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# Medicinal Plant Leaf Detection System using Machine Learning

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**Abstract**

In light of these facts one can definitely say that nature has given human beings and other living creatures 'plants' for all their needs. Ayurvedic system of medicine has more effective innovative systems for identification of therapeutic plants for the practice of health care in the battle for better life. One more use for this constructed leaf can be a way of emulating for conventional healing purposes targeting various plant-based drugs. Such as oxygen, food, medicine, fuel, gum and other basic needs for humanity can be found from plants. The presentation makes use of therapeutic leaf images to classify presenting edible plants which are known to be readily available in the region. The challenge comprises 48 distinct medicinal leaves, and it employs to 7000 images. This mathematical calculation being offered in this way through programmed thinking, there is 98'%' accuracy. Medicinal herbs are plants which have been known to be enriched by certain compounds which are good for health. This human body is complicated and biological while chemical pharmaceuticals are made purely from chemicals that are synthetic. Therefore, this is why chemical drugs are viewed as not very safe for human consumption since it may even adversely affect human health if taken repeatedly.

**Keywords**: Ayurvedic plant leaf, 49 distinct species, CNN, Medicine.

## 1. Introduction

Medicinal plants (herbs) are plants known to contain certain health-giving compounds. Each part of the medicinal plant is believed to have different properties to prevent, diversify or even cure a particular disease. There are 45,000 plant species in India and about 700 of them are classified as Ayurvedic plants (herbs) and are considered to be safer than chemical medicines. Current methods of identification are often inaccurate. Hence, this study introduces a new model based on YOLOv8 with CSPDarknetAA that enables real-time detection of medicinal plant leaves, promising better accuracy and lower computational costs. By analyzing images of leaves—through their color, size, texture, and shape using neural networks—we can identify them more effectively.

Previous studies have identified herbal medicinal plants from leaf images using artificial neural networks (ANN), gray-level co-occurrence matrix and K-nearest neighbor algorithms, local binary patterns, support vector machines, multilayer perceptrons (MPL). Our study focuses on selected Ayurvedic journals commonly used in traditional medicine.

We understand that this approach may not cover all Ayurvedic herbal medicines. Additionally, the performance of our detection model may vary depending on factors such as leaf quality, lighting conditions, and background noise. In this study, identification of medicinal plant leaves was done using YOLOv8 (You Only Look Once), which uses a convolutional neural network method and deep learning. CNN is one of the algorithms in the field of machine learning based on Artificial Neural Networks (ANN) or its evolution, namely Deep Learning, which is an evolution of Multilayer

Perceptron (MPL) that processes two-dimensional data. then YOLOv8 is used in image data to detect and recognize objects in an image. Object detection is a core task of computer vision and is used in applications such as self-driving cars, robotics and video surveillance.

This involves identifying and locating objects in images or videos, allowing machines to under- stand and interact with the visual world. Convolutional Neural Networks (CNN) have emerged as an effective method for accurate and efficient target detection. The YOLOv8 deep learning model uses CNNs to detect objects in real time with high accuracy. This development in object recognition paved the way for a variety of applications, allowing machines to perceive and understand the visual world. This study establishes a system to identify nine types of antihypertensive plant leaves using convolutional neural networks. To facilitate the user's use of the system, the system built on mobile phone software (Android) was implemented to identify the types and benefits of medicinal plant leaves for these images of 49 distinct plant leaves were used to employ 7000 images for enhancing accuracy.

## 2. Material and Methods

### 2.1. Ayurvedic leaf set:

Get a comprehensive dataset containing images of various Ayurvedic leaves. These images should cover a wide range of leaf shapes, sizes, textures and lighting conditions. Note: Manually label each image in the dataset to define bounding boxes around individual leaves and label them with the corresponding Ayurvedic leaf types. This annotated dataset is the basis for training the YOLOv8 model.

### 2.2. Model selection and training:

YOLOv8 architecture: Choose the YOLOv8 model architecture as the object detection framework due to its efficiency and accuracy.

### 2.3. Transfer learning:

Use transfer learning. starting the YOLOv8 model with large-scale pre-trained weights such as COCO (Common Objects in Context). Refine the model on the annotated Ayurvedic leaf dataset to adapt it to the leaf recognition task.

