Journal of Information Systems Engineering and Management
2025, 10(37s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Hybrid CNN-PSO Approach for Accurate Classification of Medicinal Flowers

Rajani S[1*], Veena M N[2]

[1*] Assistant Professor, Department of Computer Applications, PES University, Bangalore. rajanis@pes.edu
[2] Professor and Head, Department of Master of Computer Applications, PES College of Engineering, Mandya. veenadisha1@pesce.ac.in

ARTICLE INFO

Received: 18 Dec 2024

Revised: 17 Feb 2025

Accepted: 25 Feb 2025

ABSTRACT

Accurate classification and identification of flowering medicinal plants hold immense potential for advancing traditional medicine and biodiversity conservation. Currently, experts manually identify medicinal plants based on characteristics such as aroma, flowers, and visual features—a process that is not only time-consuming but also prone to human error and inefficiencies. To address these challenges, this study proposes a robust medicinal flower classification framework composed of three major phases: segmentation, feature extraction, and classification. The segmentation phase utilizes a deep learning-based Detectron2 model to isolate flower regions accurately. Three distinct feature extraction schemes are then applied to capture the color and texture patterns of the segmented flowers. The extracted features are optimized and classified using a Convolutional Neural Network (CNN) enhanced with an Improved Seeding Particle Swarm Optimization (IS-PSO) algorithm. Dominant features are selected using a Particle Swarm Optimization (PSO) technique prior to classification to improve computational efficiency and model accuracy. The proposed method was validated using 14 real-world medicinal flower datasets, all of which hold significant medicinal value. The CNN-IS-PSO model achieved superior performance, with an accuracy of 96.24%, precision of 96.90%, recall of 93.41%, and an F1-score of 94.69%, significantly outperforming recent state-of-the-art models. This method demonstrates the potential to enhance the reliability and accuracy of automated medicinal plant classification.

Index Terms—Convolutional Neural Network (CNN), Detectron2, Feature Extraction, Flowering Medicinal Plants, Particle Swarm Optimization

I. INTRODUCTION

The planet is home to thousands of plant species, many of which possess therapeutic qualities that can be harnessed to treat a wide range of illnesses. In addition to their medicinal value, plants play a crucial role in the ecological food chain, acting as primary producers that sustain herbivores and, in turn, provide food for higher trophic levels. Medicinal plants, in particular, offer numerous benefits to humankind, including the development of natural remedies, the prevention and treatment of various diseases, and contributions to the pharmaceutical industry. Their therapeutic properties are also vital in alternative medicine practices, offering holistic treatments with fewer side effects compared to synthetic drugs. Accurate identification of medicinal plants is essential for ensuring their proper use, preservation, and effective integration into healthcare practices. However, the manual identification of

Journal of Information Systems Engineering and Management
2025, 10(37s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

plants, based on characteristics such as morphology, aroma, shape and texture, is time consuming and prone to human error[1,2]. Acquiring accurate skills and information acquisition is necessary for many techniques in classifying and identifying plant species [3,4]. This challenge becomes even more significant as the diversity of plant species continues to increase, with many medicinal plants exhibiting similar morphological features. In recent years, advancements in computer vision and deep learning have introduced automated methods for plant species identification, which offer a promising solution to these challenges. It is suggested in various research works to automate the classification of plant species based on physical features and visual characteristics [5]. Automated techniques can be used by non-experts to identify plant species with high accuracy. Artificial intelligence-based methods like deep learning and machine learning can be applied to find the right therapeutic plants. These models can be trained using morphological characteristics of leaf texture, color, binary patterns, and many more features used to achieve high classification accuracy. According to the survey, the most often utilized techniques for automating plant classification tasks are CNNs and the different CNN models. These CNN-based schemes perform reasonably in different image classification applications [6,7]. Several research works use leaves to identify plant categories; other parts, such as stems, seeds, petals, and flowers, can also be used to automate the identification process. Among these, flower identification has emerged as a key area of interest due to the unique and often distinguishing features flowers possess. This paper proposes a novel framework for the automated classification of medicinal plant flowers using deep learning techniques. The proposed method integrates the Detectron2 model for flower region segmentation, ensuring precise delineation of flower boundaries, which is crucial for subsequent analysis. Feature extraction is carried out using advanced techniques to capture both color and texture patterns, which are then optimized using PSO [19,20] to enhance the classification performance. The primary objective of this study is to develop a reliable, efficient, and scalable method for medicinal plant flower identification that can be used by non-experts in various practical applications. By leveraging the power of deep learning and optimization techniques, we aim to improve the accuracy of medicinal plant identification, making it accessible for broader applications, from botanical research to pharmaceutical development.

II. RELATED WORKS

The systematic review [8] examines the use of deep learning for medicinal plant classification, analyzing 31 studies and highlighting trends like the use of CNNs (64.5%) and transfer learning (83.8%). It identifies key gaps, including the lack of global datasets and trust in deep learning methods, urging further research and collaboration. A hybrid approach [9] based on feature selection and deep convolutional neural networks (DCNN) is presented for classifying flower species. The features are extracted using a pre-trained DCNN composed of AlexNet and VGG16. VGG19+DensNet201 was found to have higher accuracy than the rest of the related models. Qin et al. [10] proposed a combined object detection and attention-based approach for flower species recognition from image databases. This method improves performance in complex backgrounds by integrating detection and classification, reducing training time. Experimental analysis demonstrated its effectiveness in increasing mean average precision and accurately identifying flowers in challenging settings

A modified multimodal CNN (m-CNN) is used [11] for classifying flower images. The convolutional layer in the m-CNN model extracts essential features, which are given as input to the fully connected layer for classification. The m-CNN model achieves better results compared to other data fusion techniques. Another feature selection and CNN-based flower classification method is presented in the scheme [12]. In this approach, the features selected and extracted by the CNN are concatenated. Reducing and classifying the features chosen by the feature selection strategy is the primary goal, as it increases the classification accuracy. A transfer learning based DCNN model is implemented [13] and fine-tuned to achieve higher classification accuracy. The images are preprocessed by resizing and normalizing, and the potentiality of the DCNN model was evaluated using training, testing, and validation datasets.

Journal of Information Systems Engineering and Management
2025, 10(37s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

Feature extraction is highly prominent in the flower classification process and has a profound influence on improving classification accuracy [14]. Rathna et al. [15] discussed different image processing methods for medicinal plant classification. An effective feature extraction technique is combined with the classifier to achieve the desired recognition performance. Other image processing techniques, such as the Median filter, Gabor filter, Mean filter, Morphological filter, histogram equalization methods, and Average filter, can improve the quality of plant images and help identify specific medicinal plants. The scheme [16] utilized different features, such as length, width, area, colour, textures, etc., to automatically train the model to identify medicinal plants. [17] This study improves medicinal plant classification using ensemble learning and transfer learning with CNNs like VGG16, VGG19, and DenseNet201. By combining models through averaging strategies, the VGG19+DenseNet201 ensemble achieved 99.12% test accuracy on the Mendeley Medicinal Leaf Dataset, outperforming individual models. The approach effectively captures patterns in leaf images, with future plans focusing on enhancing datasets and developing real-time applications. A CNN-based leaf image classification is presented in the scheme [18]. The dataset was created with medicinal plants collected from different regions across Bangladesh. A three layered CNN model was designed for extracting high level representational features for classification.

