. Resize the image, I to 32 × 32 × 3 pixels
2. Normalize the pixel intensity $I(p)$
3. Calculate $y_{in} = b_i + \sum I(p).w_i$
4. Apply activation function (PReLU or ReLU or ELU or L-ReLU)
5. Repeat steps 3 and 4, until no more hidden layer neurons are available for computation
6. Calculate Error function (Categorical Cross-Entropy Loss function) using Eq. (1)
7. Update w_i and b_i
8. Repeat steps 3–7, until a certain number of epochs
9. Evaluate each of the images, I belonging to 0 to N class to determine the performance metrics.

The steps involved in the process of plant species recognition using Neural Network with back-propagation method is represented in Algorithm 1. The optimum hyperparameters (Optimizers, Learning Rate, Activation Function and Epochs) are determined to improve the performance of the plant species recognition system. Optimizers are used in the updation of the weight interconnection between the layers and bias term in the neuron, during the back-propagation phase. The optimizers considered in the present work include Stochastic Gradient Descent (SGD) [25], Adam [26], Adamax [26] and Adadelta [27]. The learning rate is varied from 0.01 to 0.00001, while the number of Epoch are set from 1 to 200.

The custom-created Neural Network is developed using a Python framework in Windows 10 64-bit OS with Intel Core i7-4790 CPU and NVIDIA Titan X GPU with 3584 CUDA cores. The Python libraries utilized during the implementation process are Numpy, Keras [28] with backend as Tensorflow, Scikit-learn [29], h5py and Matplotlib.

Fig. 3 Accuracy chart obtained by varying the activation function of the network applied on different datasets

4 Results and Discussion

4.1 Determination of Activation Function

Initially, the custom-developed architecture is evaluated to determine a suitable activation function (ReLU, PReLU, ELU, L-ReLU) for the network to perform a real-time plant species recognition. The selection of the activation function is carried out by fixing the optimizer (Adam), learning rate (0.001), Epoch (50) and Batch size (32). The accuracy chart for the three datasets, obtained by varying the activation functions is presented in Fig. 3. It is observed that the PReLU activation function with an α value of 0.02 exhibited the highest accuracy (Top-1: Flavia–82.50%, Swedish Leaf–92.60%, Leaf 12–86.89%).

The influence of the tuneable hyperparameter 'α' of the PReLU activation function on the accuracy of the system is examined. The α values are varied from 0.02 to 0.35 and the corresponding accuracies are listed in Table 2. Highest accuracy (Top-1: Flavia–84.38%, Swedish Leaf–94.28%, Leaf 12–87.50%) is observed by setting an α value of 0.1.

4.2 Determination of Optimizer

The PReLU activation function with an α value of 0.1 is used in the hidden layers of the Neural Network. The learning rate is set to the default values as specified by the Keras library package (SGD–0.01, Adam–0.001, Adamax–0.002, Adadelta–1.0). The number of Epochs and Batch Size is set to 50 and 32, respectively. Figure 4

Table 2 Model accuracy (%) obtained by tuning α value in PReLU activation function

Alpha, α	D1–Flavia	D2–Swedish Leaf	D3–Leaf 12
0.02	82.50	92.60	86.89
0.05	82.71	91.72	87.33
0.1	**84.38**	**94.28**	**87.50**
0.15	80.00	89.94	86.46
0.2	81.88	79.88	86.55
0.25	75.21	93.79	85.42

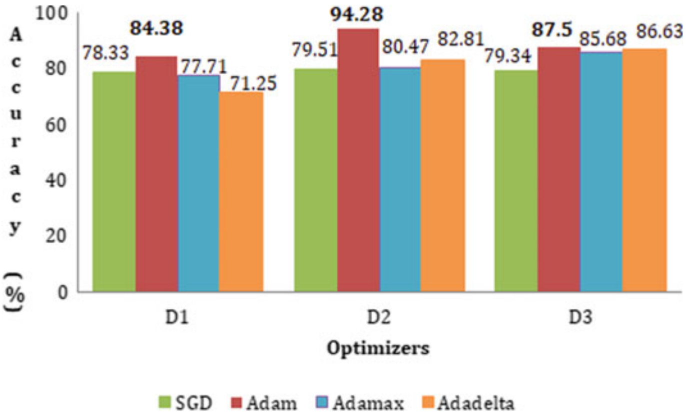

Fig. 4 Accuracy chart obtained by varying the optimizer of the network (PReLU with $\alpha = 0.1$) applied on different datasets

shows the accuracy chart obtained by varying the model optimizers for the three datasets (Flavia (D1), Swedish Leaf (D2) and Leaf 12 (D3)). It is observed that the Adam optimizer performed better (Top-1 accuracy: Flavia–84.38%, Swedish Leaf–94.28%, Leaf 12–87.50%) compared to other optimizers, irrespective of the dataset. The Top-5 accuracies obtained for Flavia, Swedish Leaf and Leaf 12 datasets are 98.75%, 100% and 99.41%, respectively. Hence, in the subsequent optimization of other hyperparameters, the Adam optimizer is utilized.

4.3 *Determination of Learning Rate*

The identification of the optimizer (Adam) is followed by determining an appropriate learning rate. The learning rate is varied from 0.01 to 0.00001. The other parameters such as α value of the PReLU activation function, the number of Epoch and Batch size are maintained at 0.1, 50 and 32, respectively.

