big data and cognitive computing

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PSR-LeafNet: A Deep Learning Framework for Identifying Medicinal Plant Leaves Using Support Vector Machines

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Abstract: In computer vision, recognizing plant pictures has emerged as a multidisciplinary area of interest. In the last several years, much research has been conducted to determine the type of plant in each image automatically. The challenges in identifying the medicinal plants are due to the changes in the effects of image light, stance, and orientation. Further, it is difficult to identify the medicinal plants due to factors like variations in leaf shape with age and changing leaf color in response to varying weather conditions. The proposed work uses machine learning techniques and deep neural networks to choose appropriate leaf features to determine if the leaf is a medicinal or non-medicinal plant. This study presents a neural network design based on PSR-LeafNet (PSR-LN). PSR-LeafNet is a single network that combines the P-Net, S-Net, and R-Net, all intended for leaf feature extraction using the minimum redundancy maximum relevance (MRMR) approach. The PSR-LN helps obtain the shape features, color features, venation of the leaf, and textural features. A support vector machine (SVM) is applied to the output achieved from the PSR network, which helps classify the name of the plant. The model design is named PSR-LN-SVM. The advantage of the designed model is that it suits more considerable dataset processing and provides better results than traditional neural network models. The methodology utilized in the work achieves an accuracy of 97.12% for the MalayaKew dataset, 98.10% for the IMP dataset, and 95.88% for the Flavia dataset. The proposed models surpass all the existing models, having an improvement in accuracy. These outcomes demonstrate that the suggested method is successful in accurately recognizing the leaves of medicinal plants, paving the way for more advanced uses in plant taxonomy and medicine.

Keywords: medicinal leaf plants; convolutional neural network; gray-level co-occurrence matrix; PSR-LeafNet; support vector machine

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Citation: Sekharamantry, P.K.; Rao, M.S.; Srinivas, Y.; Uriti, A. PSR-LeafNet: A Deep Learning Framework for Identifying Medicinal Plant Leaves Using Support Vector Machines. *Big Data Cogn. Comput.* **2024**, *8*, 176. https://doi.org/10.3390/bdcc8120176

Academic Editors: Praneel Chand, Mansour Assaf, Mohammad Dabbagh and Nandini Sidnal

Received: 18 October 2024
Revised: 26 November 2024
Accepted: 27 November 2024
Published: 1 December 2024

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1. Introduction

Plants play a crucial role in maintaining human health by providing essential resources such as food and oxygen. Due to their significance, researchers and the agricultural breeding industry are dedicating substantial efforts to ensure agriculture's long-term sustainability and efficiency [1]. A thorough understanding of plants is necessary to identify new, unusual, or uncommon species contributing to environmental preservation, pharmaceutical advancements, and agricultural productivity. Accurately identifying plant species is critical for several reasons, such as environmental conservation, pharmaceutical advancements, and agricultural productivity. Proper identification helps in conserving biodiversity and protecting ecosystems. Many plants have medicinal properties, and recognizing these plants can lead to the discovery of new drugs. Additionally, identifying and understanding plant species can enhance crop yields and sustainability [2].

One of the primary challenges in computer vision is identifying and learning about objects in images [3,4]. Plant recognition involves distinguishing subtle variations in leaf, flower, and fruit features. Researchers have developed numerous state-of-the-art methodologies using deep learning to automate this process [5,6]. Most of these methodologies focus on unique variations in leaf features. However, fewer attempts have been made to extract local characteristics from other plant parts. Several databases have been established for plant recognition research, including the Flavia database, which contains images of various leaf species; the Swedish Leaf database, which includes images of leaves from 15 distinct Swedish tree classes; the MalayaKew database, which features images of plants found in Malaysia; and the Intelligent Computing Laboratory (ICL) database, which comprises various plant species images. Despite the availability of these databases, a considerable amount of work still needs to be done to recognize and forecast plant species for different applications.

Researchers have investigated several different ways to recognize plants. O.S. Oderkvist [7] looked at 15 different types of Swedish trees and used backpropagation for the feed-forward neural network (FFNN) to obtain information about the leaf shape and moment properties. The regional contrast and additional factors were selected to characterize the vein's surrounding pixel properties. Deep neural networks are designed for bamboo plant classification [8]. This model can be studied and used for plant leaf classification. Islam et al. [9] suggested a combination of deep learning and machine learning techniques for identification of Bangladeshi medicinal plant identification. Pushpa et al. [10] proposed an unbiased lightweight deep convolutional neural network for Indian Ayurvedic plant species classification, and the accuracy results achieved were 92.27%. Deep convolutional neural networks (DCNN) are necessary to apply image classification techniques to recognize various characteristics of a picture. We need to increase the resolution of images to enhance their quality. Deeper neural networks result from this, and as recent studies have demonstrated, it becomes crucial to increase the layers that are stacked in the network [11]. According to Song et al. [12], species classification is carried out utilizing hyper-spectral leaf information using machine learning algorithms.

This section provides different types of feature extraction methods, classification models, and deep learning models discussed by various authors. In image processing, extracting features like texture, shape, and color is one of the essential aspects. Wang et al. [13] discussed the taking out of texture features which contain a sequence of entropy. Ghosh et al. [14] emphasized the ideal identification and classification of plants for medicinal use using deep learning approaches. Reddy et al. [15] utilized optimized convolutional neural networks for the identification of plant species from leaf images. Quach et al. [16] processed a neural network-based encoder and support vector machine classifier to recognize leaves. This approach extracts a refined color image, vein image, xy-projection histogram, handcrafted shape, texture features, and Fourier descriptors.

For the classification of tea leaves, Tang et al. [17] utilized local binary pattern-based texture descriptors. A hybrid structure to promote the recognition of plants with complex backgrounds was presented by Fu et al. [18]. The block local binary pattern (LBP) operators were found as the texture features, and as the shape features, they computed the Fourier descriptors. For the leaf recognition, 11 form characteristics were incorporated, seven statistical features were used, and five vein features were identified [19]. Chaki et al. [20] employed the gray-level co-occurrence matrix (GLCM) and Gabor filter to describe the texture feature. A collection of invariant moments and a set of coefficients from the curvelet transform were used to capture the shape feature. Supervised global locality preserving projection (SGLP), a unique manifold learning technique for plant leaf recognition, was introduced by Shao et al. [21]. Narmada et al. [22] employed a multilayer perceptron and a dense convolutional neural network (DenseNet) to identify some of the diseases in rice crops with the help of a leaf image. The rice disease detection model's maximum classification accuracy was 96.68%. Wang et al. [23] suggested a methodology, i.e., MobileNet and an attention-based neural network, for the purpose of identifying the disease in rice crops with the help of leaf images. Based on test data, the detection of rice crop disease with the help of input leaf data has successfully categorized the conditions with an accuracy of 94.65%.

A VGG16Net-based model for identifying rice and wheat leaf disease was implemented by Jiang et al. [24], which identified the disease in wheat leaf with an accuracy of 98.7%, and the disease in rice was 97.2%. They contrasted the model's performance with other transfer learning strategies in the identification of diseases with the help of leaf data affecting wheat and rice.

Comparably, employing U-Net architecture by Wang et al. [25] presented a model to attain the severity rate of cucumber leaf disease and obtained 92.85% testing accuracy on a leaf dataset that was associated with cucumber disease. Lin et al. [26] proposed a method for diagnosing mildew sickness in pumpkins using pumpkin leaves. The method involves the use of principal component analysis (PCA) and support vector machines (SVMs). The model accurately detected the presence of pumpkin powdery mildew on the pumpkin leaf with a precision rate of 97.3%. Caldaiera et al. [27] suggested utilizing a Resnet50 transfer learning technique to develop a model for detecting cotton lesions. With a classification accuracy of 89.2%, the model outperformed GoogleNet and conventional machine learning methods. To further balance the data counts in the dataset's classes, a super-resolution generative adversarial network (SR- GAN) as a strategy of augmentation was implemented by Cap et al. [28]. The critical factor in identifying diseases or any other plants is first identifying the leaf appropriately. Based on the models discussed, medicinal leaf identification has emerged, which is useful for living beings. Rajesh et al. [29] investigated the usage of five popular machine learning classifiers for classifying leaf images. The classifiers are k-nearest neighbor (kNN), support vector machine (SVM), logistic regression (LR), naive Bayes (NB), and random forest (RF). They are a more comprehensive range of features that can be extracted from the leaf, including length, breadth, area, perimeter, mean, average contrast, correlation, and dissimilarity. The machine learning classifier is tested on different datasets like Flavia, Swedish, and folio. The author illustrated that the SVM classifier achieved higher accuracy in his study. Wei Tan et al. [30] presented D-Leaf, a novel CNN-based technique. Six layers made up the D-Leaf model: a softmax classification layer, three fully linked layers, and three convolution layers. The results obtained by the author using the suggested model were 90.4% accuracy for the MalayaKew dataset (MKDS) and 94.6% for the Flavia dataset (FDS) and the Swedish leaf dataset (SLDS). A. Kaya et al. [31] investigated different combinations of deep learning techniques, i.e., AlexNet and VGG16, to extract the features. These deep learning models combine with classifiers like SVM, recurrent neural network (RNN), and linear discriminant analysis (LDA). The results show that VGG16 with an RNN classifier reached an accuracy of 99.1% for SLDS. AlexNet and LDA reached an accuracy of 96.2%. S. Anubha Pearline et al. [32] studied plant species identification by applying deep learning techniques and conventional methods. The conventional approach comprises feature extraction for shape, texture, and color. The deep learning techniques for extracting features are VGG16, Inception-v3, VGG19, and Inception-ResNet-v2. These networks are combined with various categories of classifiers. The findings indicate that VGG16 and LR have an accuracy of 97.1% for the Leaf12 dataset. The outcomes demonstrated that VGG16 using logistic regression obtained 97.14% accuracy for the Leaf12 dataset, 96.5% for SLDS,96.3% for folia, and 99.41% for FDS.

A multi-path multi-convolutional neural network (MPMCNN) has been suggested by Riaz et al. [33] for facilitating plant species recognition. The layers in this model used are multi-CNN blocks, pooling, flattening, and a softmax layer for classification. The ultimate distinguishing attributes were acquired by combining the qualities from each block and consolidating the concatenated outcomes. Convolution filters with sizes of 5×5, 3×3, and 1×1 were used in all blocks of the MPM-CNN architecture. The max-pooling layers also used a 3×3 filter size. The MPM-CNN attained 98.71% accuracy on the MKDS. Hybridization of machine learning algorithms was introduced by Srinivasrao et al. [34] to classify medicinal plants. The accuracy achieved by combining CNN and SVM was 97%. M. Rao et al. [35] utilized the combination of CNN and the Gaussian mixture model (GMM) to identify medicinal plants. By offering the Urban Planter dataset, Litvak et al. [36] have recently contributed to plant species categorization. Using this dataset, researchers evaluated several CNN models that had previously been trained to categorize plant species. The data included 1500 photos divided into 15 categories corresponding to different plant species. Moreover, the authors used the ImageNet and Oxford102 datasets to examine how various pre-training strategies affected the models. The results of the trial demonstrated the effectiveness of the DenseNet-201 model, which was pre-trained on the ImageNet dataset, could obtain a maximum accuracy of 96% when using the Urban Planter dataset. Rao Marada et al. [37] utilized a machine learning algorithm to identify Ayurvedic plants. Many methodologies and strategies have been investigated in the current plant classification study to provide classification findings that show promising results. Research has employed a range of techniques for plant species recognition, including CNN models, pre-trained methodologies, feature extraction methods, dimensionality reduction like independent component analysis (ICA), LDA, PCA, and various classifiers like SVM, decision tree, KNN, and deep learning. Irrespective of plant leaf processing, Tsourounis et al. [38] performed image classification using CNN-Dense SIFT descriptors and achieved an accuracy of 89.9%. Abdul Hussain et al. [39] proposed a block-processing feature extraction model for image processing. In [40], Ramaha et al. proposed a classification model based on SVM-LBP-HOG and achieved an accuracy of 97%. Even though plant categorization has come a long way, research gaps may still be filled to increase accuracy. Due to the lack of identification of medicinal plants, the use of medicinal plants is not effective, and the corresponding treatment is being delayed. To overcome the problem, the proposed work developed a robust deep learning-based framework for leaf identification that is capable of classifying plant species from images of leaves. The system should effectively handle variations in leaf appearance, extract distinctive features, and provide accurate species predictions across a diverse dataset so that we can use the proper medicinal plant for its corresponding treatment.

