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Medicinal Plant Recognition Using Shallow Convolutional Neural Network

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Abstract: Ayurvedic medicine plays an essential role in the overall care that is provided for the physical and mental wellbeing of people. It is vital to correctly identify and categorize medicinal herbs to be able to provide better therapy. Medicinal herbs come in a wide variety of forms. It is a challenging task that requires a significant amount of professional medical experience to correctly name and classify the many distinct kinds of medicinal plants. Because of this, having an approach to the identification of medicinal plants that is completely automated is something that is highly desirable. In this study, a straightforward four-layer shallow Convolutional Neural Network (S-CNN) is proposed for the aim of classifying medicinal herbs. The potential utility of S-CNN is evaluated with the help of four distinct leaf datasets such as the Swedish Leaf, Flavia Leaf, MepcoTropicalLeaf Dataset, and Medicinal Leaf Dataset. Our model is capable of achieving a level of classification accuracy of 98.22%, 96.18% and 92.89% on Swedish, Flavia and Medicinal Leaf datasets respectively and that is comparable to that of other state-of-art methodologies in this field.

Keywords: deep learning, CNN, medicinal plant

1. Introduction

Plants play a crucial role in the preservation of life and biodiversity on Earth because they purify the air and water that all forms of life consume. Therapeutic plants are one of the most important plant categories because they are used to treat a wide variety of diseases. The medicinal plant knowledge that has been passed down through generations must be protected and preserved. Numerous individuals, including farmers, foresters, landscape architects, medical professionals, and biologists, benefit from it. Taxonomists, botanists, and plant ecologists have limited control over the identification of plants. Identifying plants using conventional methods, on the other hand, can be difficult and time-consuming [1]. Locating a plant with the required quantity of a medicine is one of the most difficult tasks. Even though herbal medicine does not have negative side effects, a patient's health could be jeopardized if they use an herb that was not prescribed to them. Manually identifying something in this field can be difficult and time-consuming at times. A system for the automated recognition of medicinal plants is required so that people can correctly identify plants used for medicinal purposes. The leaf is the plant part most commonly used for crop identification because it can be obtained at any time of year and is easily recognizable. Both the plant's flowers and its roots are only available for a limited time and can be difficult to acquire. In addition, the leaf is the type of information that is most prevalent in botanical reference collections. The vast majority of a plant's effective medicinal components are found in its leaves.

In the realm of plant leaf identification, the triad of shape, texture, and color stands as the cornerstone. Among the plethora of shape features, aspect ratio [2], simple morphological descriptors [3–5], and polar Fourier transform hold a prominent place [6]. To explore into the intricate details of leaf structure, researchers employ diverse methodologies, with digital morphological analysis being a standout. For instance, Neto et al. [7] harnessed the power of a Probabilistic Neural Network (PNN) classifier to discern plant species, leveraging five geometric parameters: perimeter, physical width, length, area, and leaf diameter. In a similar vein, Wu et al. [2] meticulously categorized 32 variants of green leaves by employing a PNN classifier, honing in on their unique morphological characteristics. As the field advanced, subsequent studies [8, 9] explored deeper into the external attributes of leaves, encompassing shape, venation, margin, and texture. Noteworthy among these endeavors is Kumar's method [10] for identifying Indian medicinal plants. Here, morphological traits took center stage alongside a Multilayer Perceptron (MLP) classifier. Kumar et al. meticulously extracted a plethora of morphological features from leaf images, including major and minor axis lengths, centroid, perimeter, orientation, and solidity. These features, acting as the building blocks of classification, were examined across various classifiers such as Decision Tree, k-NN, Multilayer Perceptron, and AdaBoost MLP [11].

Moreover, the leaves of numerous species share a similar appearance. In this instance, it is not possible to identify the leaf based on its shape, but it is possible to do so based on its texture. Commonly used texture features include Histogram of Gradients [12, 13], Gray-Level Co-Occurrence Matrix (GLCM) [14–18], Local Binary Patterns (LBP) [19–21], and Scale Invariant Feature Transform (SIFT) [22, 23], etc. Chaki et al. [24] identified fragmented images of leaves by combining histograms of fuzzy color and edge texture. Anami et al. [25] presented a classification method for leaves based on the edge histogram, the color histogram, and the leaf area. Bama et al. [26] suggested an efficient texture- and color-based content-based image retrieval method for leaves. In the process of leaf recognition, Gabor filters [27–29], kernel-based principal component analysis [30, 31], and bag of words [32–34] are utilized as additional features. Priya et al. [35] used morphological,

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geometric and vein structural features along with an SVM classifier to obtain 94.20% accuracy. Paithane and Wagh [36] employed the fuzzy c-means algorithm to detect blackarm spots on cotton leaves.

