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HerbSimNet: Deep Learning -Based Classification of Indian Medicinal Plants with High Inter-Class Similarities

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Abstract: Medicinal plant species recognition is important across diverse sectors such as Ayurveda, agriculture, environment conservation and botanical research. Specific groups of plants in Indian medicinal plant ecosystem exhibit significant inter-class similarities due to varying abundance and ecological factors. To address the challenges involved in the process of classifying these species in this work a deep learning model Herb-SimNet is proposed. The Herb-SimNet analyzes similarity of plant species over other plant species using vision based deep learning and machine learning techniques. The proposed model works based on the combination of wavelet features and convolutional features extracted using three sequential convolution layers to extract the prominent features that distinguish variations among the inter class similarity plant species. To perform experiments, a dataset is created by capturing medicinal plant leaf images using box model in plain background and uniform lighting. A smart phone captured twelve Indian medicinal plant species comprising of about 1400+ samples that belongs different plant species but similar morphological structure is collected. Baseline experiments are carried out between Herb-SimNet and other state-of-the-art deep learning models for classification based on the proposed dataset. The outcomes demonstrate that Herb_SimNet provides clear interpretation one plant variety with others and achieves superior accuracy in prediction than that of state-of-the-artapproaches. Furthermore, the model demonstrates better generalization towards the other inter-class similarity groups considered for testing. In conclusion, the proposed dataset and Herb-SimNet plays a a crucial role in advancement of research concerning Indian medicinal plant species classification resulting into enhancement of AI-based technology for biodiversity conservation andethnobotanical studies.

Keywords: Classification; inter-class similarities; confusing plant species; medicinal plants; wavelet image features.

1. Introduction

The classification of Indian plant species based on leaf structure is prominent for biodiversity assessment and ecological studies. Realization of high accuracies amidst inter-class similarities and intra-class variations is a challenging research problem. As leaves exhibit diverse morphologies and scales during growth stage which introduces

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variations in shape, venation patterns, margins, and textures. The afore-mentioned features play a crucial role in feature learning by classification models for taxonomic identification. Furthermore, classification of visually similar species that exhibit inter-class similarities pose significant challenges in botanical classification.

The proposed study addresses the challenges of inter-class similarities and intra-class variations by employing deep learning models devised for classifying plant species based on their leaf morphology. In the conventional settings, taxonomists have relied on morphological characteristics of leaves to identify and classify plant species. Due to the technological advancements, use of computational methods and deep / machine learning techniques has beendominantly used for automated classification of plant species. In addition to the morphological characteristic's complexity, there also exists complexity due to several external factors such as lighting conditions, natural and complex backgrounds, varying distances for image capturing etc. Some of recent advancements in deep learning, particularly convolutional neural networks (CNNs), have gained prominence in the field of image-based plant speciesclassification. The deep learning methods are efficient at feature interpretation of handling large datasets of plant images to learn distinct features directly from raw pixel data. In a recent work, demonstrated the effectiveness of path-based tree classifiers for large-scale plant species identification, highlighting the potential of deep learning in handlingdiverse and extensive plant datasets [1]. Similarly, on the studies based on Indian medicinal plant species, Pushpa andRani (2023) developed hierarchical classification scheme using convolution features [2] and Ayur-PlantNet [3], a lightweight CNN for Ayurvedic plant species classification. The mentioned works underscores the importance of employing a fusion feature set into machine learning models to achieve enhanced classification accuracy. Subsequently, Trey et al. also explored similarity-based classification approaches to address the challenges of inter- class similarities for plant species [4].

Some of the limitations with state-of-the-art deep learning models is their dependability on large amounts of labeled data for training, which can be expensive and time-consuming especially towards unknown dataset predictions. Additionally, the existing models also suffer with inter-class similarities and intra-class variations issues, where subtle differences in morphology or environmental conditions can significantly impact classification accuracy [3]. Additionally, the interpretability of deep learning models especially in analyzing the similarity of leaf morphology from one plant species to other species remains as a crucial challenge. The deep learning is often operated as "black boxes in majority of existing works that hinders the understanding of how decisions are made during classification.