To address these challenges, we have developed the PSR-LeafNet model. Three different types of networks are created and integrated into a single deep learning model employing Inception v2 networks, named PSR-LeafNet. The integration of multi-network features using the minimum redundancy maximum relevance (MRMR) technique is the main innovation of this work. This strategy guarantees the selection of exceptionally relevant and non-redundant features, substantially improving PSR-LeafNet's efficiency. This model is designed for the recognition of medicinal plants, utilizing datasets such as the FDS, MKDS, and an Indian medicinal plant dataset (IMPDS), which include various medicinal leaves. PSR-LeafNet addresses critical challenges in plant recognition, such as improving image resolution and overcoming the vanishing gradient problem. Its application spans environmental conservation, pharmaceutical research, and agricultural productivity enhancement. By accurately identifying medicinal plants, PSR-LeafNet contributes to preserving biodiversity and advancing medical science.

The contribution of this research is as follows:

1. Optimizing the accuracy of leaf identification by using P-Net, S-Net, and R-Net to extract several feature types from the leaf images;
2. Integrate multiple networks into a single model to overcome current challenges in plant image recognition with the PSR-LeafNet model.
3. Integrating an SVM classifier with PSR-LeafNet to classify medicinal plant species and assess the model's performance with pre-existing plant image datasets.

In this work, a combination of deep learning, which is PSR-LeafNet, and a machine learning classifier, i.e., SVM, is utilized and helps improve the accuracy rate in the identification of leaf disease from three different datasets. The discussion below provides the process flow of the proposed model as shown in Section 2. The experimental results evaluated are discussed in Section 3. In Section 4, the overall conclusion of the work is presented.

2. Materials and Methods

The proposed methodology integrates three robust network approaches—P-Net, S-Net, and R-Net—to extract the features of the leaf images. The extracted features are combined into a single network using the MRMR technique, and an SVM classifier is used to predict and classify the medicinal and non-medicinal plants. Three datasets, the Flavia, MalayaKew, and the Indian Medicinal Plant (IMP), were used to assess the suggested approach.

2.1. Dataset Acquisition

Regarding computer vision and machine learning leaf classification tasks, the Flavia dataset is considered the standard. These pictures of different leaf types can be used to train and evaluate algorithms that identify and categorize them. Beikmohammadi et al. [41] produced Flavia, a well-liked dataset for leaf identification. Covering 32 different species, it contains 1907 photos of leaves. Every picture has a resolution of 1600 × 1200 pixels. Figure 1 displays some leaf pictures from the Flavia dataset (FDS). In it, you may see pictures of leaves from various plants. Leaf silhouettes on white backgrounds are standard for these images, as they facilitate the categorization process. The dataset represents a variety of animal species. Each grouping stands for a distinct flora species. Researchers extensively develop and test image processing, feature extraction, and machine learning techniques for plant species identification. Shape, texture, color, and vein patterns are some of the characteristics that researchers commonly extract from leaf photos to conduct species classification. This dataset can be used to train ML models to classify different kinds of leaves, test out new approaches to computer vision and image processing, or to compare how different methods classify leaves.

Figure 1. Illustrations of Flavia dataset images.

Along the same lines as the Flavia dataset, the MalayaKew dataset aims to classify leaves and identify different types of plants. Notably, it excels in more complicated and diverse settings, which makes it a suitable fit for more realistic and robust plant classification jobs. The collection includes pictures of leaves from many kinds of plants. Unlike the Flavia dataset, which typically contains photographs taken in artificial settings, the MalayaKew dataset frequently contains images taken in natural settings, which might have a wide range of backdrops and lighting conditions. The dataset includes a diverse array of plant species. For the purposes of training and evaluation, each species or class represents a distinct species. We utilized the MalayaKew (MKDS) leaf dataset from the Royal Botanic Gardens in Kew, England. In this collection, you can find leaf scans from 44 different classes. It is difficult to classify this dataset because the leaves of numerous species are similar. Figure 2's lower section shows a selection from this leaf dataset. For machine learning and computer vision leaf classification tasks, the Flavia dataset is the gold standard. We develop and test algorithms for leaf recognition and classification using the dataset, which contains photos of various leaf species. Beikmohammadi et al. [41] introduced Flavia, a popular dataset for leaf identification. The dataset includes a total of 1907 leaf photos, representing 32 different species. Each image has a resolution of 1600 × 1200 pixels. Figure 1 displays a selection of leaf photos from the Flavia dataset (FDS). It contains images of leaves from various plant species. To make the classification work easier, each image usually only has a leaf on a white backdrop. The collection contains information about a variety of animals. Each species or class represents various plant species. It is heavily used in research on plant species identification systems involving image processing, feature extraction, and machine learning. To identify different species of leaves, researchers commonly use image analysis techniques that extract characteristics including shape, texture, color, and vein patterns. You may use this dataset to train ML models to classify different kinds of leaves, test out new approaches to computer vision and image processing, and compare how well different methods classify leaves.

Figure 2. Illustrations of MalayaKew dataset images.

The Indian Medicinal Plant dataset is a collection of images and data related to various medicinal plants found in India. This dataset is used for research and development in botany, pharmacology, and computer vision, particularly for identifying and classifying medicinal plant species. Images of medicinal plants may be found in the IMP dataset's collection. The dataset consists of images of medicinal plants, including leaves, flowers, fruits, and other parts. The images are usually accompanied by metadata, such as species names, common names, medicinal uses, and other relevant botanical information. The pictures are taken in an unrestricted atmosphere with a variety of backgrounds. In real time, 6900 samples were captured using cell phones, comprising 5900 images of 40 distinct plant species and single-leaf photographs of 80 different plant species. The datasets offered may be helpful to researchers investigating the development of algorithmic models based on image processing, machine learning, and profound learning principles to educate people about medicinal plants. Examples of IMP dataset images are shown in Figure 3.

Figure 3. Illustrations of Indian Medicinal Plant dataset images.

2.2. Augmentation of Data

Preparation of data is a critical task before performing deep learning operations. Preprocessing, data augmentation, and data gathering are all included. The samples considered for pre-training should be in equal numbers. For better performance of the feature extraction and classification algorithms, the preprocessing of data is very important. In this model, data augmentation is the preprocessing stage. This study employed data augmentation techniques to boost the sample size without gathering more data. The dataset was augmented by applying various procedures, including rotation, affine transformation, padding, saturation adjustment, flipping, hue modification, and cropping. The data augmentation process equalized the number of images in each class. Following the augmentation phase, the dataset was partitioned into subsets for training, validation, and testing. The dataset's photos were randomly chosen using shuffling for the purposes of training, validation, and testing.

Various effects for data augmentation, such as rotation, brightness reduction, brightness enhancement, motion blur, and Gaussian noise, have been considered in this work. Figure 4 displays some example images of data augmentation. We have applied the following preprocessing to enhance the images:

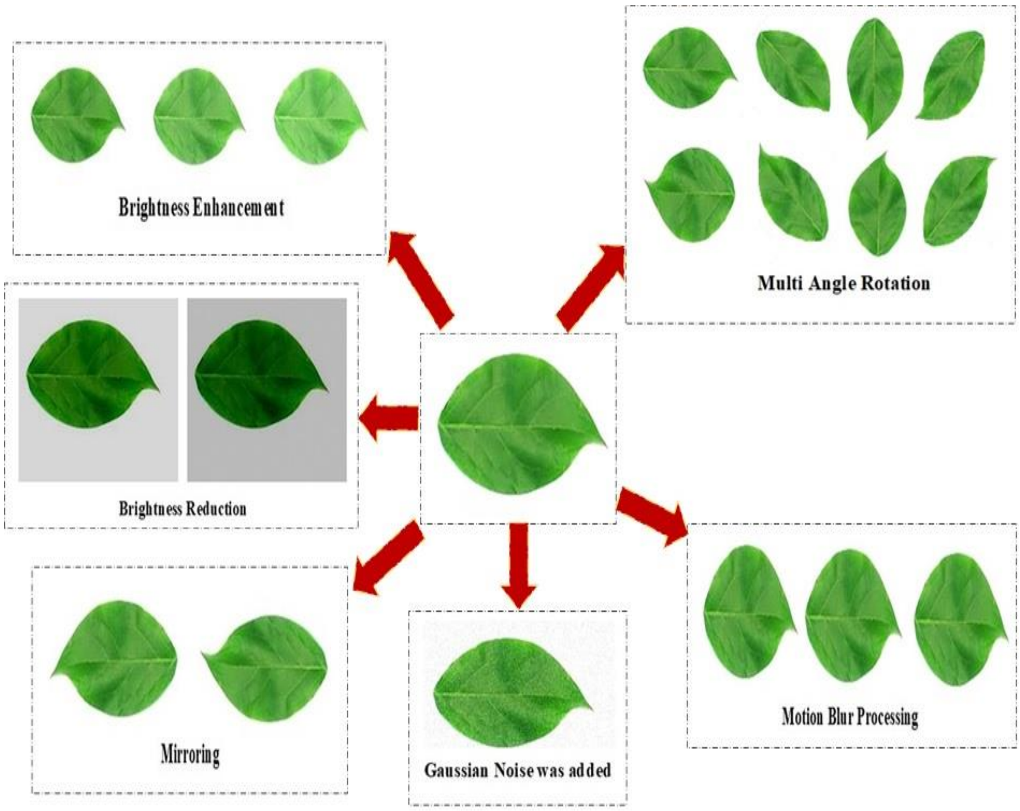


Figure 4. Data augmentation process.

2.3. PSR-LeafNet (PSR-LN) Network Model

Combining deep learning and machine learning is more beneficial to solving overfitting problems. There is a need to increase the amount of training data to achieve the best results. Extracting features from the datasets using deep convolutional networks combined with a support vector machine classifier helps predict the class labels in a newer domain. The proposed work model is shown in Figure 5.

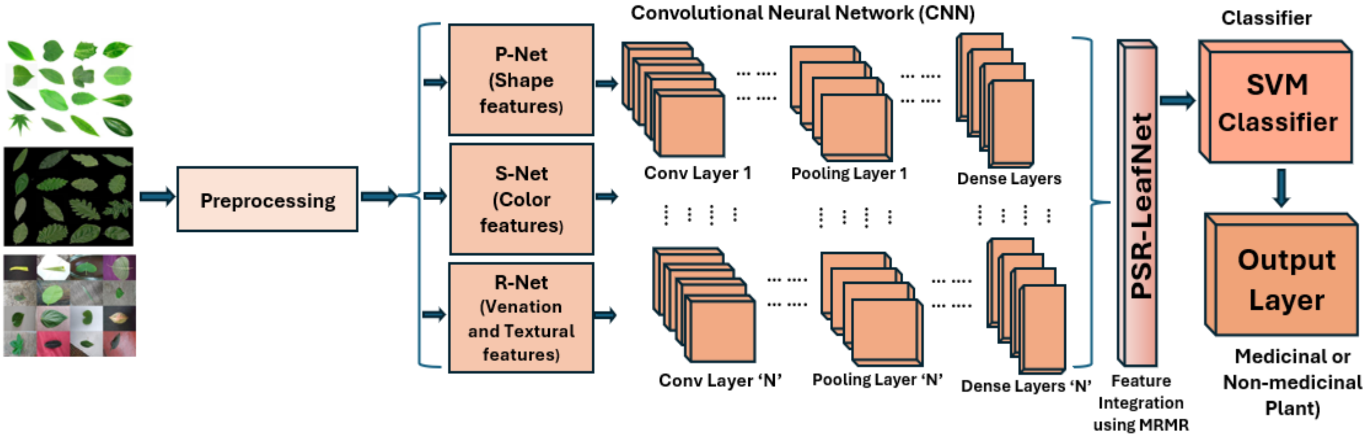


Figure 5. Architecture of the proposed model.