Deep learning facilitates the automation of feature extraction in modern computer systems by first capturing an accurate representation of training data and then constructing a reliable classification model. It has been widely applied in various research domains. Many researchers have employed convolutional neural networks (CNNs) for plant leaf identification [37–44] and disease classification [45, 46]. Zhang et al. introduced a method combining the Bag of Features (BOF) model with a Dual-output Pulse-Coupled Neural Network (DPCNN) for leaf classification [37]. Ahila Priyadharshini et al. [38] addressed the need for accurate identification of Ayurvedic medicinal plants by introducing MepcoTropicLeaf, a publicly available annotated database of Indian medicinal plant leaf images. The authors evaluated various feature extraction methods, including spatial, spectral, and machine-learned features, on a selected set of 50 species from the database. They proposed a six-level Convolutional Neural Network (CNN) that achieves an accuracy of 87.25% using machine-learned features, highlighting the potential of deep learning in medicinal plant identification. Nguyen Thanh et al. proposed a Convolutional Neural Network (CNN) model focused on classifying leaves based on the morphology of leaf veins [39]. Most existing deep learning methods for leaf recognition depend on pre-trained models and transfer learning techniques. The lack of efficient and lightweight classification models for medicinal plant identification presents a significant challenge in preserving traditional medicinal knowledge. To bridge this gap, our study proposes a shallow Convolutional Neural Network (S-CNN) designed specifically for medicinal plant classification. Unlike many existing approaches that rely on deep learning models with high computational requirements, our proposed S-CNN offers a lightweight and efficient alternative, making it more suitable for real-world applications, particularly in resource-constrained environments. The main contributions of this work are as follows:

(1) A four-layer shallow Convolutional Neural Network (S-CNN) is proposed for the classification of medicinal herbs, providing an alternative to complex deep learning models.

(2) The effectiveness of the proposed S-CNN model is assessed using four distinct leaf datasets: Swedish Leaf, Flavia Leaf, MepcoTropicalLeaf Dataset, and Medicinal Leaf Dataset, demonstrating its generalizability.

(3) Unlike many existing approaches that rely on transfer learning and pre-trained deep learning models, this work presents a lightweight, standalone CNN architecture tailored for medicinal plant classification.

(4) The study explores the impact of fine-tuning network parameters, optimizing the model for better classification accuracy.

2. Proposed Methodology

Convolutional neural networks (CNNs), a deep artificial neural network variant, find extensive application in image classification and direct extraction of visual patterns from pixel-based images. The CNN architecture closely mimics the interconnectedness observed in the neural patterns of the human brain. Through the application of suitable filters, CNNs adeptly capture both spatial and temporal dependencies inherent within an image, thereby enabling efficient feature extraction. The shallow CNN architecture utilized in this study is depicted in Figure 1.

The S-CNN comprises four tiers of convolutional layers. Batch normalization is integrated alongside each convolutional layer to stabilize the learning process, consequently minimizing the required training epochs for deep network training. After batch normalization, rectified linear unit (ReLU) activation is applied. Subsequently, average pooling is employed to decrease the dimensionality of the output feature map. The ultimate layer is fully connected, with the number of neurons in this layer determining the class labels.

2.1. Components of the proposed CNN architecture

The first layer in a CNN is always a convolutional layer, which is the building block of CNN. The input to the convolutional layer may be either an input image or an output from the previous layer called feature maps. In this layer, the Convolution operation is performed on input image/feature maps with specific filter, called kernel and results in the output feature maps. The formula for calculating the dimensionality of output feature maps is given in Equation (1).

$$O = \frac{W-K+2P}{S} + 1 \tag{1}$$

where, O is the dimension of output feature map, W is the dimension of input image/feature map, K is the filter size, P is the padding, and S is the stride.

Typically, Low-Level information like edges, colors, gradient directions, and so forth are captured by the first convolutional layer. By adding layers, the architecture adapts to the High-Level features as well, providing us with a network that shares our understanding of the dataset's images.