### 2.4. Validation set performance:

Evaluate the trained YOLOv8 model on the validation set to evaluate its performance in terms of accuracy, recall. and F1 score.

### 2.5. Visualization

visualizations of YOLOv8 model results, including annotated images with boxplots placed over them to demonstrate its effectiveness in identifying Ayurvedic leaves.

### 2.6. Health Benefits Classification

Feature extraction: Extract relevant features such as shape, color from observed Ayurvedic leaves and texture descriptors.

### 2.7. Deployment:

While research often yields positive outcomes, it is not always implemented immediately. The ML model is unacceptable to most individuals. To overcome this impediment, a smartphone app was developed. The designed ML model is deployed in the cloud. The smartphone app captures leaf photos, which are subsequently uploaded to a cloud-based deep learning model. The ML model identifies medicinal species. Figure 1 depicts the above-mentioned details using a flow chart.

### 2.8. YOLOMODEL:

Deep dive into YOLOv8 CSPDarknetAA: CSPDarknetAA is a framework architecture on top of which YOLOv8 works its magic to identify the main features in the images for object detection. CSP Traditional CNNs involve a large number of connections between layers and can thus be computationally expensive. CSPDarknet-AA addresses this issue using a technique known as Cross Stage Partial Connection.

The idea of CSP lies in taking two portions: one part passing through the regular circuit and another shortcut with fewer connections. This results in reducing computing cost and preserving data flow through the network.

### 2.9. Building blocks:

CSPDarknet-AA is built on residual data. These blocks allow the network to learn complex functions by stacking multiple layers and adding the output to the input. These blocks implement CSP in two ways: CSPConv: This is the main path for a normal convolution operation. CSPPuhelma: This is a shortcut with fewer convolutions, often point convolutions (1x1 kernels) to reduce dimensionality

**2.10. Adavantages of CSPDarknet-AA:**

- Efficiency: By reducing redundant connections, CSPDarknet-AA achieves significant speed improvements over traditional CNN spins. This is critical for real-time object detection applications.
- Accuracy: residual connections and efficient feature extraction using circumvolutions allow the network to learn complex patterns in the data, resulting in good object detection accuracy.
- Scalability: architecture can be easily scaled by altering its customized version. The number of stages in CSP layers and channel numbers in every level can be varied. Such features make it possible to create models having different complexities and efficiencies based on specific requirements. The CSPDarknet-AA supersedes previous versions in its range. For instance, this could include any extra methods like: Focus layer – helps enhance recognition of tiny targets; Efficient Bottleneck v2 – It is an adaptation of the CSPBottleneck with depth-wise separable convolutions possibly resulting to more efficient performance improvements.

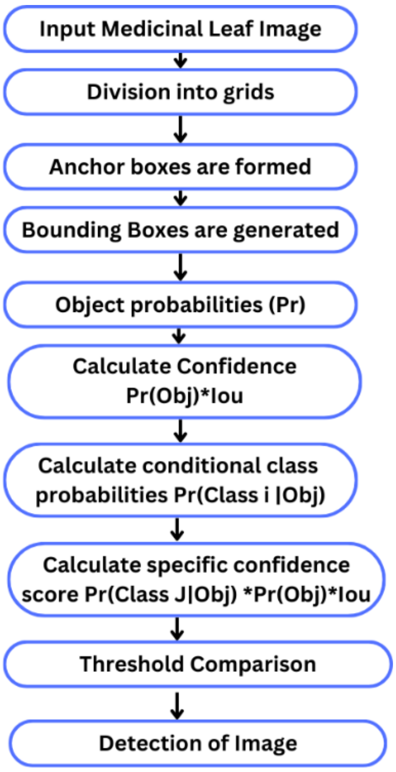


**Figure 1. Working Of Yolo Model.**

## 3. Results and Discussion

Recently, there have been advances in AI and machine learning that have further enhanced the identification and classification of Ayurvedic plants based on deep learning and shape-and texture- based studies. Plant leaf recognition using SVM and CNN methods has led to an increase in the precision of classifying Ayurvedic plants. Besides, there has been successful application of YOLO for real-time detection.