The network designed is the PSR-LeafNet. The analysis of the leaf dataset is performed using P-Net, S-Net, and R-Net, and finally, three nets are combined and formed as a PSR network for the leaf feature extraction. Finally, the features obtained using P-Net, S-Net, and R-Net are integrated using maximum relevance and minimum redundancy (MRMR), which form PSR-LeafNet features. In the PSR-LN, only limited and relevant features useful to identify the leaf are selected. The MRMR algorithm finds an optimal set of features that are maximally and mutually diverse and may be used to characterize the response variable. To increase the model's accuracy and resistance in detecting leaf diseases, PSR-LeafNet's MRMR-based feature selection process appropriately combines features from several networks while achieving a balance between relevance and redundancy. The selection of features is performed by considering a higher correlation among the features of the data class and a lower correlation between themselves. To select the best features, an F-statistic is utilized to evaluate the correlation of the relevance factor, and the Pearson correlation coefficient is utilized to evaluate the correlation of feature redundancy. The optimized features obtained after performing MRMR are finally given to the SVM classifier, and the results are obtained. Detailed ideas for the designed P-Net, S-Net, and R-Net are discussed below. The output achieved after performing neural network operations has different colors as the parula color map concept is utilized in code. The input image has different colors and intensities, and the pixel distribution in the given image has different color combinations. The layers in the network distort pixel intensity distributions, leading to different forms of output. To obtain better visual quality regarding the color features, venations of the input leaf image of different colors are produced in the output.

2.3.1. P-Net Model

The ideology is to improve the identification accuracy by designing a new network system with a different number of layers. The designed architecture of P-Net is shown in Figure 6a. In this model, the image has been converted into a form of binary. The leaf color is identified by removing the background color. The given input size for the P-Net model is 256×256 with a binary depth of 1. After the performance of the convolutional layer, the output of this layer is given as input to the ma- pooling layer. The dimensions of the image will be reduced, and the output of the MP layer will be 256×256 with a binary depth of 128. Finally, after performing all the operations, the image is given to the softmax layer. The color features are extracted using the P-Net model to identify the leaf image. Some of the color features are color histograms, color coherence vector, color moments, dominant color, color layout descriptor, color entropy, and color space transformation features. All the features are extracted and classified, and results are obtained for P-Net. The P-Net accuracy in identification of plant leaf is evaluated. Depending on the P-Net architecture procedure, for the given input the output achieved after passing through the convolutional layers is shown in Figure 6b.

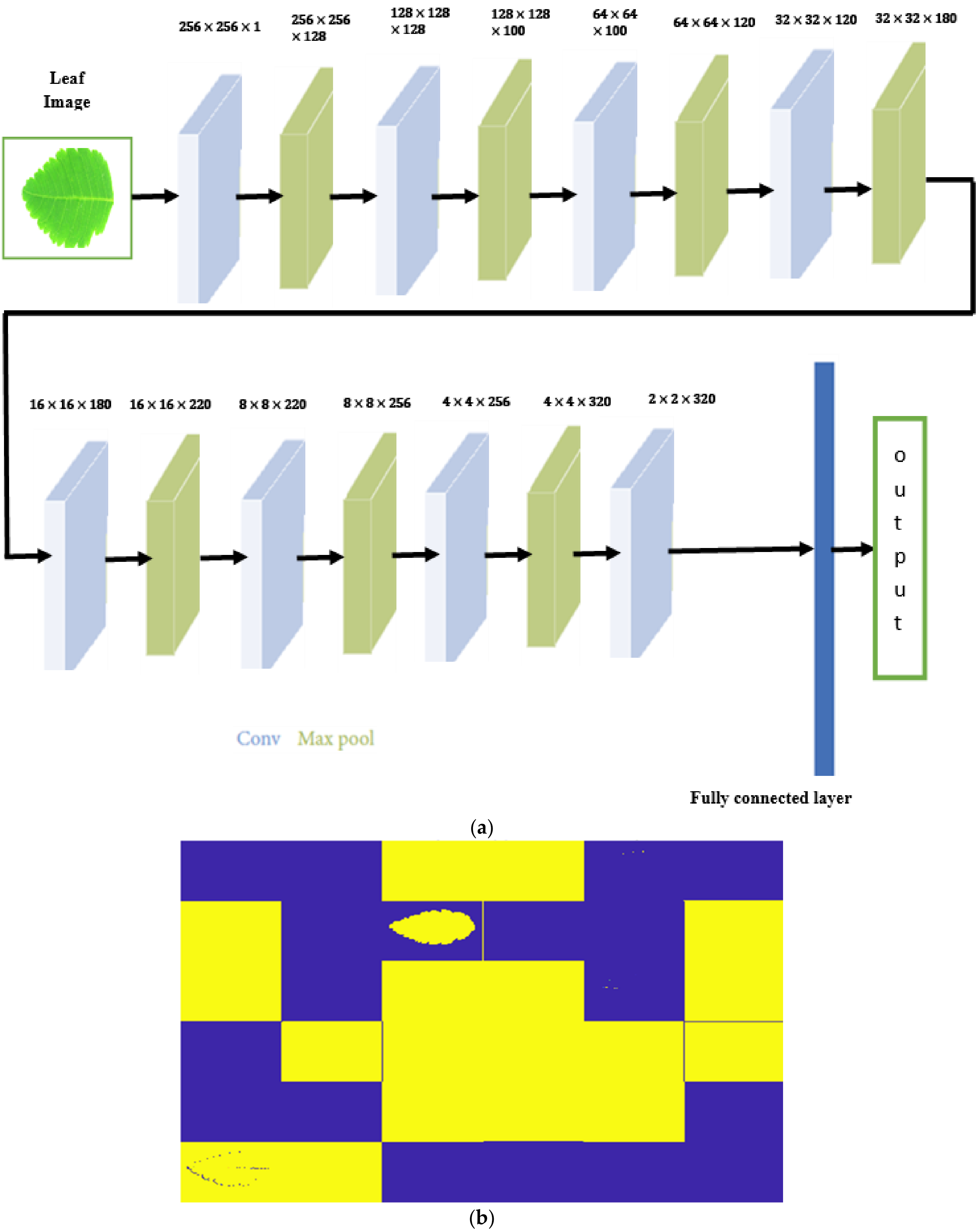


Figure 6. (**a**) P-Net architecture; (**b**) output of P-Net.

The logical sequence of the P-network is given as
Step 1. Input RGB image (H × W × C, C = 3);
Step 2. Convolutional layers detect low-level color transitions;
Step 3. Activation functions introduce non-linearities for complex relationships;
Step 4. Pooling reduces spatial dimensions while preserving significant color features;
Step 5. Deeper layers extract high-level patterns involving colors and shapes;
Step 6. Fully connected layers synthesize global color patterns;
Step 7. The output layer produces the result (e.g., class label or segmentation map).

2.3.2. S-Net Model

The design of S-Net is utilized to extract features like shape, statistics, and venation. The architecture design of S-Net is shown in Figure 7a. To make an entire set of features, shape, statistical, and venation features must be considered. The form characteristics are computed utilizing the binary leaf by performing morphological operations and are associated with the geometry of the leaf. The compact representation of the intensity picture (L) is one of the statistical characteristics. The venation features are obtained from the intensity picture (L) as morphological attributes. The assessed characteristics include measurements of leaf length, width, area, perimeter, smoothness, aspect ratio, rectangularity, form factor, elongation, longitudinal spreading, cross-sectional spreading, average intensity, and average contrast. Some of the other features are as follows:

a. Skewness: It is a measurement of the intensity image's third instant of pixel values (L). It gives the distribution of pixel values' skewness or asymmetry. A positive or negative skewness indicates that the histogram is skewed to the left or right, accordingly. The function for calculating the feature is given in Equation (1):

$$\gamma = E\left(\frac{L}{\sigma}\right)^3 \tag{1}$$

Image intensity is termed L, E is the expectation operator, mean function of image is μ, and σ is the standard deviation.

b. Kurtosis: It is the intensity picture's (L's) fourth instant of pixel values measured. The kurtosis of a picture with a regularly distributed histogram is zero, while in the case of a uniformly distributed histogram, it is negative. When kurtosis is higher than the normally distributed histogram, a positive result is achieved. The function is evaluated using Equation (2):

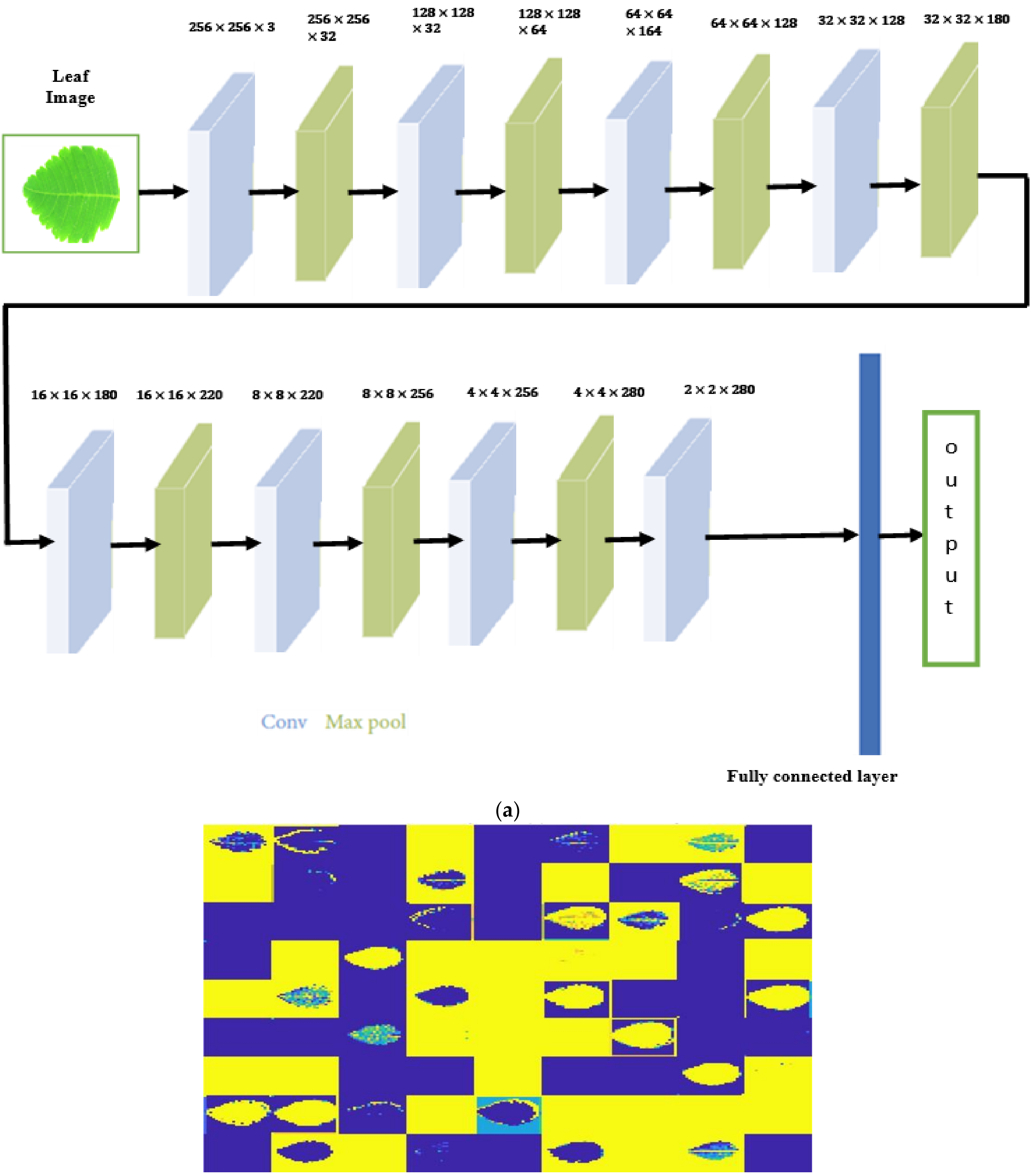
$$K = n\frac{\sum_{k=1}^{N}(L_k-\mu)^4}{\sum_{k=1}^{N}((L_k-\mu)^2)^2} \tag{2}$$

c. Smoothness: The proportion of intensity in the divided area of the picture is measured by smoothness. It may be computed using Equation (3) that follows:

$$\mathrm{S_m} = 1 - \frac{1}{(1+\sigma^2)} \tag{3}$$

d. Uniformity: The quality of the image pixels with respect to gray-scale value is evaluated using the parameter. The uniformity is evaluated using Equation (4):

$$U = \sum_{K=0}^{L-1} p^2(Z_i) \tag{4}$$



(**a**)

(**b**)

Figure 7. (**a**) S-Net architecture; (**b**) output of S-Net.