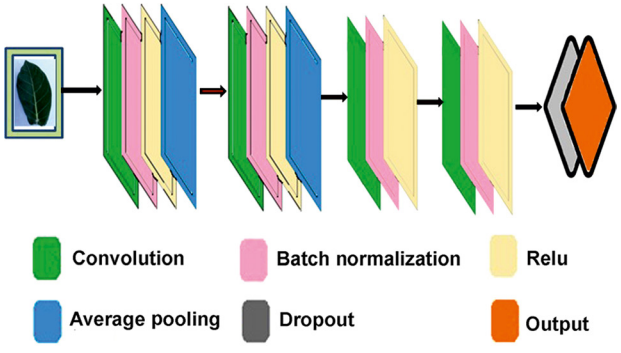
Activation functions play a crucial role in designing convolutional neural networks. They influence how effectively the network learns from the training data, with the choice of activation function in the hidden layers significantly impacting the model's learning process. Moreover, the activation function employed in the output layer dictates the nature of predictions the model can generate. In this study, the activation function utilized is rectified linear unit (reLu), which is mathematically represented by Equation (2).

$$f(x) = \begin{cases} x, & x > 0 \\ 0, & x \leq 0 \end{cases} \tag{2}$$

The rectified linear unit (reLu) function offers computational efficiency by activating only a small fraction of neurons, which effectively reduces the computational load. Its linear and non-saturating characteristics accelerate the convergence of the gradient descent optimization algorithm towards the global minimum of the loss function during training. This means that the network learns more efficiently and effectively, leading to faster convergence and potentially better performance.

Pooling layers, such as average pooling, play a crucial role in reducing the spatial dimensions of the feature maps generated by convolutional layers. This reduction in size not only decreases the computational burden but also helps in capturing the most essential information while discarding redundant details. Additionally, pooling aids in achieving rotational and positional invariance, which means

Figure 1
Proposed CNN architecture



that the network becomes less sensitive to changes in the orientation or position of features within the input data. This property is particularly advantageous for tasks like image recognition, where the same object can appear in different positions or orientations within an image. In the architecture described in the work, average pooling shown in Figure 2 is applied only in the initial two layers. This selective use of pooling ensures that the network retains spatial information adequately for effective feature extraction while still benefiting from dimensionality reduction. By omitting pooling in later stages, the network can preserve more detailed spatial information, which may be crucial for accurately identifying complex patterns in the data.

Figure 2
Average pooling

Batch normalization is a network layer designed to enhance the independent learning capability of each layer. Its primary function is to normalize the outputs from preceding layers. This normalization process involves scaling the activations of the input layer. By incorporating batch normalization, the learning process becomes more efficient, and it can also act as a form of regularization to mitigate model overfitting. In this layer, the activations of each channel are typically normalized by subtracting the mean and dividing by the standard deviation of the mini-batch. Subsequently, the input is adjusted by an offset parameter (β) and scaled by a factor parameter (ϒ). Both these parameters are updated iteratively during the training process. The batch-normalized output (yi) is calculated according to Equation (3).

$$y_1 = \Upsilon\hat{x} + \beta \equiv BN_{\Upsilon,B}(x_1) \tag{3}$$

where, $\hat{x}$ is the normalization of activation x_i which is given by Equation (4)

Figure 3
Sample images from Swedish leaf dataset, one per species

Figure 4
Sample images from Flavia leaf dataset, one per species

$$\hat{x} = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \in}} \quad (4)$$

where ϵ is the constant, μ_B is mini-batch mean and σ_B^2 is mini-batch variance and are given by Equations (5) & (6) respectively.

$$\mu_B = \frac{1}{m}\sum_{i=1}^{m} x_1 \quad (5)$$

$$\sigma_B^2 = \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_B)^2 \quad (6)$$

where, m is the mini-batch size.

Dropout serves as a training technique where randomly chosen neurons are excluded during training. This means that their influence on downstream neuron activations is temporarily removed during the forward pass, and weight updates for these neurons are not applied during the backward pass. Typically, a dropout probability hyperparameter, often set to 0.5, determines the likelihood of deactivation. Following this, the final output needs to be flattened and fed into a standard neural network for classification purposes. Introducing a Fully-Connected layer is a cost-effective method for learning nonlinear combinations of high-level information extracted by the convolutional layer's output. During training, the network receives the flattened output from each round via backpropagation. Employing the Softmax classification technique enables the model to classify images by discerning low-level features prevalent across numerous epochs. The output layer generates an N-dimensional vector, where N corresponds to the number of