Overall, images were used for training, and the performance was tested on images. Feature extraction and classification are highly prominent in the medicinal plant recognition process, and these methods play an essential role in improving the accuracy of the identification process. Most works discussed above use the complete image to train the deep learning model. As a result, these models collect more features from the background region, reducing the classifier's performance while increasing the computational overhead. Even though a few deep learning schemes use segmentation algorithms to train the flower region leaving the background, these approaches provide a higher intraclass variation since there is no uniform feature pattern during the model training if the same flower has a different contrast or texture caused during image capturing. Thus, these models try to extract a single-type feature during the training process, which minimizes the performance during flower classification. To overcome the limitations, the proposed scheme utilizes a hybrid feature extraction approach that can yield a better result than a single-type feature. Therefore, the work uses three feature extraction algorithms to extract the flowers' texture and colour patterns. To avoid the unnecessary features extracted from the flower background and obtain an accurate flower boundary, a Detectron2 model is utilized to segment the flower region. Also, training the model with complete color and texture features, including the redundant feature, will increase the computation complexity and reduce the performance. Therefore, the work uses a PSO algorithm-based feature selection that selects the dominant features that highly differentiate the flower classes. The work uses a CNN with an IS-PSO model to identify flowering medicinal plants. Optimization within CNN improves its performance in flower classification. The potential impact of this comprehensive approach on flower classification is significant and promising, as discussed in the following section.

III. PROPOSED APPROACH

The proposed medicinal flower classification involves four significant processes: preprocessing, flower segmentation, feature extraction, and classification. Fig.1 illustrates the block diagram of the proposed model, providing a visual overview of these interconnected processes. To evaluate the proposed approach, 14 different medicinal flowers are considered. The dataset contains 1400 images, with each flower category having, on average, 100 samples. The flowering medicinal plant images are collected during the blooming season. The plants were photographed using an Android mobile and resized to 512×512 pixels. The collected species are highly medicinally valuable. Fig.2 displays sample images of various medicinal flowers along with their botanical names.

Journal of Information Systems Engineering and Management
2025, 10(37s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

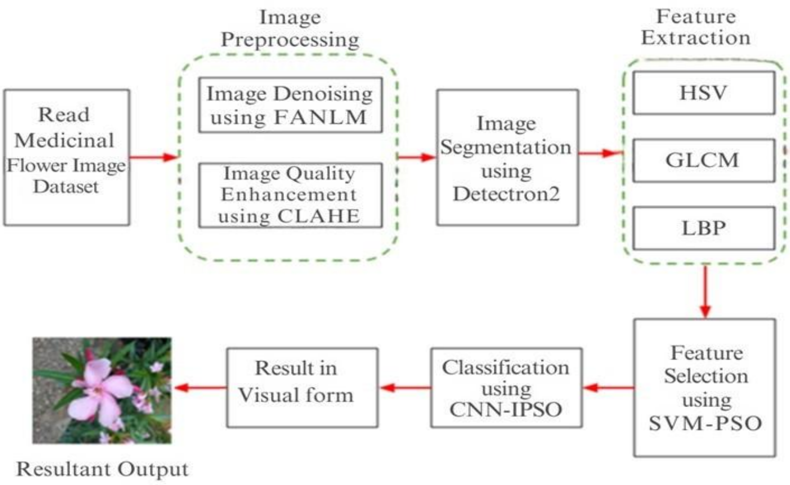

Fig. 1. Block diagram of the proposed model.

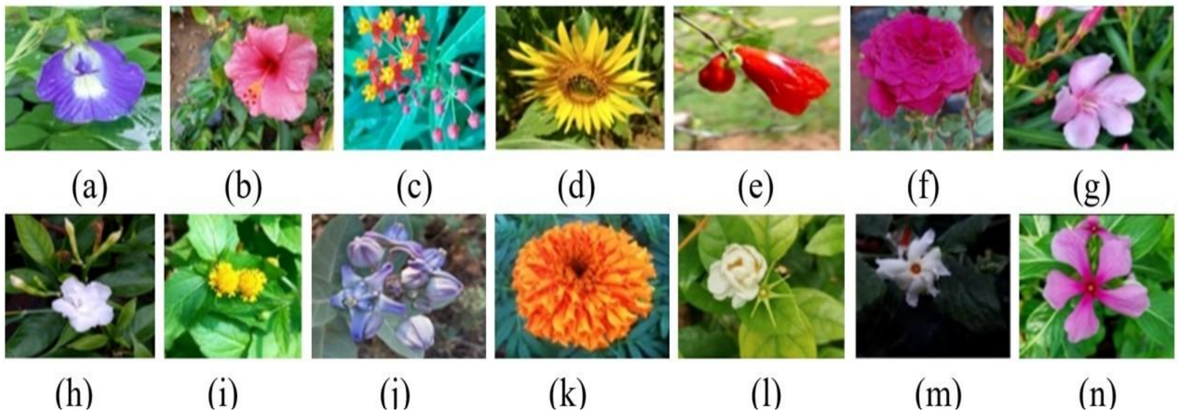

Fig. 2.Medicinal Flower images Dataset: (a) Clitoria Ternatea, (b) Hibiscus Rosa-Sinensis (c) Asclepias Curassavica, (d) Helianthus Annuus, (e) Punica Granatum (f) Rosa Hybrids (g) Nerium Oleander, (h) Tabernaemontana Divaricata, (i) Spilanthes Acmella, (j) Calotropis Gigantea, (k) Tagetes, (l) Jasminum Sambac, (m) Nyctanthes Arbortristis, and (n) Catharanthus Roseus.