All the features are extracted and classified, and the results for S-Net are obtained. The S-Net accuracy in the identification of plant leaves is evaluated. Depending on the S-Net architecture procedure, for the given input, the output achieved after passing through the convolutional layers is shown in Figure 7b.

The logical sequence of the S-network is given as

Step 1. Input the leaf image (H × W × C, C = 1);

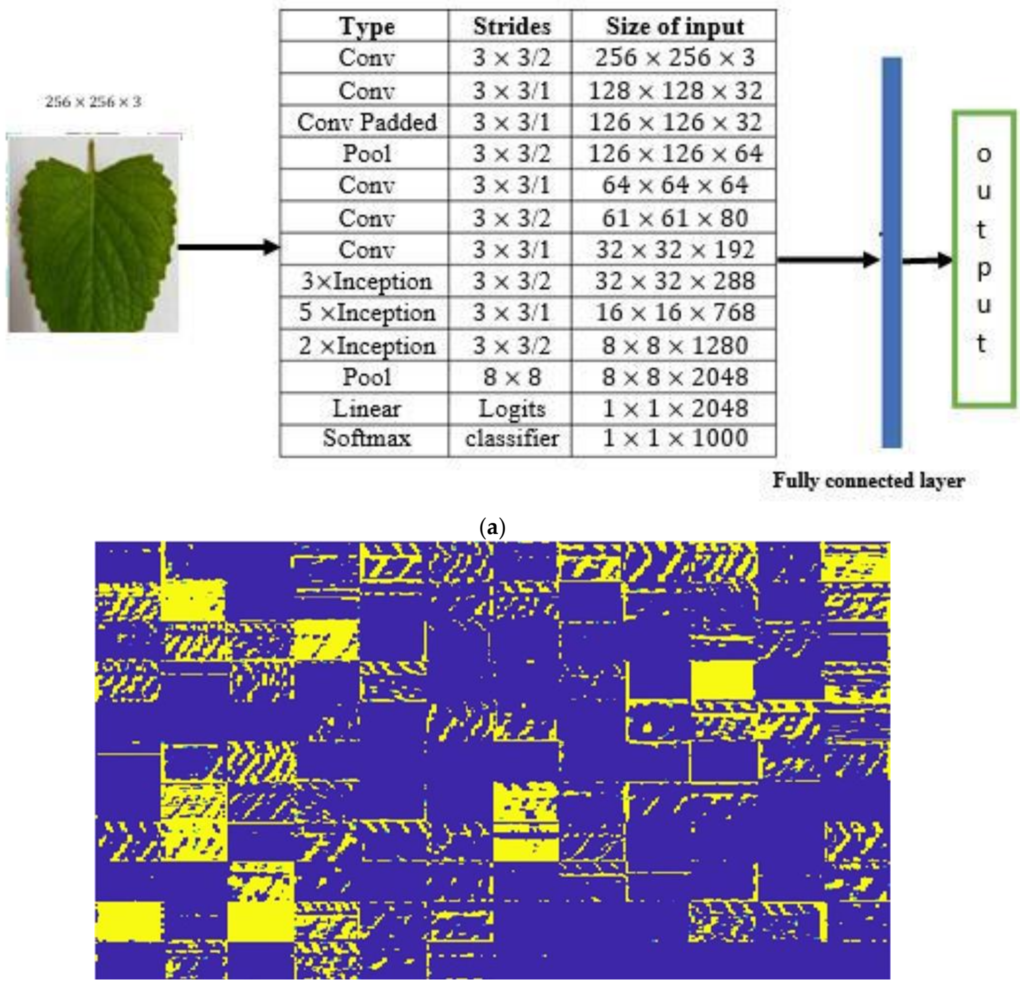
Step 2. Convolution + activation: detect low-level shape features (edges, contours);

Step 3. Pooling: downsample to retain significant shape features;

Step 4. Deeper convolution layers: learn more complex shape patterns;
Step 5. Flatten + fully connected: extract geometrical and statistical representations;
Step 6. Output: predict shape categories and compute statistical metrics.

2.3.3. R-Net Model

Further, R-Net is designed using the Inception V2 model. This R-Net is used to achieve detailed information on the leaf. It also helps extract the middle part of the leaf, which consists of venation. The R-Net architecture is shown in Figure 8a.



(**a**)

(**b**)

Figure 8. (**a**) R-Net architecture; (**b**) output of R-Net.

The inception of the v2 model is considered here to have 42 layers. The textural features of the image are extracted using the R-Net model.

Measure of venation: To differentiate between leaves with nearly identical forms, one crucial piece of information is the vein structural arrangement. Venations are computed using morphological procedures on the intensity picture to determine the vein structure; four disk-shaped morphological operators with a radius of 1–4 mm are applied on the leaf. The resulting value is then deducted from the leaf area. The vein format area is evaluated using the pixel number, and the features are calculated. The measure is performed using Equation (5):

$$VD = \frac{Count\ of\ Vein\ Pixels}{Total\ Pixel\ Count\ in\ the\ Leaf\ Area} \quad (5)$$

All the features are extracted and classified, and the results for R-Net are obtained. The R-Net accuracy in the identification of plant leaves is evaluated. Depending on the R-Net architecture procedure, for the given input, the output achieved after passing through the convolutional layers is shown in Figure 8b.

The logical sequence of R-network is given as
Step 1. Input the leaf image (H × W × C, C = 3);
Step 2. Preprocess the image to enhance vein visibility;
Step 3. Convolution + activation: detect low-level vein structures and leaf edges;
Step 4. Pooling: downsample to retain key venation and structural features;
Step 5. Deeper convolution layers: learn detailed venation hierarchies and patterns;
Step 6. Flatten + fully connected: combine venation and other detailed features for classification or regression;
Step 7. Output: predict venation type, extract statistics, or generate segmentation maps.

2.3.4. GLCM Features

The gray-level co-occurrence matrix (GLCM) is one method for examining the textures in the pixels. Some of the GLCM features are as follows:

a. Contrast: This helps in measuring the local variations in the pixel with gray-level values. The contrast needs to be maintained moderately as a higher level of contrast indicates more variations in the values of neighbor pixels. The contrast is evaluated using Equation (6):

$$Contrast = \sum i,\, (i-j)^2.\ (i, j) \quad (6)$$

where (i, j) is the value in GLCM for i and j pixels.

b. Correlation: This feature evaluates the matching probability of the pixels with neighbor pixels. A higher value of correlation indicates that the prediction of pixel value depends on the neighbor pixel. The correlation is evaluated using Equation (7):

$$Corr = \sum_{i,j} \frac{i, j.P(i-j) - \mu_x\ \mu_y}{\sigma_x\ .\sigma_{\sigma y}} \quad (7)$$

where μ_x and μ_y are the mean and σ_x and σ_y are the standard deviations of the marginal distributions of (i, j).

c. Energy: The GLCM uniformity is measured using the energy factor. The texture feature is said to be repetitive and regular when the energy is high. The energy is evaluated using Equation (8):

$$E = \sum_i (i, j)^2 \quad (8)$$

d. Homogeneity: Homogeneity is a measure of similar elements of GLCM to the diagonal progress of GLCM. If the homogeneity value is high, it indicates that the distribution of characteristics is near to the diagonal. Homogeneity is evaluated using Equation (9):

$$H = \sum_{i,} \frac{P(i, j)}{1 + |i - j|} \quad (9)$$

e. Entropy: The randomness achieved during the gray-level contribution is evaluated in terms of entropy. If the value of entropy is high, then the texture nature is more complex. The entropy is evaluated using Equation (10):

$$En = -\sum i,\, (i, j) \log (i, j) \quad (10)$$

f. Dissimilarity: This feature varies and increases linearly depending on the gray level in the image. The dissimilarity is evaluated using Equation (11):

$$Ds = \sum i,j \mid i-j \mid .\ P\,(i, j) \quad (11)$$

g. Cluster shade: The asymmetry in the texture of the image is identified using this measure. The matrix skewness is measured using the cluster shade. The cluster shade S is evaluated using Equation (12):

$$CS = \sum_{i,}(i + j - \mu_x - \mu_y)^3.\ (i, j) \tag{12}$$

h. Cluster prominence: The peak distribution function of the image is indicated. The matrix kurtosis is evaluated. The cluster prominence is evaluated using Equation (13):

$$CP = \sum_{i,}(i + j - \mu_x - \mu_y)^4.\ (i, j) \tag{13}$$

i. Maximum probability: This parameter is used to evaluate the most prevalent pair of pixels. The max probability is evaluated using Equation (14):

$$MP = \max\ (P\ (i, j)) \tag{14}$$

j. Sum of squares: The variance around the GLCM factor is evaluated. This involves mean function and is evaluated using Equation (15):

$$SOS = \sum i,\ (i - \mu)2.\ P\ (i, j) \tag{15}$$

2.4. Classification SVM Model

Classifying feature vectors to identify plant species involves several steps, with support vector machine (SVM) techniques playing a crucial role [42,43]. Initially, features are extracted from plant leaves, including attributes like shape, texture, and color. These features are then converted into numerical values, forming feature vectors which serve as input data for the SVM. The SVM is trained using labeled training data, where each example consists of a feature vector and a corresponding label indicating the plant species. During training, the SVM algorithm identifies the optimal hyperplane that separates feature vectors of different classes (plant species) with the maximum margin. Support vectors, the data points closest to the decision boundary (hyperplane), are crucial in defining its position and orientation. The SVM uses these support vectors to construct the decision boundary, and the more support vectors identified during training, the more accurately the SVM can classify new data.

Once the SVM is trained, it can classify new feature vectors by comparing them with the learned decision boundary. For a new leaf sample, the SVM computes its feature vector and determines which side of the hyperplane it falls on, classifying it into a specific plant species. The SVM classifier compares the new leaf's feature vector labels with the characteristics learned from the training data, assigning the leaf to a particular plant species and effectively identifying it [44]. The accuracy of the SVM classifier is evaluated by measuring how correctly it can identify the plant species from the feature vectors. A high accuracy indicates that the SVM effectively distinguishes different plant species based on their leaf characteristics. Using SVM techniques for classifying plant species based on leaf characteristics is particularly useful in identifying medicinal plants and can be highly accurate when adequately trained with a comprehensive dataset.

3. Results and Discussion

The PyTorch deep learning framework and the Ubuntu 22.04 Linux operating system were used to construct the proposed medicinal leaf detection and categorization technique. A system configuration was set up with an NVIDIA GeForce RTX 3090 graphics card, which was coupled to a 384-bit memory interface. We also installed an Intel i7 processor and 24 GB of RAM. We then loaded the operating system onto this machine. The GPU operated at a clock speed of 1395 megahertz. We constructed the entire model using the Python programming language making use of robust Python libraries for image processing and machine learning. In particular, OpenCV 4.10.0 and Pillow 9.2.0 made it easier to preprocess and analyze leaf images, while TensorFlow 2.13 and scikit-learn 1.5.2 were used to develop and train the models. This combination offered a versatile and effective toolkit for implementing and assessing the suggested approach. The CUDA toolkit and CUDNN library evaluated each model's performance. An IoU threshold of 0.75 was applied throughout the entire experiment.

3.1. Evaluation Metrics

The designed network performance was measured using accuracy, precision, recall, and f-score metrics [45]. These metrics were used to evaluate the strength of the proposed design. The higher the accuracy indicated, the better the performance of the model. The metric was evaluated with the help of Equations (16)–(19):

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{16}$$

$$Precision = \frac{TP}{TP + FP} \tag{17}$$

$$Recall = \frac{TP}{TP + FN} \tag{18}$$

$$\boldsymbol{F\text{-}Score} = \mathbf{2} * \frac{\boldsymbol{precision} * \boldsymbol{recall}}{\boldsymbol{precision} + \boldsymbol{recall}} \tag{19}$$

Here the term *TP* is true positive, *TN* is true negative, *FP* is false positive, and *FN* is false negative.