Figure 5
Sample images from MepcoTropicLeaf dataset

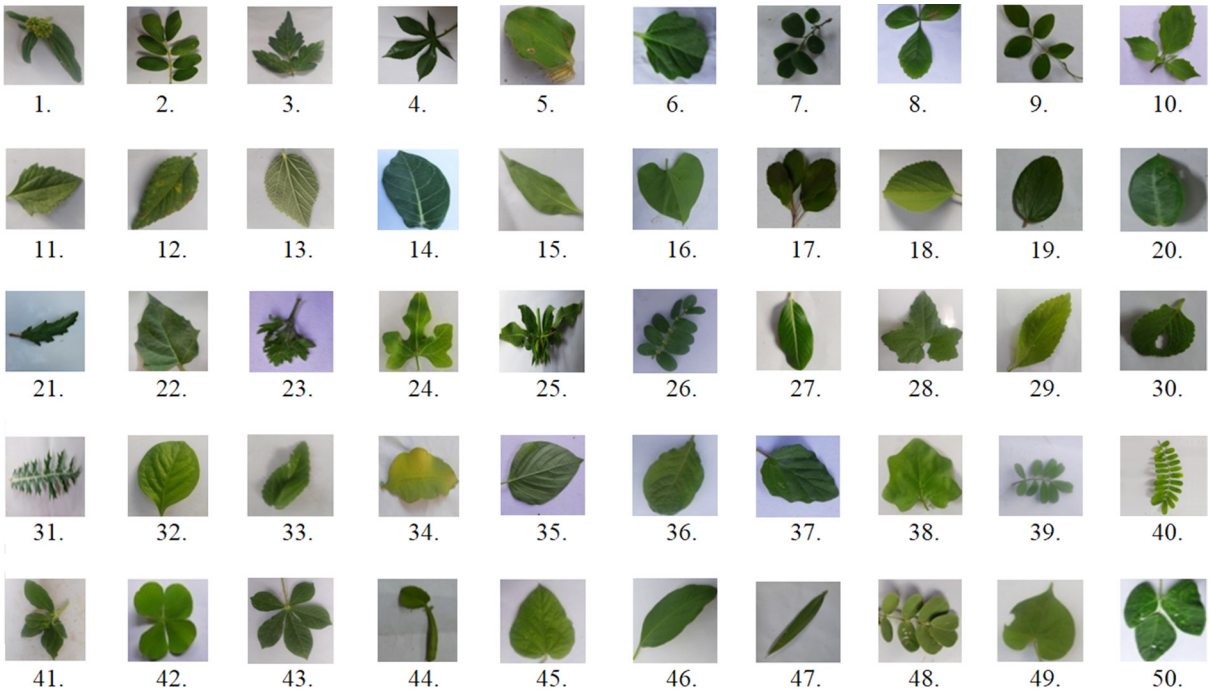


Figure 6
Sample images from Medicinal leaf dataset, one per species

classes. Each element in this vector denotes the probability of a certain class. The class with the highest probability is the identified output. This approach is known as the Softmax classifier, defined by Equation (7).

$$P(y_k/x_k;W) = \frac{e^{S_{y_k}}}{\sum_{\forall j} e^{S_k}} \quad (7)$$

where S_{y_k} is the score vector and is given in Equation (8).

$$S_{y_k} = f(x_k, W)_{y_k} = (Wx_k)_{y_k} \quad (8)$$

The Softmax classifier derives its name from the softmax function, which is used to squash raw class scores into normalized positive values that total to one in order to apply the cross-entropy loss.

3. Datasets Used

The dataset used in this work are Swedish Leaf, Flavia Leaf, MepcoTropicLeaf and Medivinal Leaf dataset

3.1. Swedish leaf dataset

The Swedish leaf dataset, developed through collaboration between Linkoping University and the Swedish Museum of Natural History [47], consists of isolated leaf scans from 15 distinct Swedish tree species against a plain background. Each species comprises 75 individual leaf scans, resulting in a total of 1125 images. Due to the significant similarities between different species, this dataset poses a considerable challenge for classification tasks. Sample images from the Swedish Leaf dataset are displayed in Figure 3.

3.2. Flavia leaf dataset

The Flavia dataset is the most widely used dataset for leaf recognition, with 1907 leaf images of 32 different types. The majority of the leaves in the Flavia dataset, as shown in Figure 4, are common plants in China's Yangtze Delta. There are at least 50 leaves in each species and these leaves are single leaves with petiole removed and have a simple background.

3.3. MepcoTropicLeaf dataset

The first version of the MepcoTropicLeaf dataset [38] as shown in Figure 5, includes 50 distinct plant species that are regularly grown in tropical settings. There are more than 50 leaf images in each species. The database includes both single and compound leaves. To make the database more robust, the frontal and rear views of the leaf images are captured. Also, the dataset contains several broken, diseased leaves and leaves with flowers.

3.4. Medicinal leaf dataset

The dataset contains thirty species of healthy medicinal herbs [48]. The dataset contains 1835 images representing thirty species.