A. Preprocessing

The medicinal flower images undergo a preprocessing phase designed to enhance their quality and ensure optimal performance in subsequent stages of classification. This stage addresses various challenges, such as image distortions, scale variations, and missing or incomplete information, which can degrade classification accuracy. This proposed approach utilizes two techniques for preprocessing, namely Fuzzy Adaptive Non Local Mean with Fuzzy k-means (FANLM) [21] for image denoising and Contrast-Limited Adaptive Histogram Equalization (CLAHE) [22] for image quality enhancement. The proposed FANLM (Fuzzy Adaptive Non-Local Means) method addresses the challenges of irregular and fuzzy image borders by leveraging fuzzy rules and neutrosophic sets to reduce uncertainties during segmentation. By utilizing predefined clusters and centroids along with gradient and intensity information, the method enhances segmentation precision. Additionally, the adaptive denoising approach optimizes the search window size based on local pixel properties, using an improved Median Absolute Deviation (MAD) estimator to mitigate Rician noise while preserving essential image clarity. This ensures better feature retention, such as petal textures and edges, crucial for accurate classification. Compared to traditional techniques, FANLM demonstrates superior performance by providing clearer segmentation, reduced noise, and enhanced feature extraction, ultimately improving

Journal of Information Systems Engineering and Management
2025, 10(37s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

classification accuracy across the dataset of medicinal flowers. The research employs the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique, an improved version of Adaptive Histogram Equalization (AHE), to enhance the contrast of medicinal plant images while avoiding overamplification. Unlike global methods, CLAHE is applied selectively to small regions, or ”tiles,” within the image. Bilinear interpolation is used to merge adjacent tiles, ensuring smooth transitions and eliminating arbitrary borders. The technique equalizes the brightness channel of RGB images, significantly improving contrast. CLAHE is configured with two parameters: the clip limit, which prevents excessive contrast amplification (set to a default value of 40), and the tile grid size, which determines the size of the regions processed (set to 8 x 8 in this study). These parameters ensure effective enhancement while preserving image details, making CLAHE particularly suited for preprocessing in medicinal plant image analysis. The following Fig.3 shows the result of pre-processed step. (a) The unprocessed image, (b) the image is converted to the Lab color space, which separates luminance (L) from color (a and b channels). a represents the color spectrum from green to red. b represents the color spectrum from blue to yellow. The color model is used in image processing for color correction and enhancement. (c) the denoised image using FANLM (d) the contrast-enhanced image using CLAHE, and (e) Histogram of input image and pre processed image. Histogram represents the pixel intensity distribution of the original image and pixel intensity distribution after applying a preprocessing technique. CLAHE modifies the histogram by redistributing pixel intensities for local contrast enhancement. FANLM smooths the image while preserving edges, reducing sharp intensity variations.

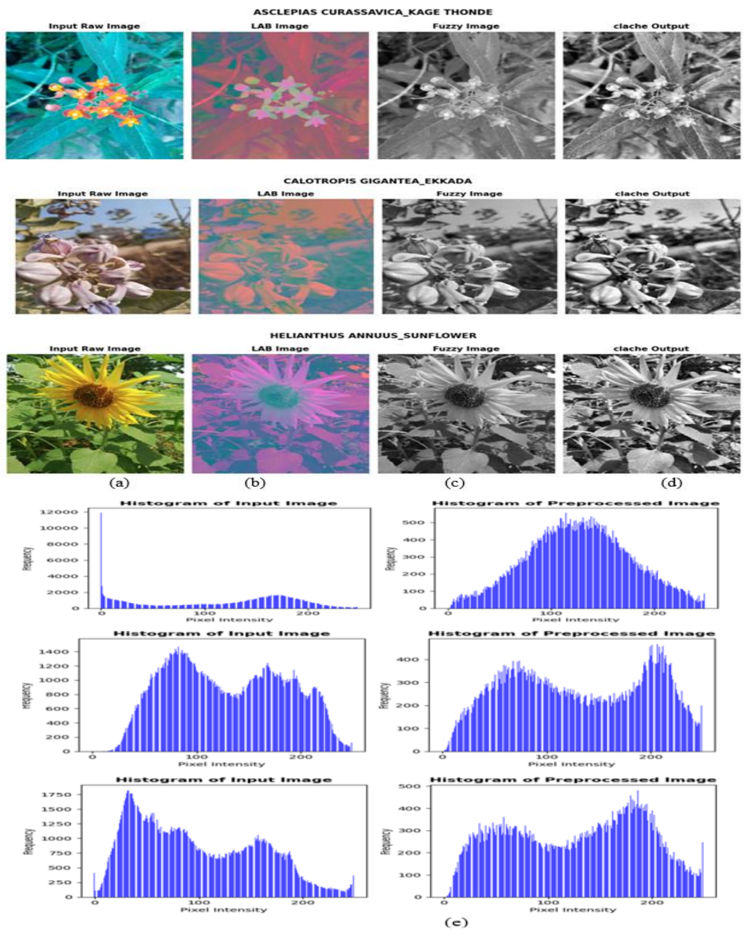

Fig. 3. Visual Representation of Preprocessing Techniques on Medicinal flower sample images.

Journal of Information Systems Engineering and Management
2025, 10(37s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

B. Segmentation

The preprocessed images are used to train the Detectron2 model to segment medicinal flower images accurately. Detection 2 is the advanced version of Detectron and Mask RCNN model [23], which is extensively used in object detection and instance segmentation tasks. The architecture of the Detectron2 model is shown in Fig.3. The Detectron2 model [24] consists of a backbone network consisting of a feature pyramid network (FPN) and Region Proposal Network (RPN) to accurately detect and localize flowers in an image. In this model, the base layer consists of R-CNN and FPN, and the model is extended to an R-CNN mask. The model can generate pixel-level masks for individual flowers, which is especially useful when flowers overlap or have irregular shapes. Accurate segmentation is critical for extracting fine-grained details that contribute to the classification task. The proposed architecture is a two-layered network and has three important blocks, namely a backbone network, a Region of Interest (ROI), and a region proposal network (RPN) head (box head). Detectron2 supports both object detection and instance segmentation simultaneously, which means it can detect flower locations while also creating masks for them which is shown in Fig.4. This dual capability allows for a richer understanding of the flowers and their context, improving the overall classification performance. Detectron 2 methods understand the plant's parts and enable it to distinguish similar-looking flowers in the image. It locates and segments individual flowers in a complex background. The boundary of the flower regions is highly preserved by the detectron2 approach even though the background leaf region and foreground flower region overlap. The annotated bounding box around the flowering image enables the CNN model to locate the

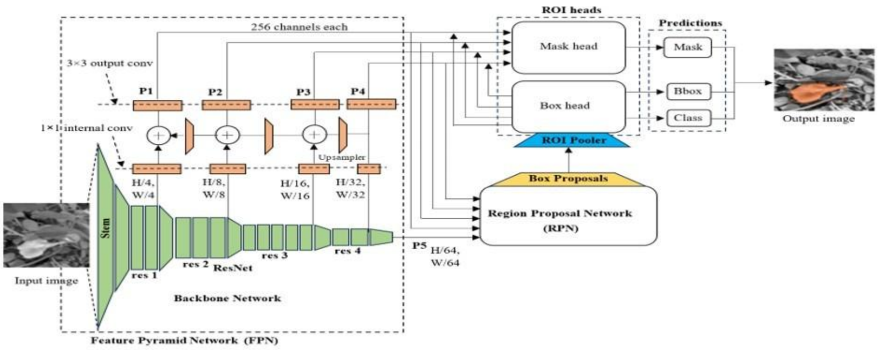

Fig. 4. The architecture of the Detectron2 model.