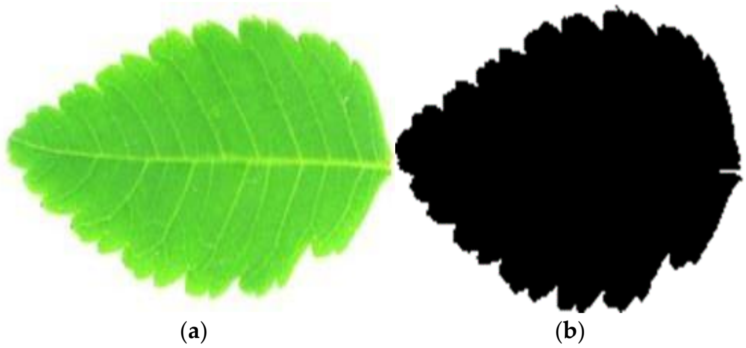
3.2. Experimental Evaluation

For the simulation process, the medicinal leaf dataset was considered. The images in the dataset were initially processed and resized. The dataset was standardized before being given to the neural networks. PSR-LeafNet was utilized to extract features and then finally classified using the machine learning SVM technique.

The analysis of the proposed model was performed on three different datasets. The results achieved are shown in the figures below.

3.2.1. Flavia Dataset Analysis

The Flavia dataset was initially considered, and the results were evaluated [46,47]. A binary image was generated for the given input image, shown in Figure 9. The sample feature maps using P-Net for different convolutional layers are observed in Figure 10. The sample feature maps using S-Net for different convolutional layers are observed in Figure 11. The sample feature maps using R-Net for different convolutional layers are observed in Figure 12. All three models have been visualized to show the analysis of Flavia dataset leaf models.



(**a**) (**b**)

Figure 9. (**a**) Input image; (**b**) binary image.

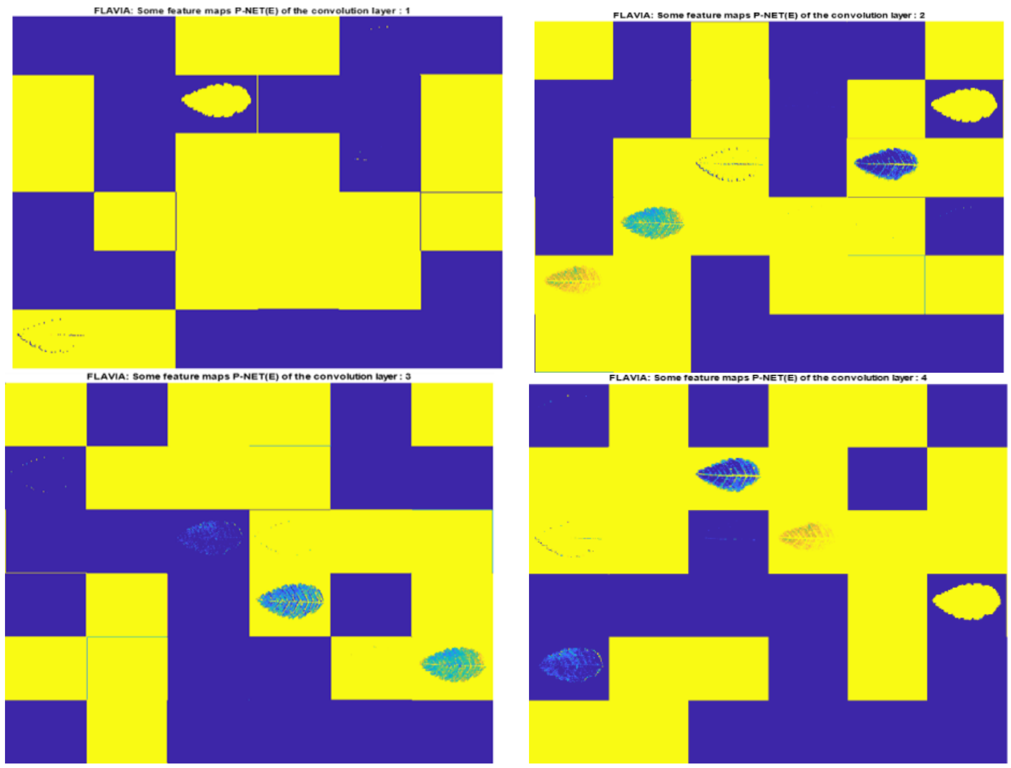


Figure 10. Feature maps obtained using P-NET convolutional layers for FDS.

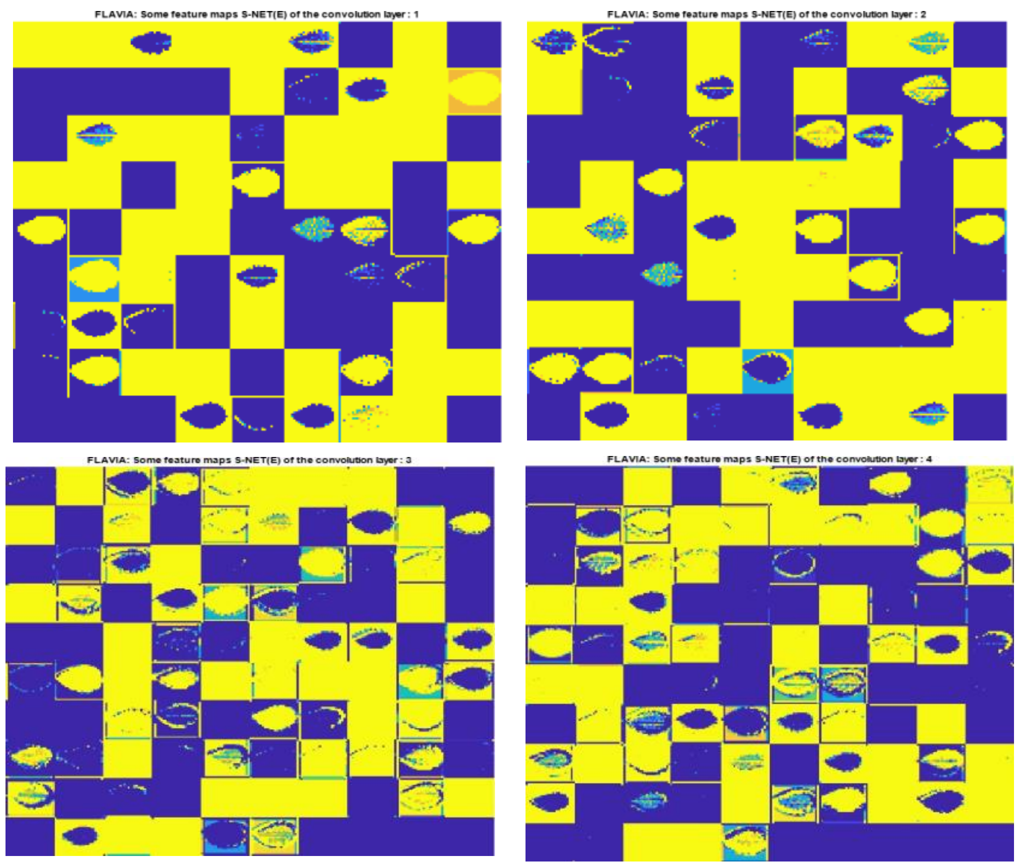


Figure 11. Feature maps obtained using S-NET convolutional layers for FDS.

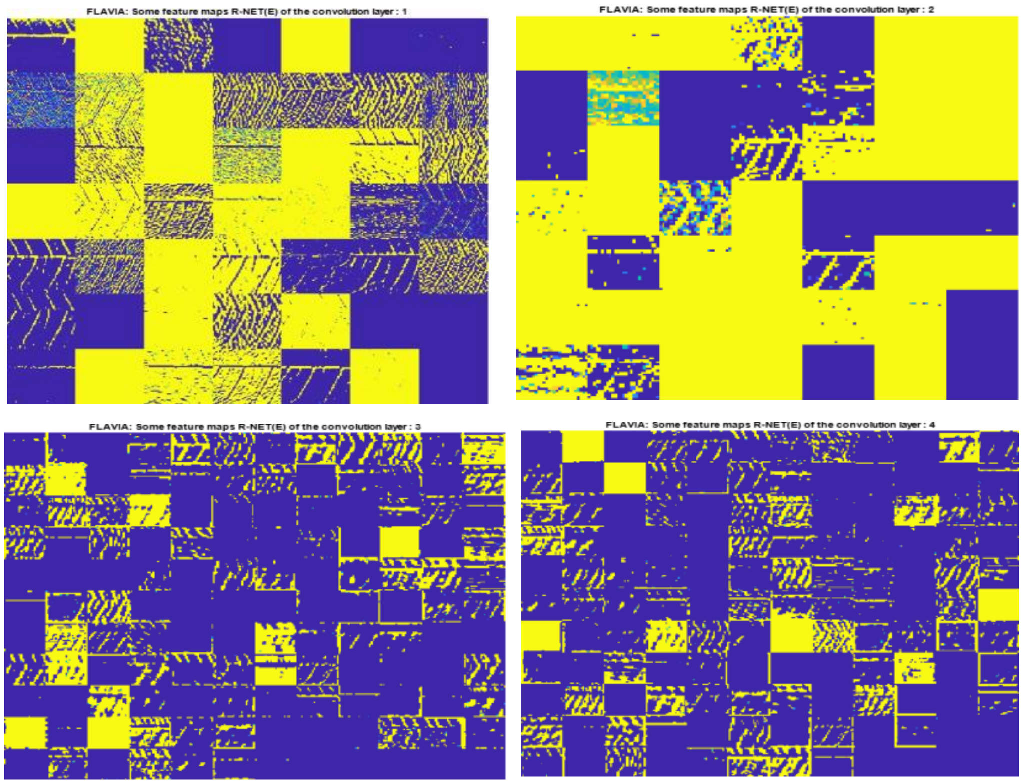


Figure 12. Feature Maps obtained using R-NET convolutional layers for FDS.

The P-Net extracts a wide range of attributes essential for identifying plant species from the Flavia dataset as part of the PSR-LeafNet model. The geometrical aspects of the leaves are described by these features, which include the aspect ratio, size, rectangularity, and eccentricity. The color composition of the leaf is revealed by color characteristics, like mean color and color variance. Vein characteristics, including density and total vein length, capture the complex structures and patterns of the veins. In addition, textural characteristics that characterize the surface texture of the leaves include uniformity, contrast, and entropy. The P-Net improves the PSR-LeafNet model's accuracy and robustness by utilizing sophisticated image processing and recognition techniques.

The first four convolutional layers in P-Network are taken as a sample to illustrate the results of the proposed model.

The convolution part is one of the essential parts in the design of networks. The S-Net-designed convolutional layers are shown in Figure 11. The convolution operator is used to convolute the input image to obtain the desired output level by saving the results of layer one and feeding them to layer two. When the Flavia dataset is subjected to the PSR-LeafNet model's S-Net (sequential network), a comprehensive set of attributes essential for precise plant species identification is extracted. It focuses on shape characteristics that characterize the leaf's geometrical attributes and general forms, such as the aspect ratio and form factor.

When applied to the Flavia dataset, the R-Net (random network) in the model extracts features that capture the leaf structure's more minute and random characteristics, improving the total feature set for precise plant species identification and its traits as in Figure 12. R-Net focuses on the textural features that characterize the leaf's patterns and surface texture. These include metrics like homogeneity, which gauge the texture's homogeneity, and contrast, which records the variation in intensity between nearby pixels, quantifying the leaf texture's complexity or randomness.

By applying the three networks on the Flavia dataset, the general shape of the leaf can be determined by the length-to-width ratio. The form factor also aids in defining the edge shape of the leaf. The color characteristics of the leaf are another essential feature which evaluates the leaf's average color value across various color regions. Various leaf forms, sizes, and orientations are included in the dataset to offer a varied collection of examples for building strong models. The networks are applied on the white background of the Flavia dataset images, which minimizes the noise and ensures the leaf is the focus of the images. The dataset images provide an extensive collection of leaf images of different species. The outcome of each of the networks would enhance the attributes of plant species prediction. When combining these properties, the model predicts and classifies the medicinal plant species.

The parameters evaluated for the Flavia dataset using different network models are shown in Table 1.