Table 1
Layers of proposed model for Swedish dataset

Layer	Filter size	Output size
Input Layer		160 × 160 × 3
Convolutional Layer 1	3×3	158 × 158 × 8
Batch Norn Layer 1		158 × 158 × 8
Average pooling Layer 1	2×2	79 × 79 × 8
Convolutional Layer 2	3×3	77 × 77 × 16
Batch Norn Layer 2		77 × 77 × 16
Average pooling Layer 2	2×2	38 × 38 × 16
Convolutional Layer 3	3×3	36 × 36 × 32
Batch Norn Layer 3		36 × 36 × 32
Convolutional Layer 4	3×3	34 × 34 × 32
Batch Norn Layer 4		34 × 34 × 32
Output Layer		1 × 1 × 15

Table 2
Recognition accuracy for Swedish leaf dataset with different train–test ratio

Train–test ratio (%)	Recognition accuracy (%)			
	50 epochs	100 epochs	110 epochs	160 epochs
70:30	95.76	92.12	95.15	95.15
80:20	98.10	96.00	98.22	97.33
90:10	95.24	95.24	95.24	95.24

Table 3
Recognition accuracy for different values of momentum

Momentum	Recognition accuracy (%)
0.90	98.22
0.94	97.33
0.96	95.56
0.98	97.33

Table 4
Performance of the architecture with different learning rates

Learning rate	Recognition accuracy (%)
0.001	93.78
0.0001	98.22
0.00001	93.33

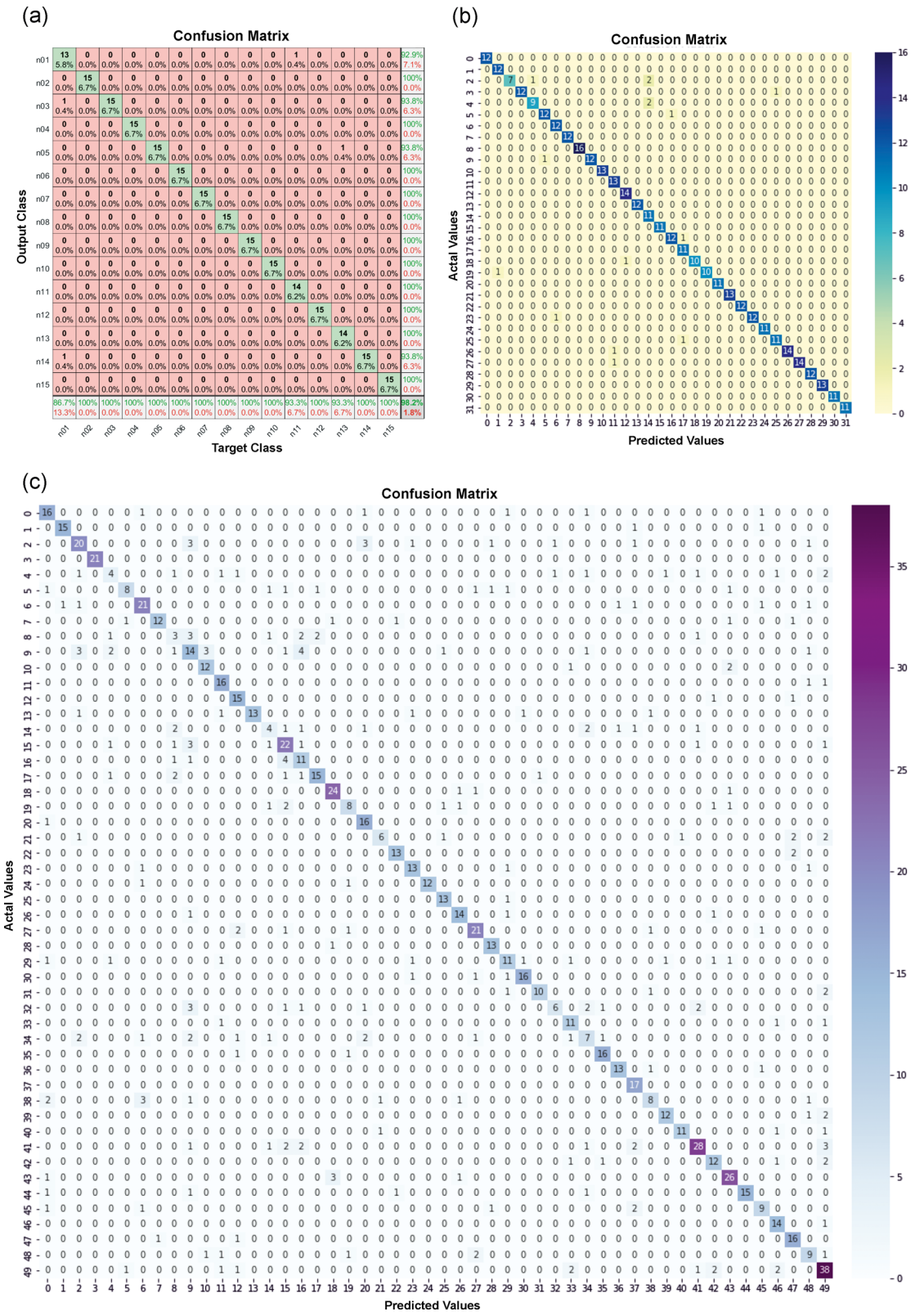
Table 5
Performance comparison of proposed architecture with state of art methods on Swedish dataset