The proposed research aims to propose a fine-grained deep learning-based classification of plant species that exhibit inter-class similarities of one species type over the rest. The primary need is also to achieve the enhanced classifier performance with respect to both controlled environment image capturing conditions and natural environment image capturing conditions as well. It is proposed to develop a Herb-SimNet to perform feature learning based on the texture and geometrical features and measuring similarity of one class over other. It is proposed to evaluate the generalizability of proposed model over datasets with two distinct environments.

2. Literature Review

2.1 Overview of Plant Species Classification

Plant species classification is a crucial task in the field of agriculture. It has a significant advancement in the field of agriculture and using AI/ML (Artificial Intelligence and Machine Learning). Conventionally, plant species classification depends on morphological characteristics like size, shape, and type of the seed which requires proficient knowledge and this will make a time time-consuming and prone to errors. With the help of artificial intelligence and machine learning, a greater number of datasets and plant images can be efficiently analyzed. To get high accuracy and by learning the features of each plant, CNN has been broadly used to classify the plant species by considering the features along with labelled images. AIML architectures can also integrate environmental and genetic data, and embellish the classification process by taking the features like climate change conditions and gene variations. Technologies involved in this not only provide the identification of plant species but also the detection of new species and monitor the biodiversity making the plant species identification and classification more scalable and accessible.

2.2 Traditional methods and recent advancements

External factors of the plant that are in-depth features of the environmental plant's species identification have highlighted the part of the chemical profiling process in identifying the plant species by YANG el al. [4]. Andrew et al. [5] identified the importance of the Internal features of the plants like shape, size, and texture have been examined in the model for species classification. moments-invariant and centroid-radii methods are used to identify the plant species. To adjust the intensity level of the plant features, a hybrid method which includes contrast stretching" and “adaptive thresholding” is implemented. Geometric features along with the hypersphere classifier are implemented by using the directional fragment histogram for plant species classification Nilsback et.al [6].

2.3 Use of Leaf Shape for Classification

The use of leaf shape for plant species classification has advanced significantly since 2010. To extract the shape features from the plant leaf images, a dimensional Fourier transform is employed for better improvement of accuracy by Wenjing, Xue Liu [7]. In a work, Weiqun Cao [7], Leaf snap computer vision system utilizes the shape features to identify the leaf shape classification. A geometric morphometric protocol-based system is implemented for the precise shape features Siraj et.al [9]. To identify the leaf vein patterns author used Deep learning to extract complex features and learn the model for the outperformance of leaf shape classification. A hybrid texture analysis and leaf shape over computer vision, enhancing classification performance. Lee, C.P et.al [10] utilized convolutional neural networks (CNNs) for multiple perspectives leaf recognition, by improving robustness and accuracy. A combination oftraditional image processing with deep learning model for high-accuracy leaf-based classification. A real-time plant leaf recognition system improved CNNs and transfer learning, providing rapid and accurate species identification.