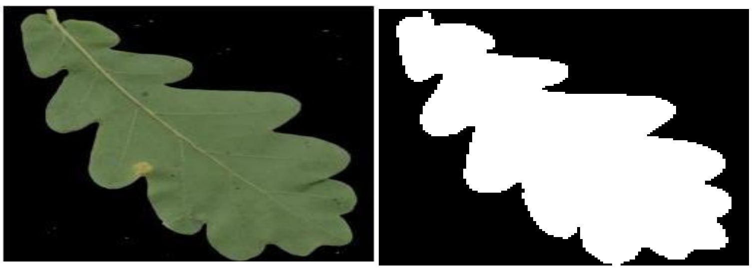
Table 1. Results obtained using FDS.

Method/Dataset	FDS			
	Precision	**Recall**	**F-Score**	**Accuracy**
P-Net	91.50%	90.30%	90.40%	91.70%
S-Net	92.70%	91.60%	91.10%	92.10%
R-Net	92.40%	91.80%	92.30%	92.20%

The outcomes presented in Table 1 illustrate how booming the feature extraction procedure was in augmenting the in-depth analysis of the Flavia dataset. The accuracy measures show that the model extracts important characteristics optimally, significantly improving plant species identification and categorization. This implies that the PSR-LeafNet model is good at capturing pertinent information from leaf images.

3.2.2. MalayaKew Dataset Analysis

The MalayaKew dataset was considered, and the results were evaluated [48,49]. A binary image was generated for the given input image, which is observed in Figure 13. The sample feature maps using P-Net for different convolutional layers are observed in Figure 14. The sample feature maps using S-Net for different convolutional layers are observed in Figure 15. The sample feature maps using R-Net for different convolutional layers are observed in Figure 16. All three models are visualized to show the analysis of MalayaKew dataset leaf models.



(**a**) (**b**)

Figure 13. (**a**) Input image, (**b**) binary image.

Now think about applying a small neural network, which is also called a filter or kernel, to a small part of this picture and showing the results vertically. Let us call it K. By moving that neural network around the whole picture, you can make a new image with different heights, widths, and depths. We now have more channels, but the old R, G, and B channels were wider and taller than the new ones.

The model raises classification accuracy by utilizing a wide range of characteristics, decreasing misclassification rates, and improving the capacity to differentiate between related species. Images of different plant leaves, particularly those used in the kitchen and medicine, can be found in the Flavia dataset. Each layer of the network has a different processing ability. Each network outcome shows four convolution layers in accessing the leaf dataset image to achieve the feature set. Incorporating several feature types enhances the model's resilience against variations in leaf appearance, including variations in dimensions, color, and texture, all prevalent in real-world datasets.

The outcome presented in Table 2 depicts the optimal accuracy obtained in the MKDS dataset. The MKDS dataset's improved feature selection and integration result in higher classification and identification accuracy for kitchen and medicinal plants depending on their leaf characteristics. They are significant since S-Net and R-Net features address additions form descriptors, such as edge smoothness and indentation depth. The parameters evaluated for the MalayaKew dataset using different network models are shown in Table 2.

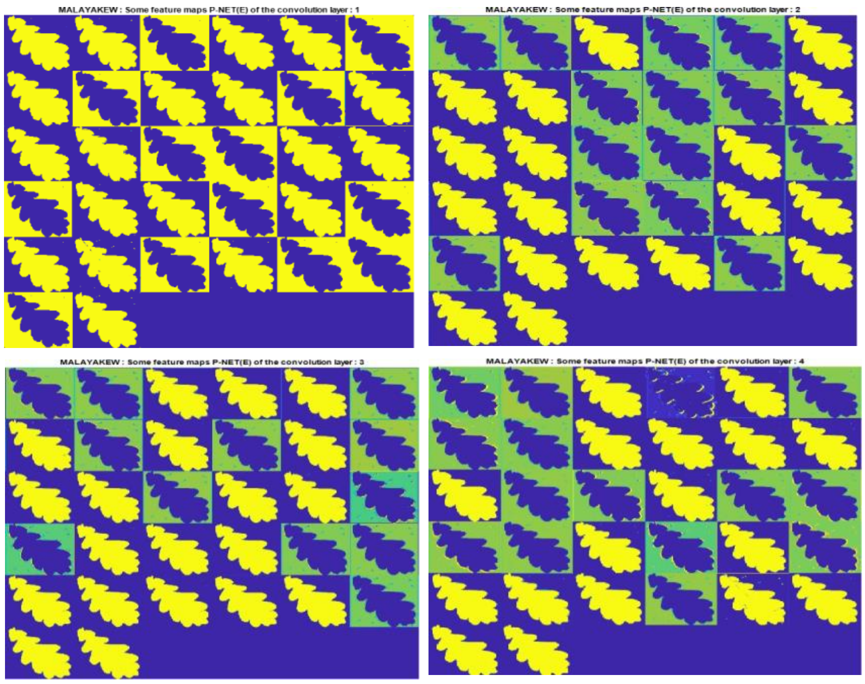


Figure 14. Feature maps obtained using P-NET convolutional layers for MK.

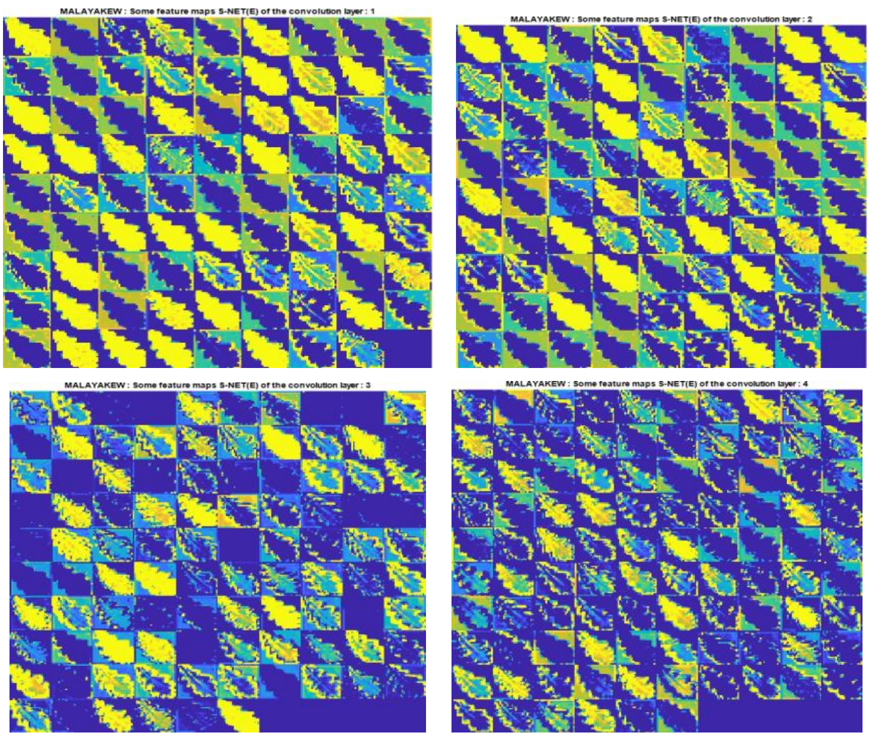


Figure 15. Feature maps obtained using S-NET convolutional layers for MKDS.

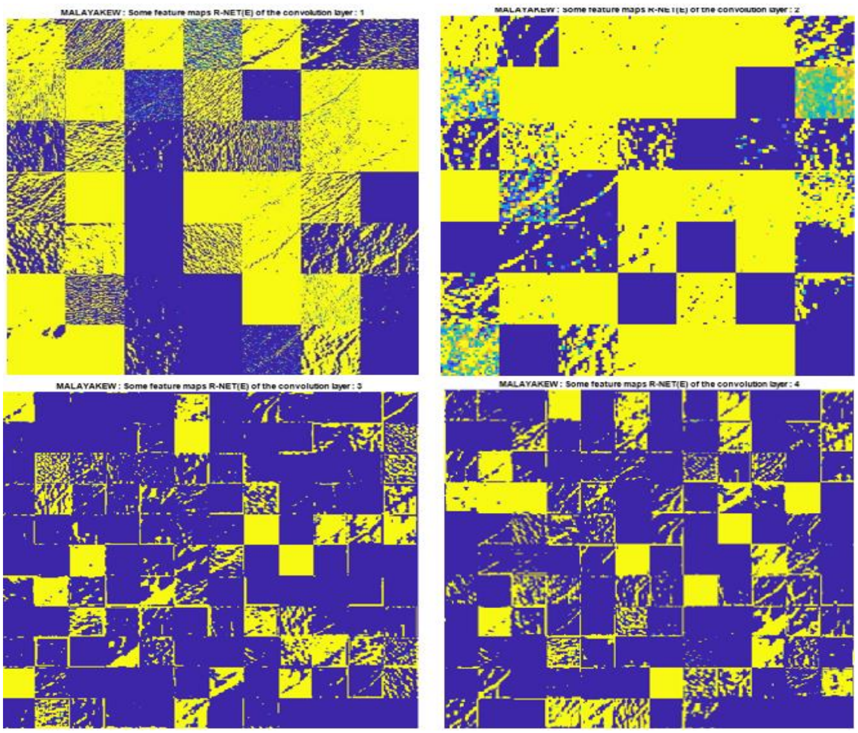


Figure 16. Feature maps obtained using R-NET convolutional layers for MKDS.

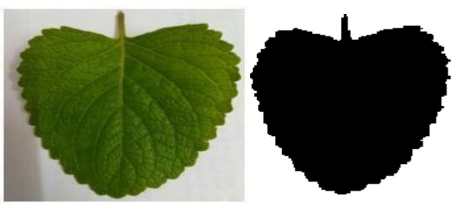
Table 2. Results obtained using MKDS.

Method/Dataset	MKDS			
	Precision	**Recall**	**F-Score**	**Accuracy**
P-Net	91.40%	91.32%	90.40%	91.70%
S-Net	92.20%	91.50%	91.10%	92.10%
R-Net	92.40%	91.20%	92.30%	92.20%

Every network has produced conceivable features in terms of the texture, color, and shape of the leaf characteristics, according to the results obtained from the MKDS dataset. Its integration will improve the PSR-LeafNet net model without losing plant characteristics.

3.2.3. Indian Medicinal Plant Dataset Analysis

Now, the Indian Medicinal Plant dataset is considered, and the results are evaluated [50]. The image data source is collected online. A binary image was generated for the given input image, which is observed in Figure 17. The sample feature maps using P-Net for different convolutional layers are observed in Figure 18. The sample feature maps using S-Net for different convolutional layers are observed in Figure 19. The sample feature maps using R-Net for different convolutional layers are observed in Figure 20. All three models are visualized to show the analysis of the Indian Medicinal Plant dataset leaf models.



(**a**) (**b**)

Figure 17. (**a**) Input image; (**b**) binary image.

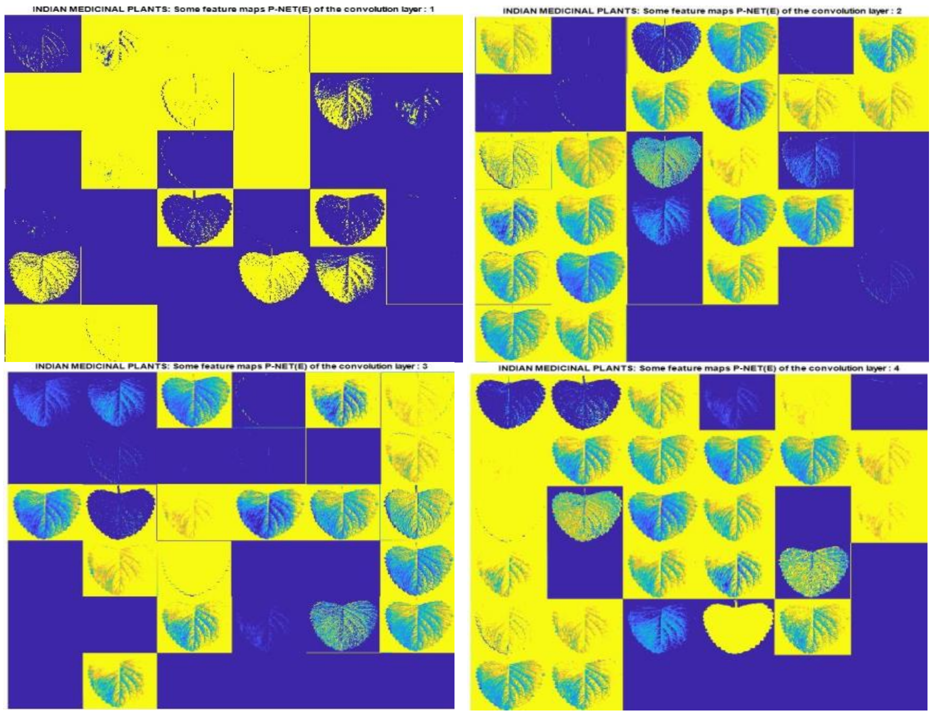


Figure 18. Feature maps obtained using P-NET convolutional layers for IMPDS.