Figure 5 shows the accuracy chart obtained by varying the learning rate of the network applied on three datasets. It is observed that the learning rate of 0.001 resulted

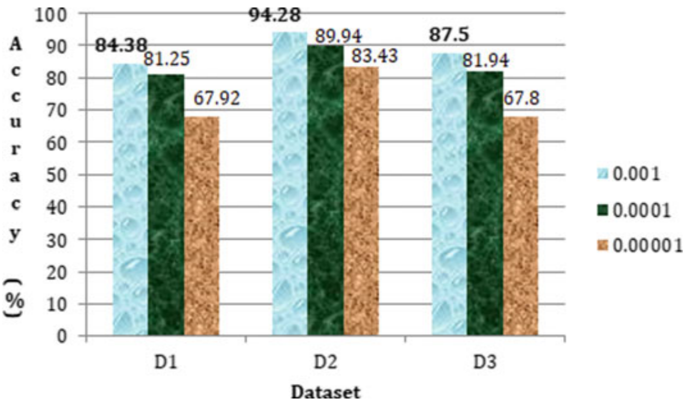

Fig. 5 Model's accuracy chart obtained by varying the learning rate of the Adam optimizer (network with PReLU ($\alpha = 0.1$)) applied on different datasets

in better performance (Top-1 accuracy: Flavia–84.38%, Swedish Leaf–94.28%, Leaf 12–87.5%) compared to other learning rates. The learning rate of 0.01 resulted in low accuracy for plant species recognition and hence is not included in Fig. 5. A similar result in which the Adam optimizer with a learning rate of 0.001 exhibited higher accuracy in comparison to other optimizers is reported by Kingma et al. [26].

4.4 Determination of Epoch

Finally, the optimization of the number of Epochs is carried out. Using Adam optimizer with a learning rate at 0.001 and α value at 0.1, the number of Epochs is varied between 50 and 200. Table 3 lists the values of accuracies obtained by varying the number of Epochs. It is observed that the best accuracy (D1–Flavia: Top-1–85.83%, Top-5–98.75%; D2–Swedish Leaf: Top-1–94.97%, Top-5–100%) is obtained at 200 Epoch. However, in the case of D3–Leaf 12 dataset, the best accuracy (Top-1–87.50%, Top-5–99.41%) is obtained at 50 Epochs.

Table 4 list the performance metrics obtained by the custom-created Neural Network with optimized parameters. The performance metrics include Top-1 accuracy, Top-5 accuracy, precision, recall and F1-score.

The results obtained by the proposed PReLU-based Neural Network with back-propagation algorithm after hyperparameter optimization is compared with those of the existing literature. From the comparison presented in Table 5, it is observed that the proposed PReLU-based Neural Network exhibits better performance in plant species recognition, compared to the existing methods.

Table 3 Model (PReLU with α = 0.1, Adam, learning rate = 0.001) accuracy (%) obtained by varying the number of Epoch

Number of Epochs	Accuracy (%)					
	D1–Flavia		D2–Swedish Leaf		D3–Leaf 12	
	Rank-1	Rank-5	Rank-1	Rank-5	Rank-1	Rank-5
50	84.38	98.75	94.38	100	87.5	99.41
100	79.58	98.12	94.08	100	84.38	99.22
150	85.83	98.54	94.28	100	85.76	98.96
200	**85.83**	**98.75**	**94.97**	**100**	86.63	99.22

Table 4 Performance metrics obtained by the optimized model (PReLU with α = 0.1, Adam, learning rate = 0.001) on three datasets

Dataset	Accuracy (%)						Computation time (s)	
	Rank-1	Rank-5	Precision	Recall	F1-Score	Epoch	Training	Test
D1–Flavia	85.83	98.75	0.86	0.86	0.85	200	31.66	0.06
D2–Swedish Leaf	94.97	100	0.95	0.95	0.95	200	23.28	0.06
D3–Leaf 12	87.50	99.41	0.88	0.88	0.87	50	18.72	0.10

5 Conclusion

In this paper, a PReLU-based Neural Network (PNN) with back-propagation algorithm is proposed and demonstrated to perform recognition of plant species. The model's hyperparameters are optimized to achieve high performance metrics. From the experimental analysis, it is observed that the PReLU-based Neural Network with optimized hyperparameters performs better compared to other existing methodologies. The optimized hyperparameters of the PNN are identified as Adam optimizer, a learning rate of 0.001 and PReLU activation function with an α value of 0.1. The model attained higher performance metrics at 200 (D1–Flavia), 200 (D2–Swedish Leaf) and 50 (D3–Leaf 12) epochs. The proposed model obtained an accuracy of 85.83%, 94.97% and 87.50% when it is subjected to Flavia, Swedish Leaf and Leaf 12 datasets.

Table 5 Comparison of accuracies obtained by the proposed PReLU-based Neural Network with existing literature

Method	Reference	D1–Flavia	D2–Swedish Leaf	D3–Leaf 12
Artificial Neural Network	Söderkvist [21]	–	82.40	–
Probabilistic Neural Network	Kadir et al. [30]	81.56	–	–
Gabor-based method	Wang et al. [31]	–	85.75	–
Fuzzy integral method	Wang et al.[31]	–	89.25	
Texture and shape features	Zhang et al. [4]	–	91.14	–
Shape and colour features	Zhang et al. [4]	–	91.66	–
Locally linear discriminant embedding	Zhang et al. [4]	–	91.86	–
Wavelet-based method	Wang et al.[31]	–	91.37	–
Shape features + K-Nearest Neighbour	Priya et al. [33]	78.00	–	–
2D-linear discriminant analysis + bagging classifier	Gaber et al. [34]	85.00	–	–
Random forest classifier	Anubha Pearline et al. [22]	85.62	87.87	82.38
Colour shape and texture features	Zhang et al. [4]	–	92.44	–
Singular value decomposition sparse representation	Zhang et al. [4]	–	92.59	–
Proposed PReLU-based Neural Network		85.83	94.97	87.50

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