2.4 Machine learning techniques applied in plant species classification.

Machine learning techniques have increasingly been applied to plant species classification, yielding significant advancements. A computer vision system that is based on leaf shape reviewed leveraging machine learning for automatic plant identification uses various machine learning algorithms that highlight their potential in dealing with complex plant image data for plant species classification Naiara Aginako [11]. The rationale is that leaves are less affected by seasonal variations and, because of their size and shape, are advantageous for easy observation,description, and capture. Some methods for identifying plant species use a combination of leaf and stem or the color,shape, and texture of the plants by Balasubramanian et.al [12] and S. Arivazhagan [13]. Classification methods are based on a combination of color, texture, and shape aspects. 103 features were used to test the system Dheeb Al S. Arivazhagan [14]. The idea of classifying plants using SIFT feature descriptors in response to both physical and spatialstimulation Bashish et.al [15] using neural networks to interpret digital images to identify local characteristics depending on plant morphology et.al H. Goeau, P [16]. Guru, D. S presented an algorithmic approach with KNN as the classifier for automatic plant classification [17]. However, due to their complex three-dimensional structures, plants have limitations that make it challenging to study their forms and structures. Mairal et.al [18] identifies system that automatically recognizes plants by looking at the information and visual content that are linked to them. A classification combined solution has been used to define the classification Ramirez, P [19]. For an effective plant categorization method, the authors of [20] merged several perspectives of plant organs (such as flowers, bark, and leaves) utilizing a late integrating procedure. In works by Pushpa et al. [21], convolution features are employed for classification of Indian medicinal plant species based on same datasets employed in proposed work along with dataset contributions in [22]. Again in [23], a method for extraction of leaf region from the complex and unconstrained background is proposed by considering multiple species of Indian medicinal plant species in varying backgrounds. In awork by Rani et al. [24], classification of Okra plants with disease affected at early stage is performed using deep convolution neural network models. In work by Prasad et al. [25], disease detection is performed on real time plant images collected using smartphones using deep learning-based object detection models. In a work reported by Pushpa et al. [26], a light weight deep convolution neural network is proposed for classification plant images of about forty Indian medicinal plant species.

These works demonstrate the increasing use of machine learning, especially deep learning, in the classification of plant species, greatly improving its accuracy, efficiency, and capacity for real-time application. Majority of works does not focus on issues related to inter-class similarities during classification.

3. Methodology

3.1 Dataset Collection with Smartphone Camera Setup

Classification of plant species poses distinct challenges including varying environmental conditions and imaging setups, especially the usage of smartphones to perform various tasks is observed high in these days. In the proposed study, we consider distinct datasets that are captured in the controlled environment. The images of plant species that

are captured using smartphone placed at a fixed distance with the help of an image acquisition setup. The controlled environment dataset comprises images captured under consistent uniform lighting in indoor environments. The images captured ensure uniformity in lighting and high contrast in the leaf's vein structure facilitating better interpretation of visual texture features. However, the dataset acquired may not fully capture the diversity of conditions that arise in real-world applications. For the study, a diverse set of plant species with inter-class similarities are considered— such as Aloevera (*Aloe barbadensis*), Bamboo (*Bambusoideae*), Bermuda grass(*Cynodon dactylon*),Coriander1(*Coriandrum sativum*), Eucalyptus(*Eucalyptus citriodora*), Gangale (*Nerum oleander*), Ginger(*Zingiber officinale*), Lemon grass(*Cymbopogon*), Marigold(*Genus tagetes*), Onion(*Allium cepa*), Peel Kaner(*Cascabela thevetia*), Tumbe(Leucas aspera) as presented in figure 1. In this paper, we investigate the model complexity to work with variable environmental conditions along with variable backgrounds for the prediction of plant species type based on the leaf structure of the image.

3.4 Overview of Herb-SimNet

A. Data preparation

Data preparation involved utilizing 1063 leaf images from a diverse set of plant species, including Aloevera, Bamboo, Bermudagrass, Coriander, Eucalyptus, Ganagale, Lemongrass, Ginger, Tumbe, Peelkaner, Onion, and Marigold. The primary aim of this stage was to preprocess the data effectively to eliminate noise and unrelated features. Several transformations were applied to ensure the dataset is in suitable format for analysis. Initially, all images were resized to 256x256 pixels, followed by a center crop to achieve a final dimension of 224x224 pixels. These images were then converted into tensors to facilitate computation and subsequently normalized using standard mean and standard deviation values. For dataset splitting, 80% of the images were allocated for training, while the remaining 20% were set aside for testing purposes. To streamline the training process, a DataLoader was employed with a batch size of 32, allowing for efficient loading and processing of the data.

