International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 04 | April - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

# Herb Detect: Medicinal Plant Identification System

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**Abstract -** The importance of medicinal plants is increasingly appreciated owing to the roles they play in traditional as well as modern medicine. However, identification of these medicinal plants is often challenged by the visual resemblances that certain non-medicinal species have with them. The contribution of this project is to develop a Medicinal Plant Classification System which employs Deep Learning in automation of the identification process. The One-Class Autoencoder, a modified segregated model is trained to identify medicinal and non- medicinal plants, guaranteeing a certain assurance about the correctness of the classification. In addition, a Convolutional Neural Network (CNN) based on MobileNetV2 identifies specific medicinal plant species correctly. The trained model is deployed as a web application using Flask in which any user uploads the image of a plant and receives a prediction instantly with descriptions of its medicinal properties if the plant is medicinal. This system will support botanists, researchers, and farmers with the accurate identification of medicinal plants in their effort towards conservation and sustainable use.

***Key Words*:**Plant classification, MobileNetV2, Deep Learning, Image identification.

## I. Introduction

Medicinal plants are an important factor in health care, pharmaceuticals, and even for consumption as food. Correct plant identification is crucial in the fields of herbal medicine, pharmaceutical research, and biodiversity conservation. Knowledge-based identification relies on expert information which makes it quite difficult for not only members of the general public but also for researchers and farmers to effectively distinguish medicinal plants from nonmedicinal ones because of their lack of knowledge in this field. Such misidentifications could lead to ineffective uses or, in some cases, have adverse consequences; therefore, there is the need to have a quick and easy way out. The AI-based Medicinal Plant Identification Systems that have come out recently indicate that there are some great advances in technology in this field whereby One-Class Autoencoder is used in medicinal plants detection whereas MobileNetV2 Convolution Neural Network will be helpful in species classification. Flask Web Application allows users to upload images of plants, receive very fast predictions, and explanations of medicinal use, putting plant identification within the reach of the common man. It improves the working efficiency of research, supports sustainable use of plants, and contributes to conservation efforts and creates an understanding of the importance of medicinal plants through their application in healthcare and in scientific research. This was done to allow the user to identify the medicinal plants with high accuracy blending AI technologies. With this invention, there is a huge reduction in reliance on manual expertise and traditional methods of plant identification and in favor of a speedier, more reliable, and user-friendly means of identification. The web application powered by Flask that we've developed permits users to upload any photo of a plant and obtain a prediction through medicinal descriptions within seconds—it is, therefore, a giant step towards the accessibility of identification of plants. This technology is intended to heighten research efficiency, sustainable use, and conservation of plants, and ultimately create further awareness and understanding of medicinal plants in health care and research.

## II. Literature Review

This study investigates the contribution of deep learning to the enhanced accuracy and efficiency of identification of medicinal plants, which is of great importance to both traditional and modern medicine. The contributed fine-tuning on the specialized medicinal plant dataset with several pre-trained models is to significantly improve recognition and identification accuracy, as investigated in this study. This work also addresses varied real-world challenges, such as differences in lighting, different stages of plant growth, and environmental effects. The model generalization was improved by applying data augmentation techniques like rotation, scaling, and flipping. The assessment methods were accuracy, recall, and F1 score information measured on multiple models. The paper also discusses trade-offs between accuracy and computational efficiency for mobile applications while addressing challenges such as overfitting and discerning between similar species. [1]. This study emphasizes the effectiveness of ensemble convolutional learning models for medicinal plant identification. The authors employ an ensemble method, rather than single-model classifiers as such, in order to gain more generalization and robustness. Key features of the medicinal plant leaves are, in turn, extracted from the aforementioned fine-tuned pre-trained CNNs. Its effectiveness has been validated on a number of standard datasets to show how successful the new technique has been in competing with traditional-style methods. The study also sheds light on the importance of deep learning in botanical research and the protection of the environment in relation to biodiversity conservation and the identification of