Method	Recognition accuracy (%)
Pattern counting approach [49]	97.07
Zernike moments + HOG [50]	98.13
BOF_DP [37]	97.93
Proposed model	**98.22**

Table 6
Performance comparison of proposed architecture with state of art methods on Flavia dataset

Method	Recognition accuracy (%)
VGG16 [51]	95.00
VGG19 [51]	96.25
GIST [52]	95.50
S-Inception [53]	95.32
Proposed model	**96.18**

Figure 7
Confusion matrix (a) Swedish leaf dataset (b) Flavia dataset (c) MepcoTropicLeaf dataset



Each species comprises sixty to one hundred high-quality images. The harvested leaves are from various plants of the same species found in local gardens. The dataset is comprised of only healthy, mature leaves. The leaf images in the dataset are rotated and tilted slightly to maximize their utility for training machine learning and deep learning models. The sample medicinal leaf images of Medicinal Leaf dataset are shown in Figure 6.

4. Experimental Results and Discussions

This study introduces a medicinal plant recognition approach utilizing a CNN architecture. The experimental setup utilizes the architecture illustrated in Figure 1. The composition of layers in the proposed architecture is detailed in Table 1. The number of neurons in both the Input layer and the output layer fluctuates depending on the image dimensions and the quantity of species present in the datasets.

Initially, the experimentation is carried out using Swedish leaf dataset. The images are resized to 160 × 160 for the experimentation purpose. First, to fix the number of epochs, the experimentation is carried with different train and test ratio. The learning rate is fixed as 0.0001. The mini batch size is 16. The optimizer used is Stochastic Gradient Descent (SGD) with momentum. The problem with SGD is that we cannot raise the learning rate when it tries to reach minima due to the high oscillation. So, convergence takes time. While incorporating momentum with SGD, exponentially weighted averages are used to compute Gradient which is then used to update the parameter. During experimentation data augmentation such as reflection and translational augmentation are carried out only for training images. The pooling used is average pooling. The recognition accuracy for Swedish leaf dataset with different train test ratio is shown in Table 2. The highest recognition accuracy is shown in bold. The formula for accuracy is shown in Equation (9).

$$Accuracy = \frac{\#\ correctly\ classified\ leaf\ images}{Total\ number\ of\ leaf\ images} \tag{9}$$

From Table 2, it is inferred that, the highest recognition accuracy is obtained at 110 epochs with train–test ratio of 80:20. So, further experimentation is carried with this specification. Momentum causes gradient vectors to accelerate in the right directions, resulting in faster convergence. Rather than relying solely on the current step gradient to lead the search, the momentum gathers prior step estimates to discover a path to convergence. As a result, both training speed and accuracy are frequently improved. The recognition accuracy for different values of momentum is depicted in Table 3.

Table 3 shows that better performance is obtained for the momentum of 0.90. Then the experimentation is repeated by changing the optimizer as Adaptive Moment (ADAM) and we got the accuracy as 96.44% which less when compared to SGD with momentum. Again, the experimentation is carried out by varying the learning rate and the performance is depicted in Table 4.

From Table 4, it is inferred that, good performance is achieved with learning rate η=0.0001. By keeping this learning rate, the experimentation is repeated by changing the pooling method to max pooling and the accuracy obtained is 93.78% which is less compared to average pooling. The performance of our own architecture on Swedish dataset is compared with other state of art methods and is given in Table 5, and our performance is comparable with others.

Table 7
Recognition accuracy of Medicinal leaf dataset for different epochs

Epochs	Recognition accuracy (%)
100	89.47
200	92.37
300	92.37
400	92.11
500	92.89
600	92.37
700	90.79
800	86.84

In order to study the proficiency of the proposed 4-layer architecture, the experimentation is carried on Flavia leaf dataset. With 400 epochs, we got the accuracy as 96.18%. The performance of the proposed architecture with the existing methods for Flavia dataset is shown in Table 6. It is observed that the performance of our method is comparable with others.