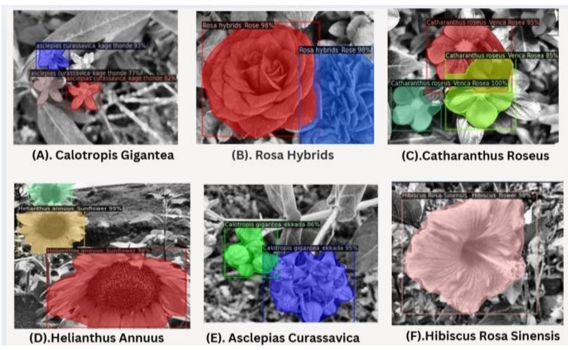

Fig. 5. Annotated with bounding box around sample medicinal flower images.

flower parts and focus on specific regions of interest, rather than analysing the entire image. Key features such as flower shape, color, and texture are extracted from the annotated box which is shown in Fig.5, aiding the model in understanding the plant's characteristics. By focusing on annotated bounding boxes and segmentation masks, Detectron2 reduces the need for vast amounts of labelled data and false positive detections. This makes the model more robust and better at generalizing to new, unseen flower images, even when data is limited.

Journal of Information Systems Engineering and Management
2025, 10(37s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

C. Feature Extraction

The study employs color and texture-based feature extraction techniques to enhance medicinal flower classification. For color features, HSV (Hue-Saturation-Value) [28] is used, where hue identifies color, saturation measures purity, and value indicates brightness. A mapping approach using MATLAB's rgb2hsv function extracts mean H, S, and V values from segmented images. For texture features, GLCM (Gray-Level Co-occurrence Matrix) [25] and LBP (Local Binary Pattern) [26-27] are utilized. GLCM calculates texture-related features like energy, contrast, correlation, dissimilarity, homogeneity, and Angular Second Moment (ASM) by analysing the spatial distribution of Gray levels in four orientations (0°, 45°, 90°, and 135°). LBP generates binary patterns for each pixel to extract unique texture features, focusing on uniform patterns that capture local intensity variations. The Fig. 6 demonstrates, Initially, the flower region was isolated through segmentation, producing a segmented image that served as the foundation for subsequent analysis. The segmented image was then converted to the HSV color space to enhance color representation, and individual Hue (H), Saturation (S), and Value (V) channels were extracted. These channels were later merged to form a composite image capturing essential color characteristics. To extract texture features, the merged image was processed using Local Binary Patterns (LBP), which emphasizes local texture variations. The corresponding LBP histogram quantifies these patterns by displaying the frequency distribution of LBP values. Additionally, Gray-Level Co-occurrence Matrix (GLCM) features were computed from the merged image to capture spatial and structural properties. These methods reduce data dimensionality, eliminate redundant features, and improve model performance by organizing data effectively and decreasing processing time. The reduced feature set was obtained after feature selection using a Support Vector Machine (SVM) optimized with the Particle Swarm Optimization (PSO) algorithm. Initially, a large number of features were extracted using image processing techniques such as HSV conversion, LBP, and GLCM. Then, PSO [29] was applied to identify and retain only the most relevant features that contribute significantly to classification accuracy. PSO is used to solve different types of continuous and mixed variables. Here, PSO optimizes the SVM, which is a supervised classification technique. One of the prominent challenges associated with the SVM is the selection of feature subsets and tuning the parameters for selecting features. The PSO optimizes two parameters of SVM, namely weight, and kernel function. Weight defines the trade off between inaccurate classification and accurate classification. On the other hand, a kernel function is used for fine-tuning the parameters of SVM and selecting the feature subset.

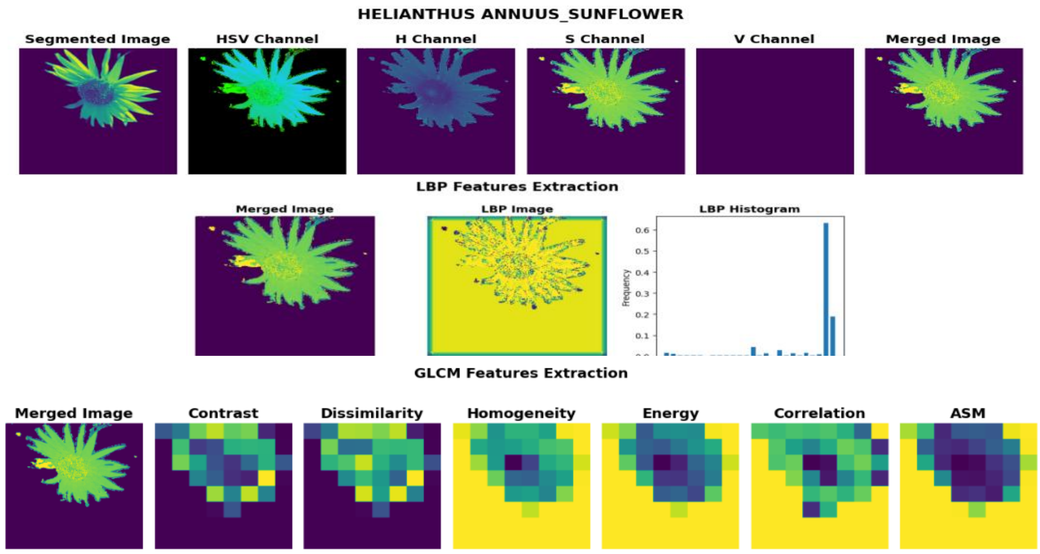

Fig. 6. Visual Representation of Feature Extraction Using HSV, LBP, and GLCM Methods.

Journal of Information Systems Engineering and Management
2025, 10(37s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

D. Classification using CNN - Improved Seeding PSO

CNN performs classification based on the extracted features automatically. CNN can learn from the extracted features while training the model [30]. CNN takes the image as input and applies filters to create a feature map and a pooling layer is applied for each feature map to reduce the dimensions of the input image. The feature maps are used in the construction of CNN and help to cope with more dense layers. CNN needs a lot of training data to properly train the model and is limited in how much it can be spatially invariant to the input data. In addition, the computational performance of the CNN model is slower since the training takes a lot of time. To overcome the drawback of the fundamental CNN, this research optimizes the CNN model using an improved seeding PSO algorithm [31]. The proposed hybrid CNN architecture consists of different layers as shown in Fig 7. The CNN-based classifier does not perform any optimization during its training process, which limits its classification performance during the testing stage. Therefore, the proposed CNN with ISPSO optimization aims to select the optimal features to train the model during the training process. This optimal feature selection reduces the classifier's training time while improving its classification performance. The optimal features are selected based on the position and velocity of the swarm of particles that correlate with different features used for training. Every particle has its value updated with both its current global best position and its previous best position. The distance from the global best location (Gbest) to the previous best position (Pbest) is used to compute the velocity. The iteration is carried out repeatedly until the algorithm reaches convergence and finds the global optimum value. The mathematical model for the proposed work is presented in the context of Medicinal Flower Classification.