Parag Bhandarkar, Rizwan Ahmed et al were able to derive a structural signature that quantifies the leaf shape feature. To determine the identification, they computed the root mean square error between the input image's feature vectors and the image stored in the database. The authors' database includes 40 leaf samples from ten distinct species. 67.5percentage was the total classification rate they were able to attain, regardless of the size or orientation of the leaves. The identification rate is too low to be useful in real-world applications.

T. Sathwik, R. Yasaswini, et al. created a system for plant identification using only textural features. Ten textural features were retrieved from the leaf image's GLCM and utilized for classification utilizing the least dissimilarity method. The 231 system attained a 95'%' accuracy rate after being trained with 63 leaves and tested with 33 leaves. A '91%' accuracy rate was attained by combining the inverse difference moment, entropy, sum average, and difference variance. The technique was not entirely invariant to leaf rotation and was only tested on a small number of samples.

Itheri Yahiaoui, Olfa Mzoughi, et al. implemented Directional Fragment Histogram, a boundary descriptor, and five geometrical traits for identification. For the experiment, they selected 897 scan- like and 3070 scanned photos from the Plant Leaves collection. Accuracy for scanned photos is 77.83'%', and accuracy for scan-like images is 67.47'%'.

### 3.1. SVM

Advantages:

a. Generalization performances are satisfactory.

b. Sparsity and the capacity restriction due to margin maximization are other features of SVM based solution.

c. Biased SVMs may perform well even with some bias in the training sample.

Disadvantages:

a. Training takes package of time.

b. Tough/stern to explain.

c. Speed and size bottlenecks in both tests and training.

**3.2. ANN:**

Advantages:

a. In the need of less formal statistical education.

b. Ability to non-statistically look for non-linear relationships between probabilistic dependent and effecting independent parameters.

Disadvantages:

a. Excessive computation burden.

b. More sensitive to overfitting.

**3.3. CNN:**

Advantages:

a. The speed and efficiency are both exceptionally good.

b. It is as CNN architecture that features are extracted via conjunction of linear and non-linear techniques which are convolutions and activation function.

Disadvantages:

a. Not so effective with sensorometric sequential data.

b. Needs a great deal of labeled data

**4. Key Improvements**

In order to create anchorless detections, YOLOv8 makes direct predictions about the center of an object, doing away with the requirement of anchor boxes that have to be defined in advance. This improves generalization of custom datasets and also makes non-maximum suppression (NMS), a post-processing step used to fine-tune detections, faster. Multiscale object detection: It's pretty flexible for different purposes and scenarios as it enables the model to identify objects in varying sizes from one image. LIFE activation function: This function speeds up the learning process by reducing the issue of vanishing gradients which facilitates faster convergence when training. GIoU Loss: This was used by YOLOv8 as its GIoU loss function which is much better than a conventional intersection over union (IoU) at handling interfacing overlaps amongst them all.

1) Convolutional operations: Convolutional layers, which is backbone of CNN model, which utilize a filter on given input data set for feature extraction purposes. It is mathematically defined as: Output(x, y) = Wi,j * Input(x+i, y+j) + bias Where: Wi,j describes the kernel weight at (i , j). Input(x, y) indicates value (x,y) in the input data. The output value (x,y) in object map is designated by Output(x, y). The summation over all core elements is repeated

The principal term is a constant added to every location's output.

2) Residual Connections: In CSPDarknet-AA there are residual connections that add an element- wise sum from the input to the convolution block output. Mathematically: F(x)=H(x)+x Where: F(x) denotes block output while x stands for its corresponding input.

3) ReLU activation: In addition to other widely known activation functions used in CNNs including CSPDarknet-AA, this one is most probably widely known: ReLU stands for Reci- fied Linear Unit. This introduces nonlinearity into the network therefore enabling model to learn complex patterns over different domains of data. Mathematically, ReLU is defined as: ReLU(x)=max(0,x) In this instance, x represents some chosen value of input variable; thus output is equal to zero if it's less than or equal than zero otherwise output is equal to itself.