Further the experimentation is carried out using MepcoTropicLeaf dataset. With 700 epochs, we got the accuracy as 72.54%. Ahila Priyadharshini et al proposed a 6 layer network for the same dataset and got the accuracy as 87.5% [38]. It is inferred that the deep layer architecture with less number of layers perform well for the database having simple background. The Swedish and Flavia dataset have simple backgrounds and single leaves whereas the background in MepcoTropicLeaf dataset is complex and moreover it has compound leaves. More specific features are learnt of higher layers. So, CNN with more layers perform well for MepcoTropicLeaf dataset. The confusion matrices obtained during testing in the proposed CNN for the three datasets are shown in Figure 7. In the case of MepcoTropicLeaf dataset, the classes Belly ache Bush, Bristly White grape, Green Chireta, Night Blooming cereus and Rosary Pea are confused.

Finally, the experiment is conducted using the Medicinal leaf dataset. In Table 7, the recognition accuracy obtained for various epochs is tabulated, with the highest accuracy highlighted in bold. Figure 8 depicts the feature maps obtained at various convolutional layers, and it can be inferred that the feature maps of deeper layers represent more specific characteristics. Table 8 displays the performance metrics of the Medicinal Leaf dataset over 500 epochs.

5. Conclusion

This study introduces a lightweight CNN model but also demonstrates how AI-driven classification can be effectively integrated into ethnobotanical research. This highlights the potential for deep learning in traditional medicinal knowledge preservation—an area that has received limited attention in existing literature. The method focuses on effectively capturing both local and global features of medicinal plant leaves. Additionally, the study thoroughly examines the CNN's performance by adjusting key parameters such as learning rate and momentum. To evaluate its effectiveness, the proposed architecture is compared against several leading methods across four diverse medicinal plant leaf datasets. Ultimately, this research contributes to the preservation of traditional medicinal knowledge by providing a user-friendly tool for

Figure 8

Feature maps (a) sample image (b) 8 maps of layer 1 (c) 16 maps of layer 2 (d) 32 maps of layer 3 (e) 32 maps of layer 4