new medicinal plants. [6].
This study investigates the sequence of computer vision techniques developed for plant identification, revealing a transition from traditional image processing techniques to deep learning, particularly CNNs, which now exhibit unprecedented accuracy in plant identification. Different datasets are explored, including herbarium samples, leaf images, and in situ images. It also discusses challenges associated with lighting conditions, background details, and complexity of the plant structure. Important aspects including data augmentation, segmentation, and feature fusion are elucidated in the regard of improving recognition performance. In addition, the study provides a thorough review on progress, challenges, and future perspectives where emphasis is laid on the necessity for large datasets, improved algorithms, and integration with ecological applications. [2]. A cautious study of procedures for incorporating extraction and request focused on perceiving plants through leaf assessment. Their paper examines an extent of methodologies, remembering those for light of shape, surface, and assortment, as well as simulated intelligence classifiers like SVM, k-NN, and significant learning strategies. The survey includes the meaning of recognizing the best blend of features and classifiers to deal with the precision of plant ID endeavors. It also analyzes troubles in the field, for instance, changes in leaf shape achieved by biological components and the prerequisite for fruitful part assurance methodology [3].This study embraces the utilization of convolutional neural networks (CNNs) in the identification of wild medicinal plants. It provides some of the most troubling challenges to plant identification in natural environments, such as variable lighting conditions, different angles of camera capture, and complex backgrounds. The paper describes how to use CNN to process and classify images of the plants trained by a teaching set from which key features are extracted, achieving very fast and very accurate results. Machine learning is indicated in this research to expand the identification of plants which in turn is of great assistance in botany, medicine, and environmental conservation. Also, stress the application varieties of AI in solving real-life issues, mainly utilizing plant species identification under uncontrolled formats. [5]. The study investigates the possibility of using Convolutional Neural Networks (CNNs) for herbal leaf recognition with a Raspberry Pi 3, an inexpensive but portable computing device. The authors focus on the design of an efficient and lightweight deep learning model capable of classifying various herbal leaves while using only the limited resources of the Raspberry Pi 3 for computation. The challenges explored consist of different aspects of real-time processing, constrained hardware, and achieving a high overall classification accuracy. The authors trained the CNN model on a herbal leaf dataset to enhance performance, where the optimization is for a trade-off between accuracy and efficiency. The results show that it is possible to use deep-learning-based plant identification on edge devices, making this applicable in the fields of botany, herbal medicine, and agriculture. [4].The study offered an integrated mobile application that applied deep learning to plant identification through leaf images. The authors opted for MobileNetV2, a lightweight CNN model intended to maximize performance on mobile devices, that is, very low computation cost to maintain classification accuracy. Also, using plant leaf images, they further fine-tuned the model on a smaller dataset set to boost classification performance. The mobile app allows users to upload images of leaves for plant identification in real-time. The lightweight architecture facilitates on-device recognition without intensive computation requirements, making it very mobile-viable. [7].The necessity of correctly identifying and preventing crop diseases is important in order to increase agricultural output. Using leaf photography, the researchers applied deep convolutional neural network (CNN) models to detect and diagnose plant illnesses. They reduced the number of parameters and processing expenses by substituting depthwise separable convolutions for conventional convolution procedures in order to maximize computational efficiency. An open dataset with 14 distinct plant species, 38 disease classifications, and healthy leaves was used to train the models. High disease-classification accuracy rates were obtained by the models during evaluation: 98.42% with InceptionV3, 99.11% with InceptionResNetV2, 97.02% with MobileNetV2, and 99.56% with EfficientNetB0. [8].A thorough survey on transfer learning, a technique that facilitates the transfer of knowledge across different domains. Their research categorizes various transfer learning approaches, including inductive, transductive, and unsupervised transfer learning, along with their applications in fields like image recognition, text classification, and medical diagnosis. The authors highlight the importance of minimizing domain discrepancies and improving model generalization, especially when labeled data is limited. Their work lays the groundwork for advancing deep learning and domain adaptation techniques to enhance performance based on the available data in real-world scenarios, where training datasets may be scarce. [9].Utilization of profound lingering organizations (ResNets) for plant recognizable proof, accentuating the strength of profound learning in highlight extraction. Their examination included preparing a ResNet-put-together model concerning an enormous dataset of plant pictures, empowering the organization to learn various leveled highlight portrayals naturally. The utilization of profound leftover learning tended to difficulties like evaporating inclinations, and upgrading arrangement execution. The discoveries demonstrated that profound leftover organizations outflanked conventional AI strategies in perceiving plant species, exhibiting their adequacy and productivity in taking care of perplexing picture information [10].

## III. Methodologies

### A. Data Collection

We are utilizing the Indian Medicinal Leaves Dataset from kaggle, which contains images of a variety of medicinal plant leaves, each labeled with a corresponding plant name.