**4.1. Feature Extraction:**

Shape Features: Some geometric properties that can be used to characterize shapes include aspect ratio, perimeter, area or circularity

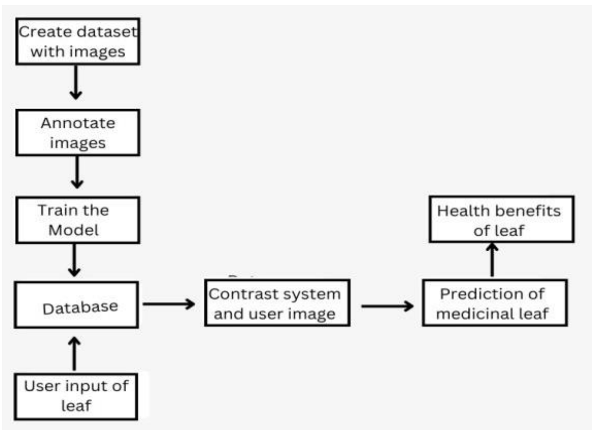


**Figure 2. A system Model**

**5. Training and Validation Result**

Metrics such as loss, recall, and precision are used to evaluate the performance of the model in the training and validation stages. Figure 4 shows the obtained metric values. In the training and validation phase, the loss value of the DL model is 1.05 and 1.5 at epoch 0. The value of the loss gradually decreases and reaches values of 0.3,0.4 when the number of epochs increases.

Another metric to consider is resilience. The second metric considered is recall performance. During training, the score begins at 0.7 on the 0th epoch and steadily rises to 0.98.