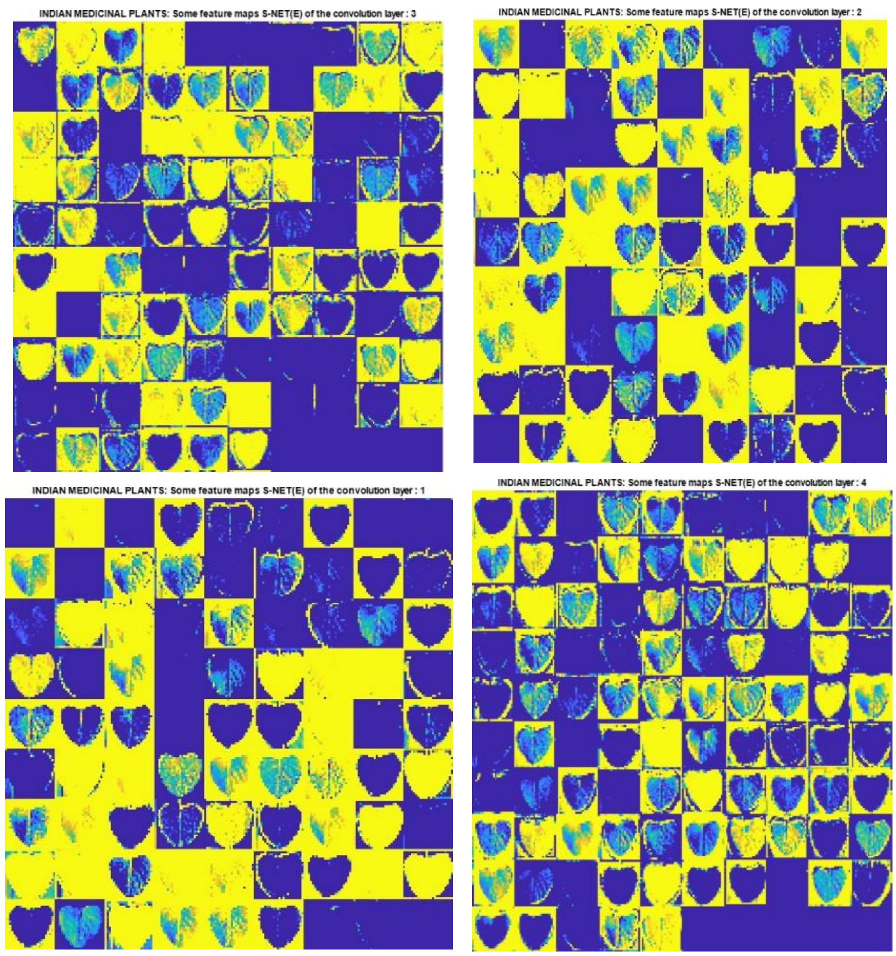


Figure 19. Feature maps obtained using S-NET convolutional layers for IMPDS.

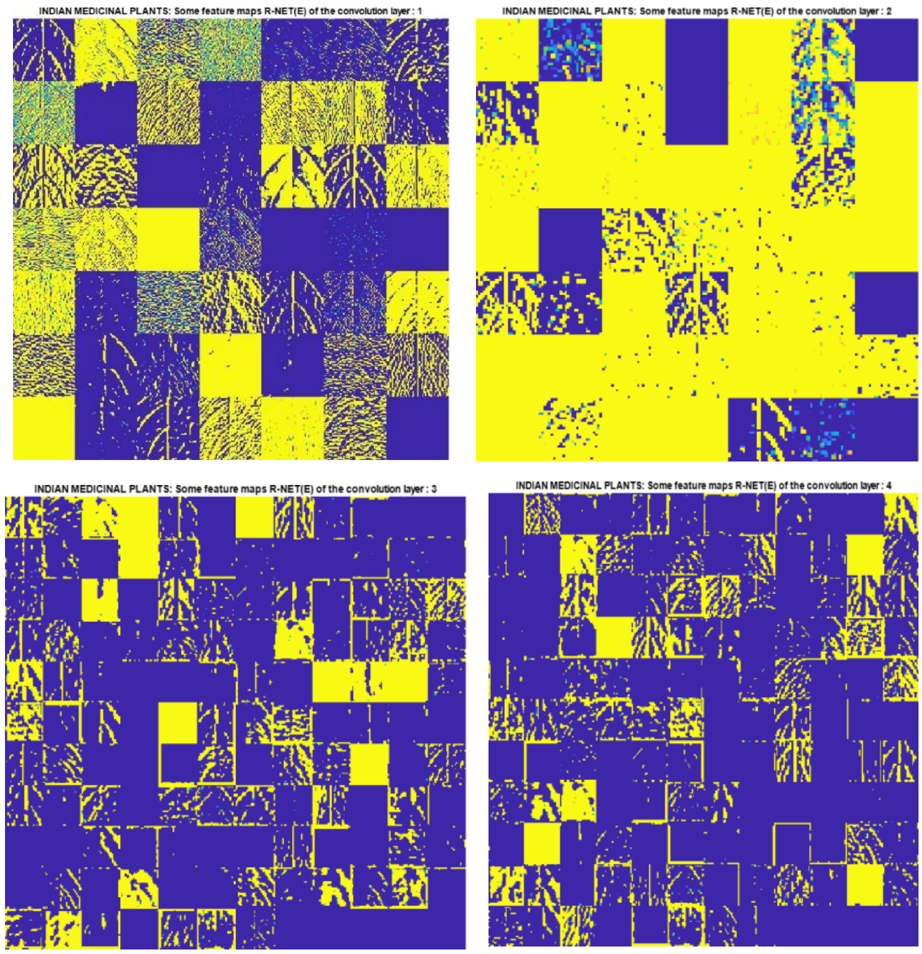


Figure 20. Feature maps obtained using R-NET convolutional layers for IMPDS.

The first model's processed convolutional layers focus on obtaining the general color features, as shown in Figure 18. The second model focuses on the shape and venation of the images, as shown in Figure 19. Finally, the third model gives the textural features, as shown in Figure 20. The dataset guarantees diversity and thorough coverage of common therapeutic plants by incorporating images from several types of medicinal plants. The reduction of background interference improves the visibility of the leaf's features. The dataset has a diverse collection of leaves, which enhances the replication of the training of the model with all possible features. The training of the model aids in separating more rounded leaves from elongated ones. It shows the degree to which the leaf shape adheres to a convex contour and reflects the compactness of the leaf, differentiating between lobed and dense leaves. The IMPDS dataset's analysis and classification will be greatly improved using the PSR-LeafNet model, which includes P-Net, S-Net, and R-Net components.

The parametric evaluation for the Indian Medicinal Plant dataset using different network models is shown in Table 3.

Table 3. Results obtained using IMPDS.

Method/Dataset	IMPDS			
	Precision	**Recall**	**F-Score**	**Accuracy**
P-Net	91.70%	91.50%	91.70%	91.50%
S-Net	92.10%	90.40%	91.50%	92.50%
R-Net	92.70%	92.30%	92.27%	92.57%

As the result depicts, the model's accuracy and resilience increases, indicating its competence in recognizing and categorizing medicinal plants from their leaf images.

3.3. PSR-LeafNet

Identifying different plant species is essential in several disciplines, including botany, environmental science, and agriculture. Proper identification of plant species is useful for ecological research, crop management, and biodiversity conservation. This work created a specialized neural network called PSR-LeafNet to recognize plant species (PSR) from leaf photos. PSR-LeafNet uses the visual characteristics of leaf photos to categorize various plant species. Traditional methods involve extracting features such as texture, shape, and color. PSR-LeafNet automates this by using CNN to learn features directly from the images by combing and selecting the best features extracted using P-Net, S-Net, and R-Net. Convolutional neural networks (CNNs) are highly effective for tasks like plant identification due to their ability to automatically learn and extract relevant features from images. The key reasons why CNNs are a strong choice for this application and their effectiveness in the model are automatic feature extraction, handling complex data, spatial hierarchy of features, robust to variations, high classification accuracy, scalability, interpretability with attention mechanisms, and integration with real-world applications. Due to these abilities in CNNs, CNNs have superior performance compared to traditional methods. These strengths make CNNs an indispensable tool in modern plant classification tasks. The advantage of the PSR-LeafNet is that it automatically learns relevant features from raw images. The network designed will handle more extensive datasets and help recognize various plant species ranges.

The PSR-LN extracts the best features based on the following:

- Shape, which includes counters, edges, leaf apex and base, aspect ratio, and leaf margin;
- Texture, which includes vein patterns, surface textures, and micro patterns;
- Color, which includes leaf color, color histogram, and color variations;
- Morphology, which includes leaf area, perimeter, and circularity;
- Spatial aspects, which include the position of critical points and geometric features.

PSR-LeafNet, proposed in this work, is a deep learning application in plant species identification. It offers a reliable and effective method for classifying and extracting features from leaf photos, automating the process of plant species identification. The designed PSR-LN increases the reliability and adaptability of monitoring ecological systems and studies related to biodiversity. By utilizing the unique qualities of each network, these networks are integrated through the PSR-LeafNet architecture to produce an extensive and exclusive feature set. By capturing all pertinent details of the leaf photos, our combination method improves the resilience and accuracy of classifying and recognizing medicinal plants from the three datasets. The combination of P-Net, S-Net, and R-Net produces a model that works exceptionally well to manage the complexity and unpredictability of leaf images.

3.4. MRMR Technique

The minimal redundancy maximum relevance (MRMR) feature selection approach commonly minimizes duplication and identifies the most relevant features from a dataset. Machine learning pipelines that incorporate the MRMR technique could improve the model's performance in leaf detection using various datasets by selecting the most valuable characteristics for classification. The MRMR is used after feature extraction. The PSR-Net feeds the MRMR integration model with features extracted using P-Net, S-Net, and R-Net. The technique was crucial in increasing detection accuracy because it successfully chose features that were minimally redundant and highly relevant to the classification of leaf diseases, guaranteeing strong model performance.

The process of MRMR feature selection is as follows:

Step 1. Calculation of relevance

Determine the importance of each trait to the target class using mutual data or another suitable statistical metric. The relevance is evaluated using Equation (20):

$$mRMR = max(MI(X_i,\ Y) - \frac{1}{|s|}\sum\nolimits_{X_j \in S} MI\left(X_i, X_j\right)) \quad (20)$$

Step 2. Calculation of redundancy

Using the same statistical metric, such as the correlation coefficient, chi-squared test, mutual information, or ANOVA F value, determine how redundant the characteristics are. The redundancy is evaluated using Equation (21):

$$mRMR = \max\left(\frac{MI(X_i,\ Y)}{\frac{1}{|s|}\sum\nolimits_{X_j \in S} MI\left(X_i, X_j\right)}\right) \quad (21)$$

Here 'S' is the set of selected features.

Step 3. Optimize feature set

To choose a subset of characteristics that optimizes relevance and reduces redundancy, apply the MRMR criteria. The goal is to strike a balance such that, without being repetitive, the chosen features convey the most information about the target class.

The MRMR is implemented using two methods, such as the following:

- Mutual information difference (MID): select features based on the difference between relevance and redundancy;
- Mutual information quotient (MIQ): select features based on the ratio between relevance and redundancy.

By choosing the most pertinent and non-redundant information, MRMR is used in this study to improve network performance and create more accurate and practical models. Reduced computational complexity from fewer feature selections results in quicker training and inference durations. One is to improve the model's capacity to precisely and quickly identify leaves from dataset photos by including the MRMR approach in the medicinal leaf recognition process. This will ultimately lead to improved results and more successful screening programs.