1. Input Layer

Let the input image be represented as:

$\mathbf{X} \in \mathbb{R}^{H \times W \times C}$,

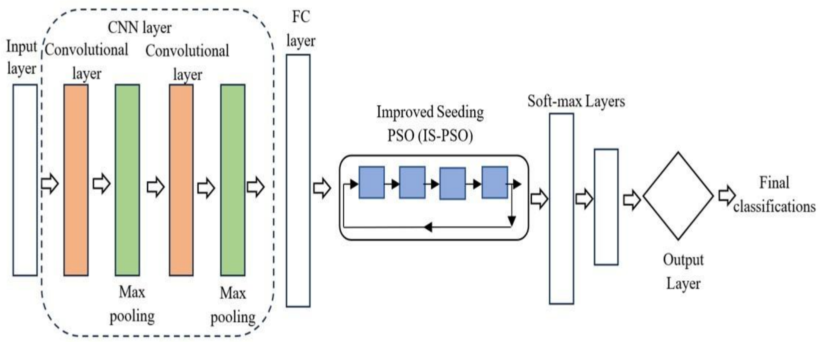

Fig. 7. Proposed Hybrid CNN with IS-PSO architecture.

where:

- H: Height of the image,
- W: Width of the image,
- C: Number of channels (e.g., RGB has $C = 3$).

2. Convolutional Layers

The output of the l-th convolutional layer is defined as:

$\mathbf{F}^{(l)} = \sigma(\mathbf{W}^{(l)} * \mathbf{F}^{(l-1)} + \mathbf{b}^{(l)})$,

where:

- $\mathbf{F}^{(0)} = \mathbf{X}$ (input image),
- $\mathbf{F}^{(l)}$: Output of the l-th layer,
- $\mathbf{W}^{(l)}$: Learnable weights of the convolutional filter in layer l,
- $\mathbf{b}^{(l)}$: Bias term,
- $*$: Convolution operation, • σ: Activation function (e.g., ReLU).

Journal of Information Systems Engineering and Management
2025, 10(37s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

3. Max-Pooling Layers

The max-pooling operation for the l-th layer is given by:

$$\mathbf{P}^{(l)}(i,j,k) = \max_{(m,n)\in R} \mathbf{F}^{(l)}(i+m, j+n, k),$$

where R is the pooling region (e.g., 2 × 2).
The output of pooling replaces the feature map for the next layer:
$\mathbf{F}(l+1) = \mathbf{P}(l)$.

4. Fully Connected (FC) Layer

The flattened feature vector from the final CNN layer is passed through a fully connected layer:
$\mathbf{z} = \mathbf{W}\mathrm{FC}\mathbf{f} + \mathbf{b}\mathrm{FC},$
where:
- $\mathbf{f}$: Flattened output of the last CNN layer, • $\mathbf{W}_{FC}$: Weight matrix of the fully connected layer,
- $\mathbf{b}_{FC}$: Bias vector.

5. Improved Seeding PSO (IS-PSO)

The Improved Seeding Particle Swarm Optimization (IS-PSO) optimizes the network parameters θ. Let:
- θ_t: Position of a particle at iteration t,
- v_t: Velocity of the particle at iteration t, • p_t: Best position of the particle (personal best),
- g_t: Global best position.

The update equations for IS-PSO are: $vt+1 = \omega vt + c1r1(pt - \theta t) + c2r2(gt - \theta t)$, $\theta_t+1 = \theta_t + v_t+1$,
where:
- ω: Inertia weight,
- c_1,c_2: Acceleration coefficients,
- $r_1,r_2 \sim U(0,1)$: Random values.

The objective function to optimize is typically the classification loss.

6. Softmax Layer

The output of IS-PSO is fed into a softmax layer for classification:

$$\hat{y}_i = \frac{\exp(z_i)}{\sum_{j=1}^{K} \exp(z_j)},$$

where:
- $\hat{y}_i$: Predicted probability for class i,
- K: Total number of classes, • z_i: Input to the softmax layer for class i.

7. Final Classification

The softmax layer produces a vector of probabilities:
$\hat{\mathbf{y}} = [\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_K],$
These probabilities satisfy:

$$\sum_{i=1}^{K} \hat{y}_i = 1,$$

ensuring the output is a valid probability distribution.
The final predicted class is determined by selecting the class with the highest probability:

$$\text{Class} = \arg\max_i \hat{y}_i,$$

where:
- $\arg\max_i$ returns the index i of the maximum value in the vector $\hat{\mathbf{y}}$,
- The index i corresponds to the predicted class label.

Journal of Information Systems Engineering and Management
2025, 10(37s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

STEPS FOR MEDICINAL FLOWER CLASSIFICATION USING CNN WITH IS-PSO

1) Input Dataset: Load the dataset containing images of medicinal flowers. The dataset is typically split into training, validation, and testing subsets. Each image should be pre-processed (e.g., resized, normalized) to ensure compatibility with the CNN model.

2) Generate Particle Population: Initialize the particle population for the IS-PSO algorithm. Each particle represents a candidate solution, such as a set of CNN hyperparameters or weights. The population is defined by:

- Initial positions θ_0 for each particle.
- Initial velocities v_0 for each particle.
- A random initialization of global best (G_{best}) and personal best (P_{best}) values.

3) Set Up CNN Model: Define the architecture of the CNN model, including:

- Convolutional layers for feature extraction.
- Max-pooling layers to reduce dimensionality.
- Fully connected (FC) layers for classification.
- A softmax layer to output probabilities for each class.

The CNN is initialized with random weights.

4) Training and Validation: Train the CNN model on the training dataset. The training process involves:

- Forward propagation to calculate predictions.
- Backpropagation to adjust weights using gradient descent.
- Validation on a separate dataset to evaluate model performance and prevent overfitting.

5) Evaluate Objective Function: Compute the objective function to assess the model's performance. The objective function could be:

- Cross-entropy loss for classification problems:

$$L = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{K} y_{ij}\log(\hat{y}_{ij}),$$

where y_{ij} is the true label and $\hat{y}_{ij}$ is the predicted probability for class j.

- Accuracy or another performance metric.

6) Update PSO Parameters: Use the IS-PSO algorithm to optimize the CNN model's hyperparameters or weights. For each particle:

- Update the velocity:

$vt+1 = \omega vt+c1r1(Pbest,t-\theta t)+c2r2(Gbest,t-\theta t)$, where:

– ω: Inertia weight to balance exploration and exploitation.
– c_1,c_2: Acceleration coefficients for personal and global best contributions.
– r_1,r_2: Random numbers uniformly distributed in [0,1].
– $P_{best,t}$: The personal best position of the particle at time t.
– $G_{best,t}$: The global best position of the swarm at time t.