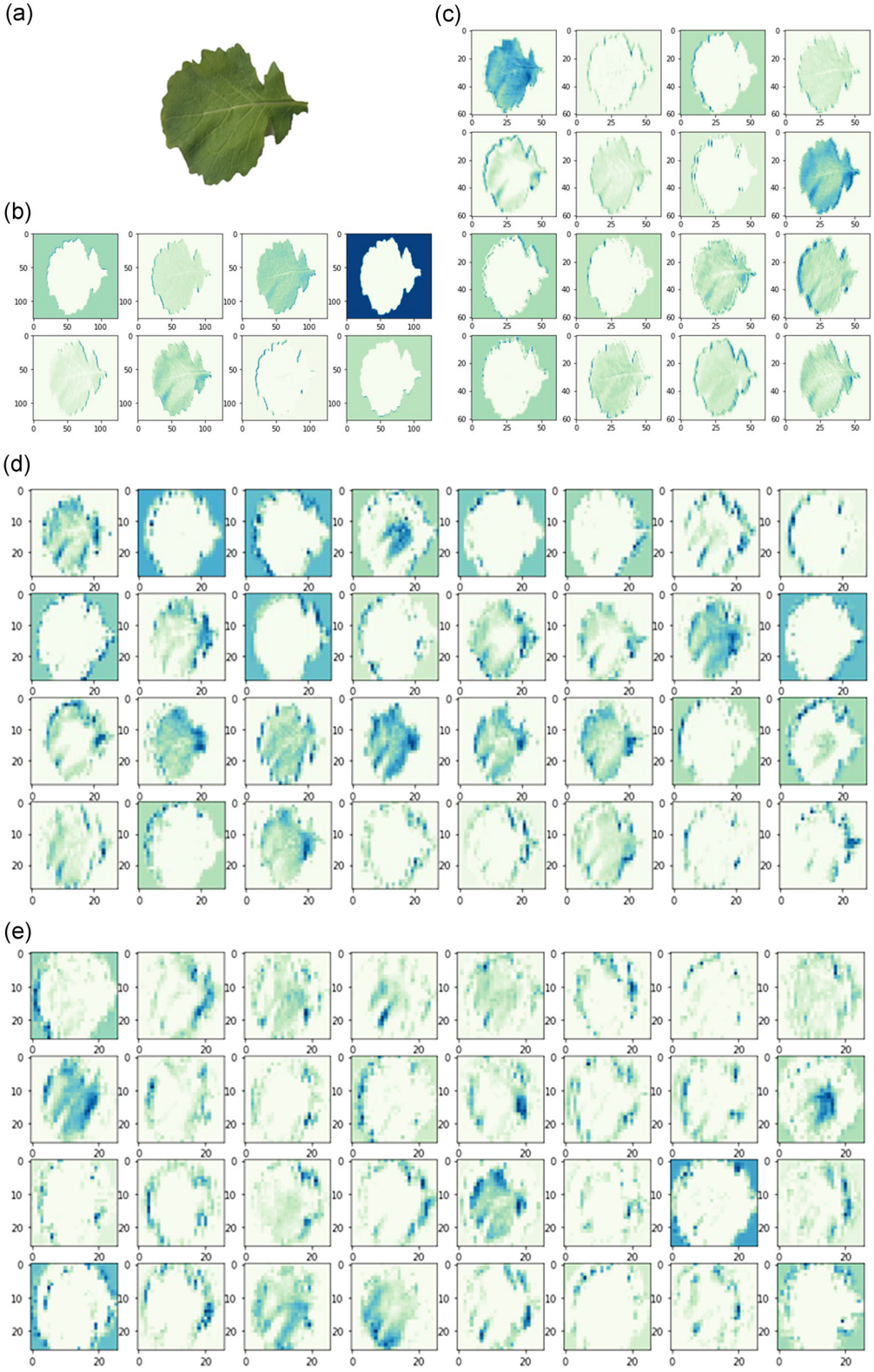


Table 8
Performance measures of Medicinal leaf dataset for 500 epochs

Medicinal plant	Precision	Recall	F1-score
Alpinia galanga (Rasna)	1.00	1.00	1.00
Amaranthus viridis (Arive-Dantu)	0.96	0.88	0.92
Artocarpus heterophyllus (Jackfruit)	0.86	1.00	0.92
Azadirachta indica (Neem)	1.00	0.75	0.86
Basella alba (Basale)	0.87	0.95	0.91
Brassica juncea (Indian Mustard)	0.78	1.00	0.88
Carissa carandas (Karanda)	0.88	1.00	0.94
Citrus limon (Lemon)	1.00	0.83	0.91
Ficus auriculata (Roxburgh fig)	0.78	0.70	0.74
Ficus religiosa (Peepal Tree)	1.00	1.00	1.00
Hibiscus rosa-sinensis	0.82	1.00	0.90
Jasminum (Jasmine)	0.93	0.87	0.90
Mangifera indica (Mango)	1.00	1.00	1.00
Mentha (Mint)	1.00	1.00	1.00
Moringa oleifera (Drumstick)	1.00	0.94	0.97
Calabura (Jamaica Cherry-Gasagase)	1.00	1.00	1.00
Murraya koenigii (Curry)	1.00	0.75	0.86
Nerium oleander (Oleander)	1.00	1.00	1.00
Nyctanthes arbor-tristis (Parijata)	0.89	1.00	0.94
Ocimum tenuiflorum (Tulsi)	0.91	0.91	0.91
Piper betle (Betel)	0.90	0.90	0.90
Plectranthus amboinicus (Mexican Mint)	0.77	1.00	0.87
Pongamia pinnata (Indian Beech)	0.87	1.00	0.93
Psidium guajava (Guava)	1.00	1.00	1.00
Punica granatum (Pomegranate)	0.94	0.94	0.94
Santalum album (Sandalwood)	1.00	0.92	0.96
Syzygium cumini (Jamun)	1.00	0.75	0.86
Syzygium jambos (Rose Apple)	1.00	1.00	1.00
Tabernaemontana divaricata (Crape Jasmine)	0.77	0.83	0.80
Trigonella foenum-graecum (Fenugreek)	1.00	0.88	0.93

identifying and categorizing therapeutic plants. The model's lightweight design enables its seamless integration into mobile or handheld devices for real-time identification of medicinal plants. This holds significant practical value for researchers, herbalists, and conservationists operating in remote areas.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in Swedish Leaf Dataset at https://www.cvl.isy.liu.se/en/research/datasets/swedish-leaf/, reference number [47]; in Medicinal Leaf Dataset at https://data.mendeley.com/datasets/nnytj2v3n5/1, reference number [48].

Author Contribution Statement

Ramar Ahila Priyadharshini: Conceptualization, Methodology, Software, Validation, Investigation, Data curation, Writing - original draft, Visualization, Supervision, Project administration. **M. Arun:** Software, Formal analysis, Data curation, Writing - review & editing, Visualization.

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