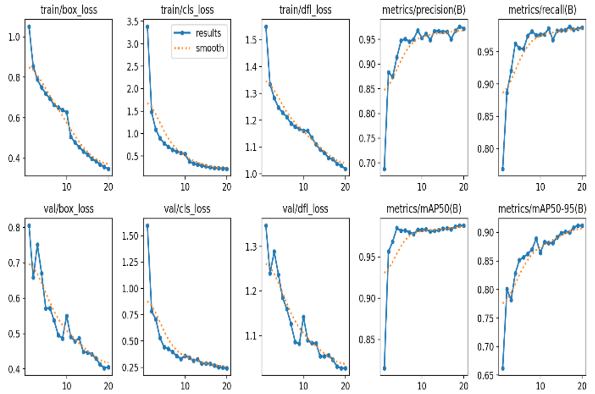


**Figure 3. Results**

| epoch | train/box_loss | train/cls_loss | train/dfl_loss | metrics/precision(B) | metrics/recall(B) | metrics/mAP50 | metrics/mAP50 | val/box_loss | val/cls_loss | val/dfl_loss |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1.0513 | 3.3856 | 1.5503 | 0.68767 | 0.7686 | 0.81538 | 0.66241 | 0.80489 | 1.5959 | 1.3466 |
| 2 | 0.85532 | 1.4791 | 1.3345 | 0.88346 | 0.88623 | 0.95629 | 0.80077 | 0.65868 | 0.78184 | 1.2396 |
| 3 | 0.78842 | 1.0844 | 1.2834 | 0.87451 | 0.92044 | 0.96857 | 0.7815 | 0.75107 | 0.70659 | 1.2889 |
| 4 | 0.74947 | 0.89878 | 1.2479 | 0.91359 | 0.96249 | 0.98481 | 0.82827 | 0.67013 | 0.531 | 1.2369 |
| 5 | 0.72057 | 0.78379 | 1.2284 | 0.94721 | 0.95526 | 0.9815 | 0.85171 | 0.57101 | 0.44206 | 1.1854 |
| 6 | 0.6941 | 0.70519 | 1.212 | 0.95134 | 0.95442 | 0.98222 | 0.85621 | 0.57187 | 0.42586 | 1.16 |
| 7 | 0.6636 | 0.63763 | 1.188 | 0.94545 | 0.97463 | 0.97956 | 0.8626 | 0.53691 | 0.39742 | 1.1265 |
| 8 | 0.65044 | 0.60242 | 1.176 | 0.95032 | 0.98149 | 0.97762 | 0.87022 | 0.49521 | 0.35899 | 1.0862 |
| 9 | 0.6384 | 0.57135 | 1.168 | 0.96816 | 0.97531 | 0.98275 | 0.88894 | 0.48629 | 0.33068 | 1.082 |
| 10 | 0.62679 | 0.54301 | 1.1608 | 0.95319 | 0.97635 | 0.98288 | 0.86408 | 0.54987 | 0.36039 | 1.142 |
| 11 | 0.50634 | 0.38291 | 1.1611 | 0.96153 | 0.97678 | 0.9832 | 0.88303 | 0.49062 | 0.34208 | 1.0899 |
| 12 | 0.47773 | 0.331 | 1.1347 | 0.94872 | 0.9858 | 0.98067 | 0.88147 | 0.47853 | 0.31277 | 1.0835 |
| 13 | 0.45526 | 0.30828 | 1.1097 | 0.96681 | 0.96833 | 0.98175 | 0.88132 | 0.4872 | 0.32751 | 1.0829 |
| 14 | 0.4331 | 0.28707 | 1.0906 | 0.96717 | 0.98261 | 0.98234 | 0.89188 | 0.44805 | 0.28806 | 1.0539 |
| 15 | 0.41787 | 0.26934 | 1.0785 | 0.96537 | 0.98282 | 0.98401 | 0.89884 | 0.44667 | 0.28623 | 1.0541 |
| 16 | 0.39731 | 0.25011 | 1.0593 | 0.96557 | 0.98355 | 0.98441 | 0.90109 | 0.4414 | 0.28522 | 1.0566 |
| 17 | 0.38602 | 0.23596 | 1.0546 | 0.95049 | 0.98894 | 0.98346 | 0.90016 | 0.43006 | 0.26733 | 1.0465 |
| 18 | 0.36864 | 0.226 | 1.037 | 0.96786 | 0.98397 | 0.98659 | 0.90862 | 0.41315 | 0.25237 | 1.0314 |
| 19 | 0.35658 | 0.22314 | 1.0307 | 0.97619 | 0.98578 | 0.98786 | 0.9119 | 0.40255 | 0.248 | 1.0275 |
| 20 | 0.34665 | 0.21095 | 1.0178 | 0.97192 | 0.98702 | 0.98777 | 0.91164 | 0.40534 | 0.24344 | 1.0276 |