wavelet features and a dense fully connected neural network. The initial process begins by loading the image dataset by applying transformations such as resize, crop, and normalize to prepare the data for processing. The dataset is subject to splitting for training in the proportions of training (80%) and testing (20%) sets to evaluate the model's performance. The data loaders are initialized with a specified batch size of 32 for data during training and evaluation. Next, feature extraction is carried out using the PyWavelets library to decompose images into wavelet coefficients to capture primary image details. The decomposed wavelet images are then fed to learning layers of the neural network for feature interpretation by specifying the input size as 256x256. The model is then trained in forward and backward passes by computing the loss and updating model learnable parameters using a gradient descent optimizer. The model is evaluated on the test dataset for computation of accuracy, precision, recall, and F1 score to assess the model's generalization capability.

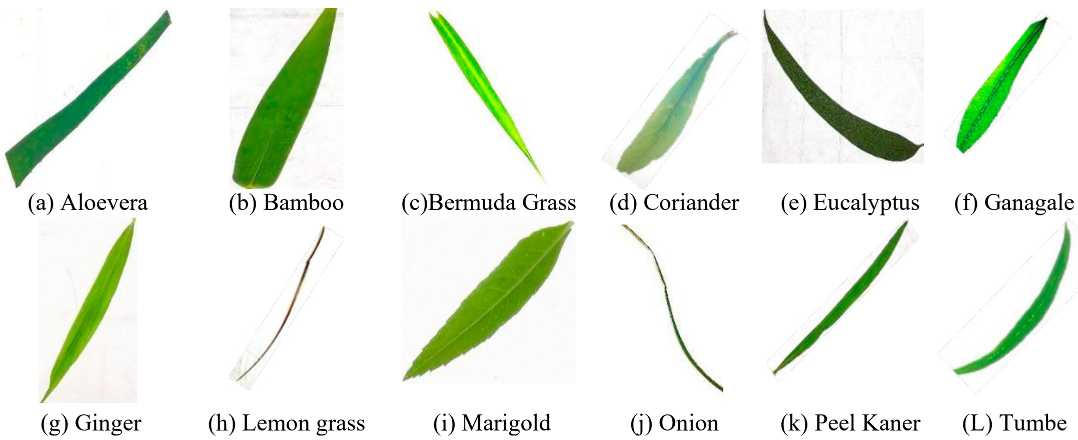


Figure 1: Samples of leaf images under controlled environment in uniform lighting conditions.

Table 1: Dataset statistics and accessibility

Plant species details	Brief description of morphological characteristics	Number of samples	Refer for Datas
Aloevera	thick, fleshy, lance-shaped, tall spikes	136	
Bamboo	hollow, segmented, woody stems (culms) and lanceolate leaves	140	
Bermuda grass	fine-textured, dark green leaves, dense	136	
Coriander	Bright green, delicate, lacy appearance, resembling parsley with rounded shape	136	
Eucalyptus	long, narrow, and lance-shaped with a leathery texture, a bluish-green to greyish-green color	138	Pushp al. [2
Ganagale	long, blade-like leaves, bright green and glossy	128	
Ginger	long, narrow, lance-shaped, smooth texture and a vibrant green color	131	
Lemon grass	long, slender, and arching leaves with sharp edges and a strong citrus aroma, dense clumps, up to 6 feet in height.	131	
Mari gold	bright, green, pinnate leaves with sharply toothed, lance-shaped leaflets	132	
Onion	long, hollow, and cylindrical, with a bright green color and a smooth texture	142	
Peel kaner	narrow, lance-shaped leaves that are leathery and arranged in spirals along the stem	135	
Tumbe	small, oval, and green leaflets with feather-like pattern along the stem	118	

A. Method:

In the proposed method, the classification of plant species with inter-class similarities is performed through a step-by-step process. Figure 2 depicts the steps involved in the process of classification.

B. Wavelet transform for feature extraction

Wavelet features are employed due to their effectiveness in capturing both spatial and frequency information, which is particularly useful for image analysis. The wavelet transform is a mathematical tool that decomposes an image into components at various scales or resolutions, providing a multi-resolution analysis. This capability is beneficial for leaf image analysis as it can highlight features at different levels of detail.