The output features obtained for the PSR-LN model after performing the integrating operation are shown in Table 4, and the results obtained for different datasets are shown in Table 5. The input image has been convoluted with the designed layers, and its feature values are obtained within a range from 1 to −1. There were thousands of features obtained, from which we have considered 12 features as shown as an example in Table 4.

Table 4. Feature set values derived using PSR-LN.

S. No	FDS	MKDS	IMDS
1.	0.0166	0.0035	0.0279
2.	0.0090	0.0019	−0.0047
3.	−0.0093	−0.0089	0.0175
4.	−0.0058	0.0138	−0.0013
5.	−0.0145	−0.0113	0.0058
6.	0.0125	−0.0027	0.0179
7.	−0.0115	0.0066	−0.0085
8.	−0.0144	−0.0165	0.0078
9.	0.0086	−0.0024	−0.0081
10.	−0.0075	0.0060	−0.0143

Table 4. *Cont.*

S. No	FDS	MKDS	IMDS
11.	0.0152	0.0085	−0.0190
12.	0.0014	0.0249	0.0028

Table 5. Results obtained using PSR-LN-SVM.

Leaf Dataset/Parameter	Precision	Recall	F-Score	Accuracy
Flavia	94.40%	95.60%	94.99%	95.88%
MalayaKew	95.30%	96.60%	95.94%	97.12%
Indian Medicinal Plant	96.10%	97.80%	96.94%	98.10%

3.5. SVM Classifier

Support vector machine (SVM) is a critical component in the classification process after the integrated PSR-LeafNet model extracted a complete set of features from leaf pictures. The SVM classifier's task is to correctly identify the leaf pictures based on the features after they have been retrieved and integrated. For every leaf image, the many features that PSR-LeafNet retrieved are merged into a single feature vector. Every pertinent detail about the leaf is contained in this vector. The SVM method is trained to choose the best hyperplane that maximizes the margin between distinct classes, thereby enabling it to distinguish feature vectors of various classes (species). Finding the hyperplane that best divides the data points requires solving an optimization issue. Non-linear correlations between features can be handled by SVM by using different kernel linear functions to change the feature space. When there is no linear separability of the feature space, this is especially helpful. Upon training, the SVM model establishes a decision boundary in the feature space that divides several classes. The extracted features are fed through the trained support vector machine (SVM) model for every new leaf image. The model classifies the image according to the side of the decision boundary where the feature vector lies. As a result, the leaf image is associated with a particular type of plant.

The results of the suggested PSR-LeafNet model's classification of medicinal plants, as shown in Table 5, clearly demonstrate its high accuracy and superior performance. Along with the SVM classifier, the feature extraction integration of P-Net, S-Net, and R-Net guarantees a comprehensive dataset analysis and precise extraction of valuable features, surpassing alternative methods and solidifying the model as an effective tool for medicinal plant identification.

The pseudo code of proposed model is as follows:

Step 1. Load the dataset of plant leaf images (images and their corresponding labels);

Step 2. Split the dataset into training, validation, and test sets;

Step 3. Apply data augmentation to increase variability: rotate images randomly, flip images horizontally/vertically, add noise or blur to simulate environmental conditions, add just brightness and contrast, normalize image pixel values to the range [0, 1];

Step 4. Design of CNN model for P-Net, S-Net, and R-Net

Define the CNN architecture:

a. Input layer:
   Input size = (image_height, image_width, color_channels);
b. Convolutional layers:
   Use filters to extract features like edges, colors, and textures;
   Apply ReLU activation to introduce non-linearity;
   Use batch normalization for faster convergence;
c. Pooling layers:
   Apply max-pooling to reduce spatial dimensions and computational complexity;

d. Additional convolutional + pooling layers: increase the number of filters for deeper layers to capture complex features;
e. Flattening layer:
Flatten the feature maps into a 1D vector for the dense layers;
f. Fully connected layers:
Use Dense layers to learn non-linear combinations of extracted features;
Apply dropout for regularization to avoid overfitting;
g. Output layer:
Dense layer with softmax activation;
Number of units = Number of plant species (classes);
Step 5. Extraction of features using P-Net, S-Net, R-Net;
Step 6. Extraction of GLCM features;
Step 7. Integration of feature using MRMR model;
Step 8. Model training
Compile the model;
Train the model;
Save the trained model for future use;
Step 9. Model testing
Load the saved model;
Pass test images through the model;
Evaluate performance using metrics such as accuracy, precision, recall, F1-score;
Step 10. End of process.

The results are obtained by considering 60% of data for training and 40% of data. In the preprocessing stage, data augmentation with rotation of −30 to 30; horizontal mirroring, zooming or scaling of 0.8 to 1.2; and horizontal and vertical shifts are utilized, which helps in improving the performance of networks and the classification process. The overall comparison and performance metrics of the individual networks and integrated model on the proposed datasets is represented in the graphical view in Figure 21.

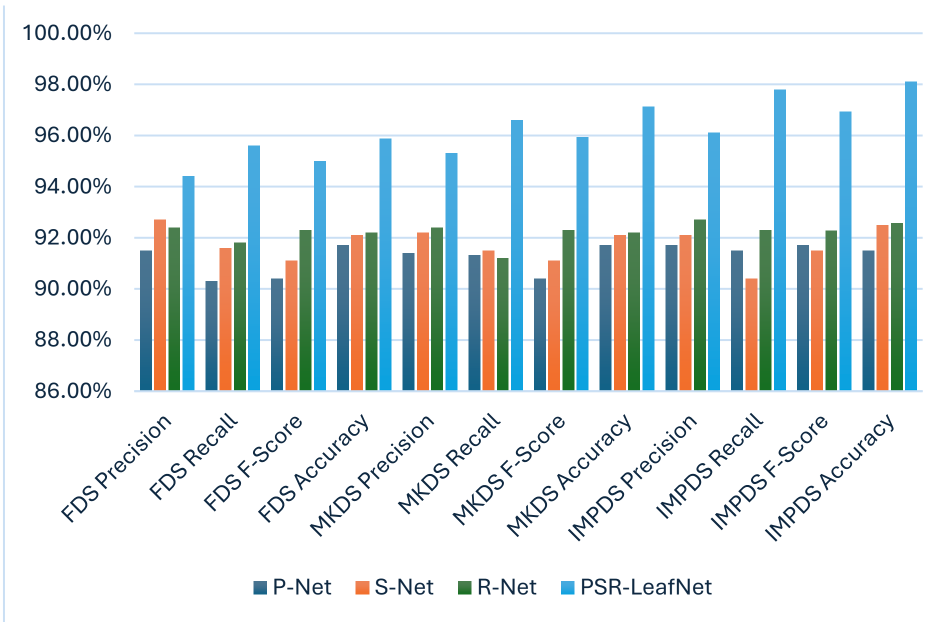


Figure 21. Comparison of performance metrics of proposed model.

It is evident from the graphical representation that the best accuracy is achieved with the proposed PSR-LN-SVM model. As shown in Figure 22, we also compare the recommended approach with various other approaches and existing methods to evaluate the efficiency of the model.

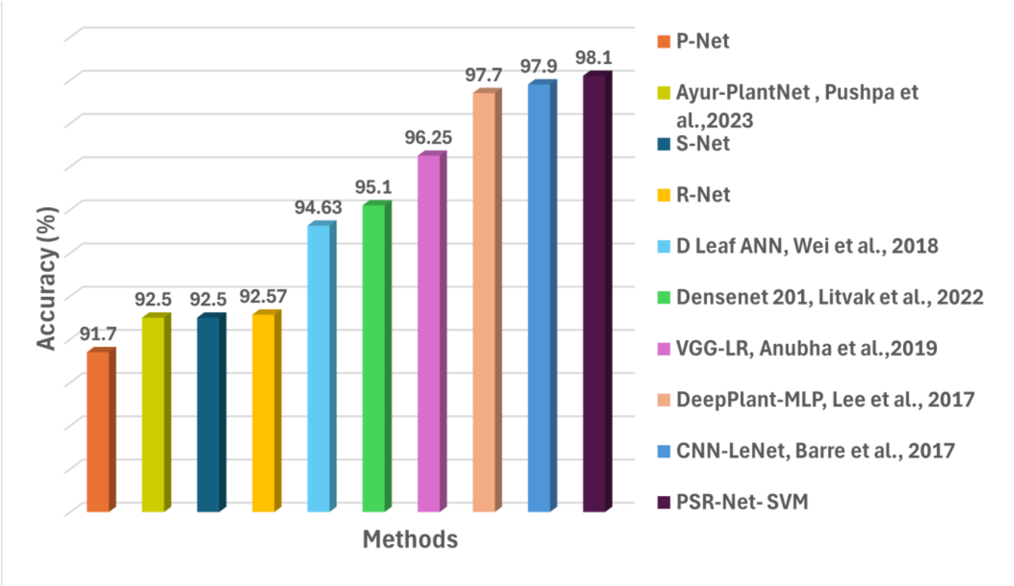


Figure 22. Comparison of performance metrics of proposed model with existing models [10,30,32,36,51,52].

The model performs significantly better than alternative methods, guaranteeing reliable and accurate leaf image classification. The accuracy of CNN-LeNet [51] and DeepPlant-MLP [52] closely aligns with the proposed work. However, our model distinguishes itself by focusing on a diverse range of medicinal plant species, and varied datasets representing a significant advancement in the field. This demonstrates how successful the PSR-LeafNet framework is at identifying medicinal plants.

4. Conclusions

The work presents a comfort model in the identification of medicinal plants depending on the leaf image. A medicinal or non-medicinal plant is identified for the given leaf input using our proposed PSR-LeafNet model. In this paper, the identification is performed utilizing the process of feature extraction and classification. A new network is designed, i.e., P-Net, S-Net, R-Net, in which the number of layers in convolution is designed to achieve better performance results compared with existing methodologies. The feature selection is performed by integrating all the network features using the MRMR model and forming a PSR-LN feature set. The use of a machine learning SVM algorithm along with deep neural networks achieves a higher rate of accuracy in the identification of medicinal plants. The rate of accuracy obtained is 98.1%, where other techniques like DeepPlant-MLP, CNN-LENet, DLeaf-ANN, Ayur-PlantNet have an accuracy of 97.7%, 97.9.%, 94.6%, and 92.5%, respectively. The results prove that the proposed model can be used in any other image processing applications, such as biomedical, video processing with lower resolution, and remote sensing image processing. The limitation of the work is regarding the consideration of leaf image condition. The environmental influence of light on the leaf, low-resolution image processing, and weather effects need to be considered in the dataset. The removal of external noise and image enhancement need to be performed in future to enhance the quality of images. This helps the network to process more accurately and in less time for the identification of plants. The designed model can be used for other datasets and other applications. In the future, other available medical leaf datasets can be used and implemented for analyzing the results. The work is limited to the SVM classifier. In the future, different classifiers like random forest, naïve Bayesian, logistic regression, etc. will be incorporated with PSR-LeafNet so that the efficiency of the ML model can be identified.

Author Contributions: Conceptualization, P.K.S., M.S.R., A.U., and Y.S.; methodology, P.K.S. and M.S.R.; software, Y.S. and P.K.S.; formal analysis, P.K.S., M.S.R., and Y.S.; resources, M.S.R. and Y.S.; data curation, P.K.S. and M.S.R.; writing—original draft preparation, P.K.S., A.U., and M.S.R.; writing—review and editing, P.K.S. and M.S.R.; supervision, M.S.R. and Y.S.; project administration, Y.S.; and funding acquisition, M.S.R., A.U., and Y.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data is contained within the article.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

CNN	Convolutional neural networks
DCNN	Deep convolutional neural networks
FDS	Flavia dataset
MKDS	MalayaKew dataset
IMPDS	Indian Medicinal Plant dataset
Acc	Accuracy
SVM	Support vector machine
SOS	Sum of squares
MP	Maximum probability
CP	Cluster prominence
GLCM	Gray-level co-occurrence matrix
K	Kurtosis
Sm	Smoothness
U	Uniformity
FFNN	Feed-forward neural network
LR	Logistic regression
RF	Random forest
AC	Average contrast
γ	Skewness
CS	Cluster shade
H	Homogeneity
En	Entropy
Ds	Dissimilarity

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