- Update the position:

$\theta_t+1 = \theta_t + v_t+1,$

where θ_t represents the current position of the particle.

- Evaluate the updated particle positions and update P_{best} and G_{best} based on the objective function.

This step iteratively improves the CNN's parameters to minimize the objective function.

7) Check Stop Criteria: Evaluate whether the stopping criteria are met. Common criteria include:

- A maximum number of iterations or epochs.
- Convergence of the objective function (e.g., minimal change in loss or improvement).
- Achieving a desired accuracy or performance threshold.

If the stopping criteria are not met, return to Step 4 (Training and Validation).

Journal of Information Systems Engineering and Management
2025, 10(37s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

8) Select Optimal Features: Once the stopping criteria are met, finalize the CNN model with the optimized parameters. The selected features and parameters represent the best-performing configuration for classifying medicinal flowers.
9) Repeat (if necessary): If new data or additional requirements emerge, repeat the process from Step 1 to further optimize the model.

IV. RESULTS AND DISCUSSION

The performance of the proposed flower classification system was compared with traditional models like CNN+LSTM [28], CNN+GRU [29], and CNN [30]. Fig.8 illustrates the class-wise performance measurement of the 14 flower image categories. For all classes of medicinal flowers, the CNN proposed with IS-PSO optimization results in higher accuracy, precision, recall, and F1 score than the traditional approaches. Combining LSTM and GRU [32-33] with CNN can leverage both spatial and temporal relationships, leading to improved accuracy. In flower classification, both long-term and short-term dependencies are important; by considering these dependencies, the model gains an understanding of the flower characteristics and more accurate classification. Flower datasets have high dimensionality and variability.

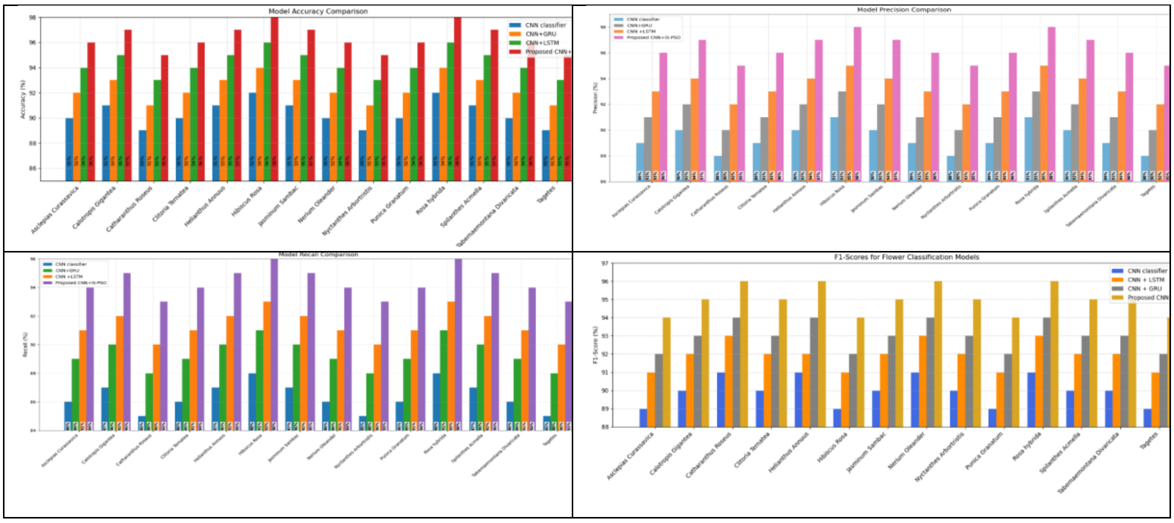

Fig. 8. Class-wise Performance comparison of CNN+IS-PSO with other classifiers: Accuracy, Precision, Recall, F1-score.

The GRU and LSTM have limited ability to handle high dimensional datasets and are not suitable for non-sequential data. LSTM and GRU are effective in temporal relationships between flower images, not spatial relationships. It is suitable for missing data and irregular time series applications. The proposed model reduces overfitting by selecting relevant features and improving interpretability, due to their recurrent nature in traditional-based CNN with LSTM and GRU suffering from overfitting. The optimized CNN hyperparameter makes the models generalize to new or unseen flower species. The optimized features selection and extraction reduce a large amount of labelled training data.

Journal of Information Systems Engineering and Management
2025, 10(37s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

TABLE I PERFORMANCE COMPARISON OF CNN+IS-PSO WITH OTHER CLASSIFIERS.

Metrics	CNN [29]	CNN+LSTM [27]	CNN+GRU [28]	Proposed CNN+ISPSO
Accuracy (%)	77.31	65.27	83.59	97.64
Precision (%)	77.31	65.27	83.59	97.64
Recall (%)	80.21	67.59	85.70	97.72
F1-score (%)	77.31	65.27	83.95	97.64

Table 1 demonstrates that the performance matrices of the proposed CNN + IS-PSO model significantly outperform traditional classifiers, including CNN, CNN + LSTM and CNN + GRU, in terms of accuracy, precision, recall and F1 score. The proposed method achieves the highest accuracy of 97. 64%, precision of 97. 64%, recall of 97.72%, and F1-score of 97.64%, demonstrating its ability to optimize feature extraction and parameter tuning effectively. In comparison, CNN + LSTM achieves the lowest performance, with an Accuracy of 65.27%, while CNN and CNN+GRU show incremental improvements but fall short of the proposed method. The integration of IS-PSO (Improved Swarm Particle Optimization) enhances the CNN framework by refining feature selection and hyperparameter optimization, reducing overfitting, and improving generalization. Unlike LSTM and GRU, which focus on sequence modeling, IS-PSO ensures a more efficient and precise learning process, leading to a balanced trade-off between computational efficiency and model performance. This makes CNN+IS-PSO an ideal choice for complex tasks like medicinal flower classification.