Once the data is loaded, the images are subject to wavelet decomposition with depth two to obtain the decomposed wavelet transformed images, which highlights the prominent image details. Then, the decomposed wavelet coefficients are then subject to feature learning and interpretation through a sequence of three fully connected layers. The wavelet coefficients are determined by the using PyWavelets libraries of python. Specifically, the Daubechies wavelet (db1) is employed in the proposed method for feature analysis. The wavelet decomposition is achieved by pywt.wavedec2 function, which is two dimensional wavelet decomposition function with decomposition level two.

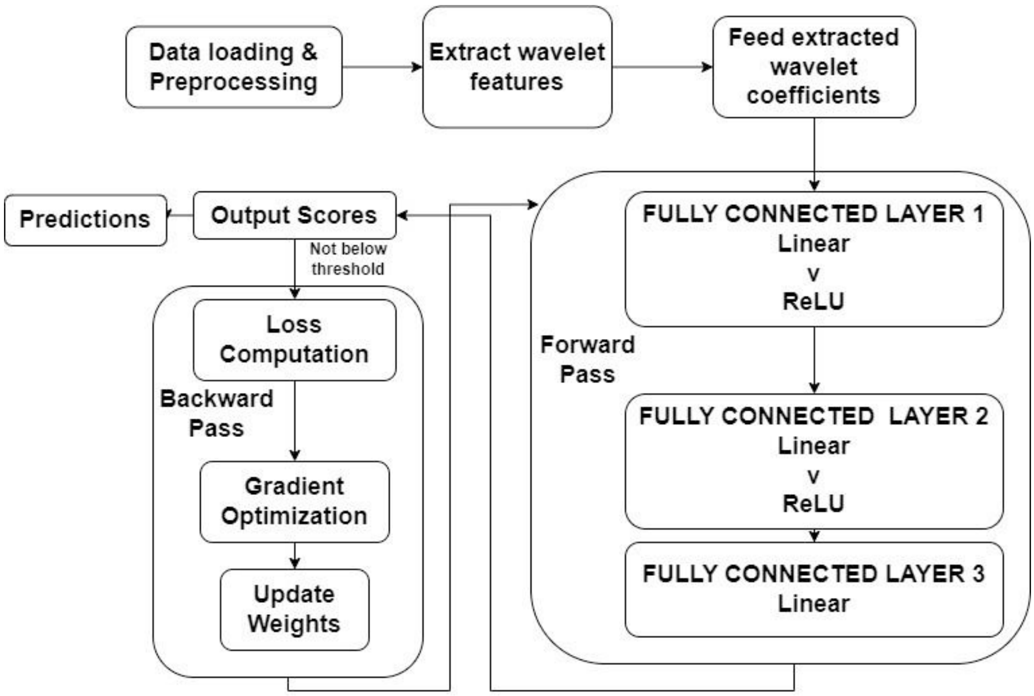


Figure 2: Architecture of proposed model for classification

The proposed method initiates the process of image classification of plant species with inter-class similarity usingy. The decomposition process would result into a list of wavelet coefficients that are flattened and stored as a single feature array. For an image I, the wavelet coefficient is given by (1).

$$W(a,b) = \int_{-\infty}^{+\infty} I(\psi)\ (t).dt \tag{1}$$

where, ψ _(a,b) (t).dt is the wavelet function scaled by a and translated by b and is given by (2).

$$\psi_{a,b}(t)dt = \frac{1}{\sqrt{a}}\psi\frac{(t-b)}{(a)} \tag{2}$$

The decomposition is performed at level two by breaking down the image into different frequency components across two levels of resolution. At each level, the image is decomposed to represent the approximation (low-frequency components) and three detail coefficients (high-frequency components capturing horizontal, vertical, and diagonal details) which is expressed as in (3).

$$I = A_2 + \sum_{i=1}^{2} H_i V_i D_i \tag{3}$$

In (3), A_2, H_i, V_i and D_i represents the approximation, horizontal, vertical and diagonal coefficients. Once the features are extracted, flattening is performed to transform the multi-dimensional wavelet coefficients to one dimensional wavelet coefficients format as suitable for processing by fully connected layers. The flattened features are represented as F given by (4).

$$F=[A_2, H_1, D_1, V_1, H_2, D_2, V_2] \quad (4)$$

The features in (4) implies the first and second level wavelet coefficients.