**Figure 4.**

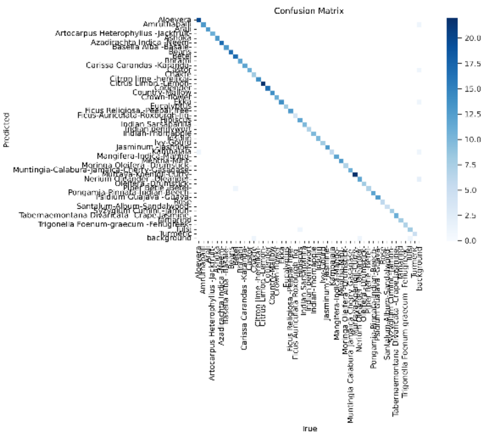


**Figure 5. Confusion matrix**

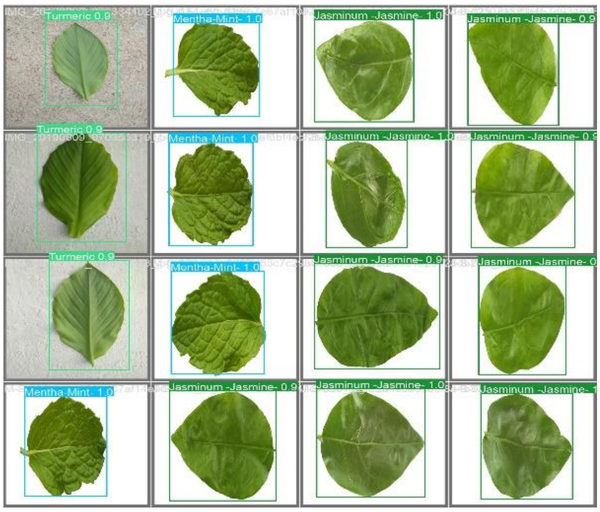


**Figure 6. Batch1 prediction**

## 6. Results

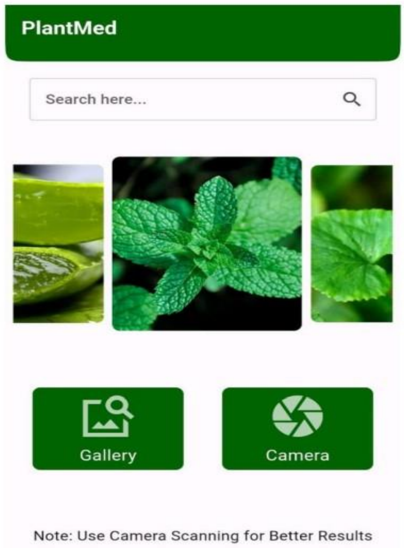


**Figure 7. Home Page of application**

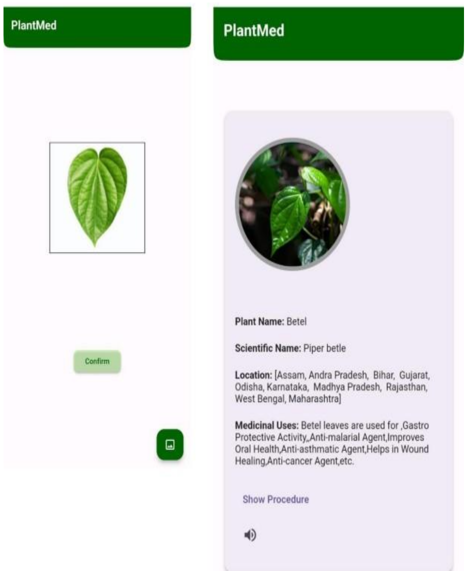


**Figure 8.**

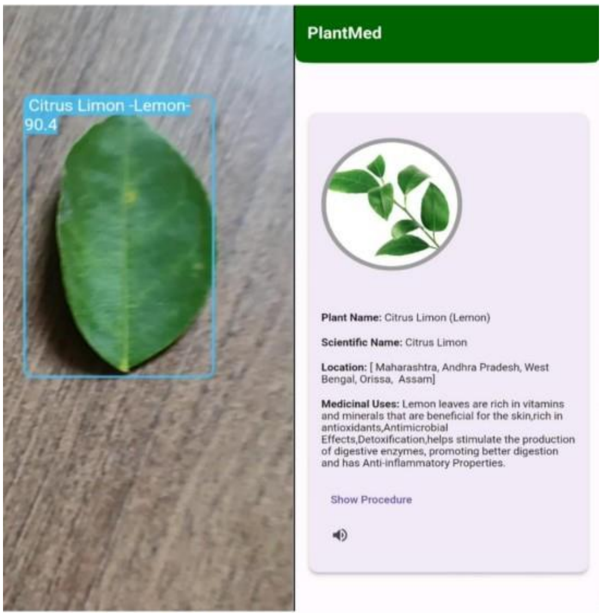


**Figure 9. Final Output Page**

## 7. Conclusion and Future Work

The basis of this work is the identification of leaf images from the collection, together with an explanation of the image's intended medical application. Numerous methodologies are pertinent to the automatic recognition of plant leaves. The purpose of this survey is to identify several classifiers and features that are used for medicinal plant leaf recognition. Through this study we can see that the YOLOv8 model possess remarkable capacity to identify multiple species of plants that have been traditionally used in medicine and its reliability for Ayurvedic botanical detection. As the model has high recall and precision rates, it can be of great use in research on herbs and plants. The possible changeover of AYURVEDA plant identification would be enabled by the ability of YOLOv8 to provide practitioners and researchers with a reliable and efficient tool. Its successful implementation testifies to this claim. The result is that it could hasten the progress of plant identification speeding up herbal drug application with accuracy and knowledge More development studies should get prioritized to include not only more varieties of vegetations but also to further enhance the model's precision and robustness. Additionally, other machine learning techniques or additional features can be combined to the present model for better performance. The entire study gives more importance to advanced computer vision technology by stating the substantial difference it can make in the traditional ways. That is, the improvement in the accuracy and the modification of the app enables Ayurvedic plant detection which in turn serves for preserving and advancing the knowledge of traditional medicine.

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