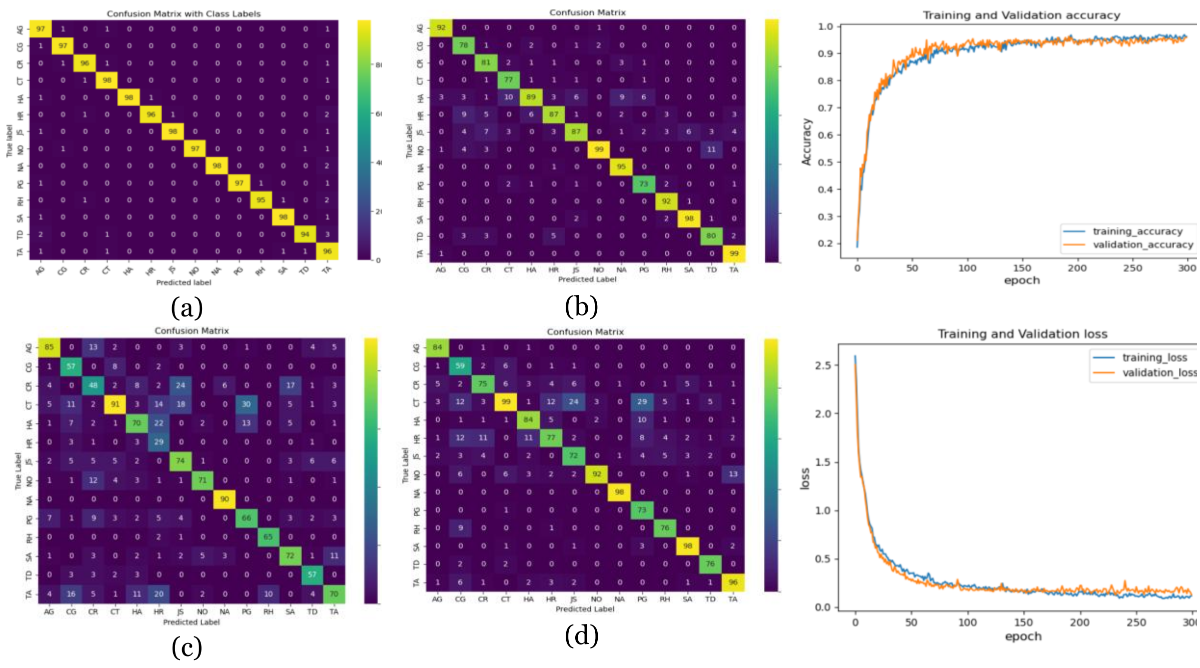

Fig. 9. Confusion matrices for medicinal flower classification were obtained using proposed CNN+IS-PSO, CNN+GRU, CNN+LSTM, and CNN.

Fig. 9 shows the performance of different deep learning models for classifying medicinal flowers using confusion matrices and training graphs. The proposed CNN model with ISPSO (a) achieves the highest accuracy with very few misclassifications, showing strong and stable learning. The CNN+GRU model (b) also performs well, but with slightly more classification errors. CNN+LSTM (c) shows signs of overfitting, as seen in its lower validation accuracy and higher loss. The baseline CNN (d) performs the weakest, with noticeable misclassifications and limited accuracy. Overall, the proposed CNN with ISPSO clearly outperforms the other models in both accuracy and reliability. The proposed CNN+IS-PSO method excels because it integrates Improved Swarm Particle Optimization (IS-PSO), which enhances feature selection and hyperparameter tuning. This leads to higher accuracy, as evident from the sharp diagonal dominance, and lower misclassifications, with minimal off-diagonal elements. By combining CNN's feature extraction capabilities with IS-PSO's optimization, the proposed method reduces overfitting, improves generalization, and ensures more robust and precise classification performance. This makes the CNN+IS-PSO approach the most effective for medicinal flower classification tasks. Both training and validation accuracies steadily increase and plateau around 0.95–0.98, which indicates that the models learned well. The gap between training and validation accuracy is minimal, suggesting low overfitting. Training and validation loss both decrease sharply and stabilize. The loss curves show good convergence, which indicates that the training process was efficient and stable.

V. CONCLUSION

The proposed CNN-IS-PSO system efficiently identifies medicinal flowers using advanced feature selection and optimization. FANLM denoises images, CLAHE enhances them, and Detectron2 segments flower regions while preserving boundaries. Key features (HSV, GLCM, LBP) are extracted and optimized using SVM-PSO, with the dominant features trained using CNN-IS-PSO. The system achieves high performance with accuracy 97.64%, a precision 97.64%, recall 97.72%, and F1 score 97.64%, surpassing other classifiers. Feature selection is controlled by a parameter with optimal results. The selection parameter α is set to 0.8, balancing efficiency and precision. This makes the system suitable for real-time classification in complex backgrounds, showcasing its potential for practical applications.

REFERENCES

[1] Y. M. Mbuni, S. Wang, B. N. Mwangi, N. J. Mbari, P. M. Musili, N. O. Walter, G. Hu, Y. Zhou, and Q. Wang, "Medicinal plants and their traditional uses in local communities around Cherangani Hills, Western Kenya," *Plants*, vol. 9, no. 3, p. 331, 2020.

[2] R. Azadnia, M. M. Al-Amidi, H. Mohammadi, M. A. Cifci, A. Daryab, and E. Cavallo, "An AI Based Approach for Medicinal Plant Identification Using Deep CNN Based on Global Average Pooling," *Agronomy*, vol. 12, no. 11, p. 2723, 2022.

[3] K. Pushpanathan, M. Hanafi, S. Mashohor and W. F. Fazlil Ilahi, "Machine learning in medicinal plants recognition: a review," *Artificial Intelligence Review*, vol. 54, no. 1, pp. 305-327, 2021.

[4] T. N. Quoc and V. T. Hoang, "Medicinal Plant identification in the wild by using CNN," in *2020 International Conference on Information and Communication Technology Convergence (ICTC)*, Jeju, South Korea, 2020, pp. 25-29.

[5] M. Kansara and A. Parikh, "Indian Ayurvedic plant identification using multi-organ image analytics: Creation of image dataset of Indian medicinal plant organs," in *Proceedings of the International Conference on Innovative Computing & Communications (ICICC)*, 2020.

[6] S. H. Krishnan, C. Vishwa, M. Suchetha, A. Raman, R. Raman, S. Sehastrajit, and D. E. Dhas, "Comparative performance of deep learning architectures in classification of diabetic retinopathy," *International Journal of Ad Hoc and Ubiquitous Computing*, vol. 44, no. 1, pp. 23-35, Sep. 2023.