C. Fully connected layers:

The proposed model is defined with a sequence of three fully connected layers to learn the complex patterns in the wavelet decomposed data. The first fully connected layer is defined as a linear module by assuming input size of feature tensor with size of 512. The feature vector size specifies the number of input features subject to learning through fully connected layers. The first fully connected layer produces an output of size 512 denoting the number of neurons. Each neuron in the fully connected layer calculates a weighted sum of the input features by supplementing a bias term, and then directing through an activation function. Finally, the first fully connected layer transforms the original input data to dimensions of 512 features. Then, the second fully connected layer is defined with input size of 512, which produces an output size of 256. The second layer in turn processes the features and there by reduces the dimensionality of features from 512 to 256 leading to representation of more complex and abstract representations of the data. Following which, there is a third fully connected layer that receives input from the second fully connected layer. The final layer maps the reduced 256 feature map to the number of classes involved in the classification task. The final fully connected layer produces the final output in the form of raw scores (logits) corresponding to each class. These logits can be further processed to determine the predicted class labels. The output scores are then subject to evaluation of error/loss through forward pass to error analysis block. The first fully connected layer is defined with ReLU (Rectified Linear Unit) activation function. The ReLU outputs the input directly in case if the features extracted are positive; otherwise, it outputs zero by introducing non-linearity there by enabling the model to learn complex patterns. Similarly, ReLU is also introduced in second fully connected layer to maintain the non-linearity. The output from the second layer is fed to the third fully connected layer without any activation function to produce the raw scores (logits) for each class in the output layer. The final raw scores are directed to a loss function during training process to evaluate the error and adjust the network weights.

4. Training Process:

During the training phase, the model is subject to rigorous learning process involving a dataset, consisting of 1063 leaf samples. The inputs are preprocessed through resizing, center cropping, tensor conversion, and normalization. The learning rate is one of the critical hyperparameter in training deep learning models. The wavelet features are trained using the Adam optimizer with a learning rate of 0.00001 using CrossEntropyLoss function with 50 epochs. Each epoch involves a forward pass where predictions are made, loss is calculated along with a backward pass for weight updates via backpropagation model. The preprocessed dataset is input for training and testing by application of the transformations including resizing to 256x256 pixels, cropping to 224x224 pixels and then conversion of the images to tensors which results into normalized pixel values. To achieve minimum loss by the model, in the proposed method, the step size of 100 is followed at each iteration to balance the speed of convergence with the learning stability. The Adam optimizer, such as stochastic gradient descent: AdaGrad and RMSProp are employed in the proposed model for training with batch size of 32. As a larger batch size would delay the weight updates per epoch, therefore to speed up the training processand achieve better generalization, a small batch size is considered.

For data sampling, random sampling is employed to split the dataset into training and testing sets with sampling proportions of 80-20. Thus, helping to ensure a balanced overall data distribution by proposed model.

5. Experimental analysis:

To evaluate the experiments based on the proposed model for plant species classification with inter-class similarities, several key metrics are employed. Training and test set accuracy and loss are the key metrics used for analysis. The training loss implies the performance over epochs to measure how well the model is learning from the training data. A decrease in training loss over time indicates that the model efficiency as the learning progresses.

Thetraining accuracy is defined as the percentage of correct predictions made by the model on the training dataset. The higher training accuracy signifies that the efficiency of the model in successfully learning the prominent patterns andfeatures of the leaves. Test accuracy indicate the percentage of correct predictions on the test dataset implying how well the model generalizes to unknown data. The performance metrics of medicinal leaf classification is evaluated using metrics such as precision, recall, and F1-score.

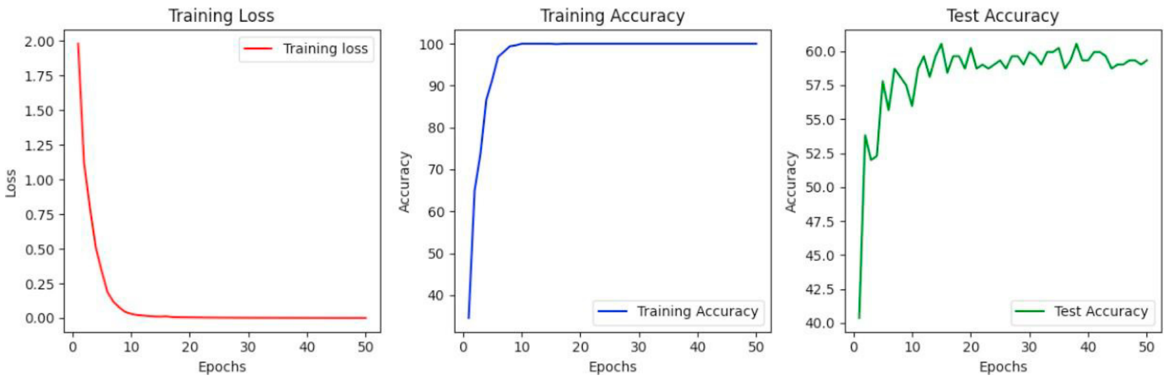
Precision measures the ratio of correctly predicted positive observations to the total predicted positives, the higher precision implies the better model. For instance, the precision of a plant species is 0.60 indicates that 60% of the leaves predicted are actually positive. Then, the recall measures the ability of the model to identify the ratio of correctly predicted positive observations to all observations in the actual class. For instance, the recall of 0.55 for a particular plant species implies the model correctly identifies 55% of all specified species type. Then, the F1-score is the harmonic mean of precision and recall useful to understand model performance when the class distribution is imbalanced. A higher F1-score is always better. Finally, accuracy is the ratio of correctly predicted observations to the total observations. According the defined training procedure, the outcomes obtained by the proposed model is presented in table 2 and figure 3.

From figure 3, it is noticed that HerbSimNet is trained for over 50 epochs to monitor the training loss, training accuracy, and test accuracy. It is observed that the training loss initially is relatively high and showed a steep decline as the training progresses. Eventually, the loss is observed to be plateauing near zero. There exists a rapid decrease in training loss which imply that the model quickly learns the patterns in the training data. Further, training accuracy began to be very low and showed a rapid increase by reaching close to 100% within the first 20 epochs and continued to be consistent for the remaining epochs. The realization of 100% accuracy towards training dataset suggests that the model has learned very well, though there might be an overfitting towards test set. Consequently, the test accuracy showed an upward trend initially and then reaching around 60% and then fluctuating slightly with consistency above 60%. Though there is initial increase of test accuracy, there are fluctuations after 20 epochs and the model is predicting only 60% of predictions as correct. Thus, it is required to improvise the dataset in the classes with few sample sizes to achieve better generalization towards new datasets. As per the table 2, the plant species Bamboo and Peel Kaner both exhibits the highest precision of 0.80, resulting plantspecies classification with few false positives. Similarly, Ganagle and Marigold demonstrate the lowest precision of 0.55 implying more false positives compared to other classes.