[7] VSS Bala Tripura Sathvika, et al., ”Pipelined Structure in the Classification of Skin Lesions based on Alexnet CNN and SVM Model with Bi-sectional Texture Features,” *IEEE Access*, 2024.
[8] A. Kiflie, M. D. Prasad Sharma, and A. H. Mesfin, ”Deep learning for medicinal plant species classification and recognition: a systematic review,” *Frontiers in Plant Science*, vol. 14, Jan. 2024, doi: 10.3389/fpls.2023.1286088.
[9] M. Cıbuk, U. Budak, Y. Guo, M. C. Ince, and A. Sengur, ”Efficient deep features selections and classification for flower species recognition,” *Measurement*, vol. 137, pp. 7-13, 2019.
[10] W. Qin, X. Cui, C. A. Yuan, X. Qin, L. Shang, Z. K. Huang, and S. Z. Wan, ”Flower species recognition system combining object detection and attention mechanism,” in *Intelligent Computing Methodologies: 15th International Conference, ICIC 2019*, Nanchang, China, Aug. 3–6, 2019, Part III, pp. 1-8.
[11] K. I. Bae, J. Park, J. Lee, Y. Lee, and C. Lim, ”Flower classification with modified multimodal convolutional neural networks,” *Expert Systems with Applications*, vol. 159, p. 113455, 2020.
[12] M. Togac¸ar, B. Ergen, and Z. C˘ omert, ”Classification of flower¨ species by using features extracted from the intersection of feature selection methods in convolutional neural network models,” *Measurement*, vol. 158, p. 107703, 2020.
[13] N. Alipour, O. Tarkhaneh, M. Awrangjeb, and H. Tian, ”Flower[31] image classification using deep convolutional neural network,” in *2021 7th International Conference on Web Research (ICWR)*, pp. 1-4, May 2021.
[14] T. Tigistu and G. Abebe, ”Classification of rose flowers based on[32] Fourier descriptors and color moments,” *Multimedia Tools and Applications*, vol. 80, no. 30, pp. 36143-36157, 2021.
[15] B. Pukhrambam and R. Rathna, ”A Smart Study On Medicinal Plants Identification And Classification Using Image Processing[33] Techniques,” in *2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV)*, Tirunelveli, India, 2021, pp. 956-962.
[16] A. Gokhale, S. Babar, S. Gawade, and S. Jadhav, ”Identification of medicinal plant using image processing and machine learning,” in *Applied Computer Vision and Image Processing: Proceedings of ICCET 2020*, vol. 1, Springer, Singapore, 2020, pp. 272-282.
[17] M. A. Hajam, T. Arif, A. Mohi Ud Din Khanday, and M. Neshat, ”An Effective Ensemble Convolutional Learning Model with Fine-Tuning for Medicinal Plant Leaf Identification,” *Information*, vol. 14, no. 11, p. 618, 2023, doi: 10.3390/info14110618.
[18] R. Akter and M. I. Hosen, ”CNN-based leaf image classification for Bangladeshi medicinal plant recognition,” in *2020 Emerging Technology in Computing, Communication and Electronics (ETCCE)*, Bangladesh, 2020, pp. 1-6.
[19] W. H. Bangyal, K. Nisar, T. R. Soomro, A. A. Ibrahim, G. A. Mallah, N. U. Hassan, and N. U. Rehman, ”An Improved Particle Swarm Optimization Algorithm for Data Classification,” *Appl. Sci.*, vol. 13, no. 1, p. 283, 2023, doi: 10.3390/app13010283.
[20] M. T. Islam, W. Rahman, M. S. Hossain, M. A. Sama, and M. A. Samad, ”Medicinal Plant Classification Using Particle Swarm Optimized Cascaded Network,” *IEEE Access*, Jan. 2024, pp. 1-1.
[21] C. Singh and A. Bala, ”A local Zernike moment-based unbiased nonlocal means fuzzy C-Means algorithm for segmentation of brain magnetic resonance images,” *Expert Systems with Applications*, vol. 118, pp. 625-639, 2019.
[22] S. Sahu, A. K. Singh, S. P. Ghrera, and M. Elhoseny, ”An approach for de-noising and contrast enhancement of retinal fundus image using CLAHE,” *Optics & Laser Technology*, vol. 110, pp. 87-98, 2019.
[23] P. Udawant and P. Srinath, ”Cotton Leaf Disease Detection Using Instance Segmentation,” *Journal of Cases on Information Technology*, vol. 24, no. 4, pp. 1-xx, 2024. [Online]. Available: http://creativecommons.org/licenses/by/4.0/.

[24] A. Suljovic, S.´ Caki ˇ c, and T. Popovi´ c, ”Detection of Plant´ Diseases Using Leaf Images and Machine Learning,” in *Proc. 21st Int. Symp. INFOTEH-JAHORINA*, Jahorina, Bosnia and Herzegovina, Mar. 2022, pp. xx-xx, doi: 10.1109/INFOTEH53737.2022.9751245.
[25] A. Mathew, A. Antony, Y. Mahadeshwar, T. Khan, and A. Kulkarni, ”Plant disease detection using GLCM feature extractor and voting classification approach,” *Materials Today*, vol. 58, pt. 1, pp. 407-415, 2022, doi: 10.1016/j.matpr.2022.02.350.
[26] S. Ariyapadath and R. Neethu, ”Classification of plant leaf using shape and texture features,” in *Inventive Communication and Computational Technologies (ICICCT 2020)*, vol. 145, Springer, 2020, pp. xx–xx, doi: 10.1007/978-981-15-7345-3$_2$2.
[27] A. Sujith and S. Aji, ”An optimal feature set with LBP for leaf image classification,” in *2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC)*, pp. 220-225, Mar. 2020. [28] T. Kusnandar, J. Santoso, and K. Surendro, ”Enhancing color selection in HSV color space,” *International Information and Engineering Technology Association*, vol. 29, no. 4, pp. 1483–1491, Aug. 2024, doi: 10.18280/isi.290421.
[29] V. P. Kour and S. Arora, ”Particle swarm optimization based support vector machine (P-SVM) for the segmentation and classification of plants,” *IEEE Access*, vol. 7, pp. 29374-29385, 2019.
[30] B. Dey, J. Ferdous, R. Ahmed, and J. Hossain, ”Assessing deep convolutional neural network models and their comparative performance for automated medicinal plant identification from leaf images,” *Heliyon*, vol. 10, no. 1, e23655, Jan. 2024, doi: 10.1016/j.heliyon.2024.e23655.
[31] A. Gupta, D. Gupta, M. Husain, M. N. Ahmed, A. Ali, and P. Badoni, ”A PSO-CNN-based approach for enhancing precision in plant leaf disease detection and classification,” *Informatica*, vol. 47, no. 9, pp. 173–182, 2023, doi: 10.31449/inf.v47i9.5188.
[32] J. Banzi and T. Abayo, ”Plant species identification from leaf images using deep learning models (CNN-LSTM architecture),” *Tanzania Journal of Forestry and Nature Conservation*, vol. 90, no. 3, pp. 93103, 2021.
[33] J. Yu, X. Zhang, L. Xu, J. Dong, and L. Zhangzhong, ”A hybrid CNN-GRU model for predicting soil moisture in maize root zone,” *Agricultural Water Management*, vol. 245, p. 106649, 2021.
[34] Bharathi M P and Dr. Samitha Khaiyum, Dr. Shivakumar Sawmy S, “Predictive Analysis of Colorectak Cancer via CT scans using Convolutional Neural Networks”, International Journal of Membrane Science and Technology,2023, Vol:10, No:3, pp3378-3387.
[35] Rajani S, Veena M. N, “Ayurvedic Plants Identification based on Machine Learning and Deep Learning Technologies”, 2022 Fourth International Conference on Emerging Research in Electronics, Computer Science and Technology (ICERECT), 978-1-6654-5635-7/22/$31.00, 2022 IEEE.
[36] Rajani S, Veena M.N, “Medicinal plants segmentation using Thresholding and Edge based Techniques”, International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-8,Issue-6S4, April 2019.