With respect to recall, once again Bamboo and Peel kaner both demonstrate the highest recall of 0.85, indicating the model's ability to correctly identify instances of theseclasses. On the other hand, low recall is reported towards the species Alovera and Tumbe indicating that these classeshad more false negatives. Finally, the highest F1-score of 0.82 is reported by Bamboo and Peel kaner signifying a good balance between precision and recall for the proposed classes. It is noticed that, Ganagle and Marigold had reported the lowest F1-score of 0.57 indicating low precision and recall for these classes. Over all, it is noticed that better performance is reported by classes like Bamboo, Peel kaner, and coriander. On the otherhand, classes such as Bermuda Grass, Ginger, and Onion shows a moderate performance and also classes Ganagle and Marigold reported lower performance due to higher inter-class similarity and also small sample size.

Table 2: Performance evaluation results of proposed model

Class label	Class	Precision	Recall	F1-Score
0	Alovera	0.60	0.55	0.57
1	Bermuda Grass	0.65	0.60	0.62
2	Coriander1	0.70	0.75	0.72
3	Ganagle	0.55	0.60	0.57
4	Tumbe	0.60	0.55	0.57
5	Bamboo	0.80	0.85	0.82
6	Euclyptus	0.70	0.75	0.72
7	Ginger	0.65	0.60	0.62
8	Lemongrass	0.75	0.70	0.72
9	Marigold	0.55	0.60	0.57
10	Onion	0.65	0.70	0.67
11	Peel kaner	0.80	0.85	0.82



(a) (b) (c)

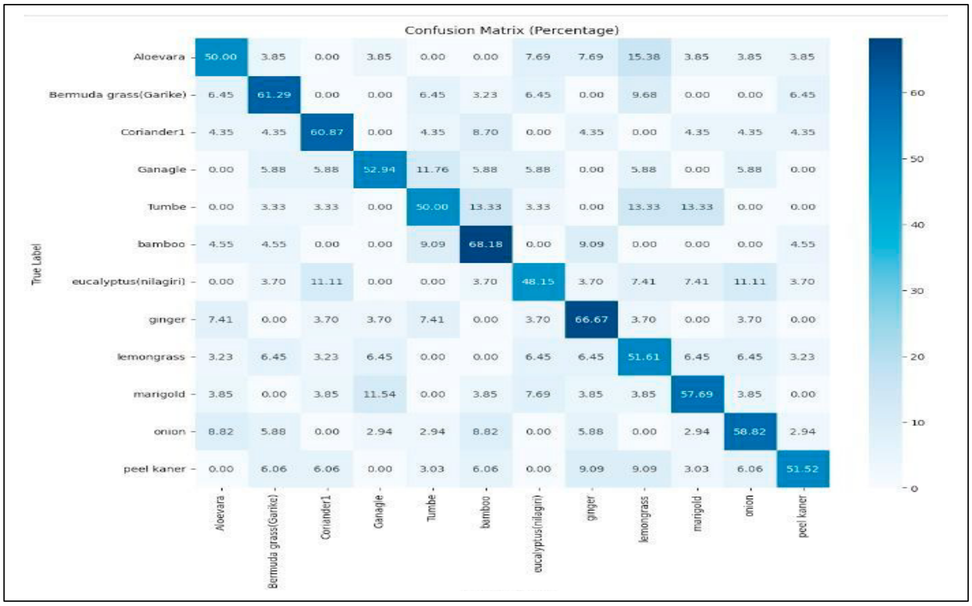


Figure 3: HerbSimNet performance (a) Training loss (b) Training accuracy (c) Test loss (d) confusion matrix of testset

6. Conclusion

The HerbSimNet model exhibits an efficient performance towards the classification of medicinal plant species with high inter-class similarities based on learning from the wavelet features and convolution features. During the experimentations on training data, the model demonstrates high positive performance towards the training data by reporting near-zero training loss. However, the proposed model signifies the indication of overfitting towards the test set implying low generalization capabilities to unseen data. The possible reason for overfitting in the proposed work is due to the small sample size and lack of capturing fine details of image samples. In future, the work can be extended for the development of additional datasets for training. Also, the model is required to be fine-tuned to include techniques such as regularization, dropout, and augmentation of datasets to achieve better generalization and increase the model performance.

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