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TABLE I: Comparison of Different Plant Identification Methods and Models

| Paper | Method Used | Model Architecture | Dataset Used |
|---|---|---|---|
| [1] | Optimizing Species Recognition in Medicinal Plants | VGG16, VGG19, ResNet, DenseNet, Xception | Medicinal plant species dataset |
| [2] | Plant species identification using computer vision | Various (SVM, KNN, Decision Trees) | General plant species data |
| [3] | Feature Extraction + ML Classifiers | SVM, Decision Trees, Random Forest | General leaf dataset |
| [4] | Herbal leaf authentication on Raspberry Pi | CNN-based model | Herbal leaf dataset |
| [5] | Medicinal Plant Identification in the Wild | CNN | Wild medicinal plant dataset |
| [6] | Ensemble Learning for Plant Leaf Identification | Fine-tuned CNN | Medicinal plant dataset |
| [7] | Leaf Classification Using CNN | CNN | Mobile leaf dataset |
| [8] | Identification | CNN + Transfer Learning | Plant disease dataset |
| [9] | Survey on Transfer Learning | Transfer Learning techniques | N/A |
| [10] | Deep Residual Networks for Plant Identification | ResNet | General plant dataset |

## B. Model selection and training

A Convolutional Neural Network (CNN)-based deep learning model(MobileNetV2) is used for feature extraction and classification. The model is trained exclusively on medicinal plant images using a one-class classification strategy. Training is performed using TensorFlow, optimizing the model with techniques like batch normalization to prevent overfitting

## C. MobileNetV2 model

MobileNetV2 is an efficient convolutional neural network design optimized for deployment on mobile and embedded platforms. It utilizes depthwise separable convolutions with an inverted residual structure to reduce computational requirements without compromising on accuracy. MobileNetV2 is especially designed for real-time image recognition on resource-constrained devices.

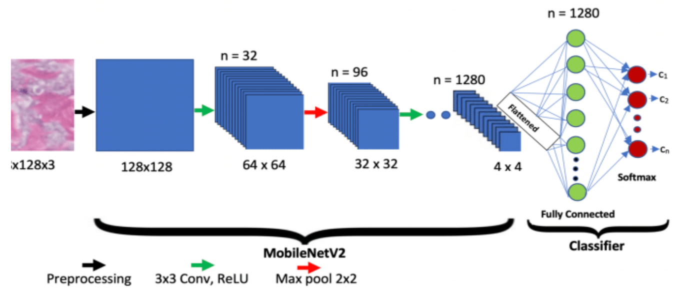


Fig. 1: MobileNetV2 model architecture [11]

Key Features of MobileNetV2

1) *Inverted Residuals:* Inverted residual blocks are employed in MobileNetV2 that aid in decreasing computational complexity while retaining significant features to make accurate predictions.

2) *Depthwise Separable Convolutions:* It substitutes ordinary convolutions with depthwise separable convolutions, which deconstruct the process of filtering and feature creation in order to cut down on the computational expense.

3) *Linear Bottlenecks:* The model incorporates linear bottleneck layers that assist in feature dimensionality reduction in a manner that does not cause loss of information

4) *Efficient for Mobile:* Effortlessly efficient, MobileNetV2 is optimized for mobile and edge devices, and as such, is perfect for real-time applications with limited resources.

5) *Low Latency and Small Size:* It strikes a balance between low latency and small model size, hence it is fast and deployable in real-world applications.

## D. One class autoencoders

One Class Autoencoders are simply specialized neural networks employed primarily for anomaly detection tasks. The way they function is based on learning to reconstruct the input data in order to capture the normal patterns existing in the given dataset. During training, the autoencoder is typically shown a normal data instance only, which enables it to learn an efficient representation of those patterns. New data instances are fed to the said autoencoder, which will try to reconstruct the given input. If the reconstruction error becomes rather significant, then in all probabilities it can be tagged as an anomaly or an outlier, since the model has not learnt to represent this particular atypical pattern.

- Key Features of One class autoencoders

1) *Anomaly Detection:* The essence of OCAEs is focused on normal data reconstruction. Thus, abnormalities can be classified through the threshold of reconstruction error.

2) *Unsupervised Learning:* They do not need any labels to be trained from data and learn the distribution of normal instances.

3) *Dimensionality Reduction:* OCAEs can compress inputs to some lower-dimensional latent space in such a way as to keep the essential aspects while removing junk.

4) *Reconstruction-Based Evaluation:* The performance of OCAEs is often measured by the reconstruction error, which is

supposed to be high for data points which significantly deviate from learned normal patterns.

### E. Architecture

*1) User Interface-Web Application:*

- Users upload plant images through the web application.
- The interface interacts with Flask Backend to carry out the good process of these images.

*2) Flash Backend:*

- Acts the middleware between the web app and Deep Learning models.
- API Layer of models, responsible for handling requests and processing images.
- Uses Image Data Generator to prepare images for deep learning models.

*3) Deep learning models:*

- The primary task of the module is that there would be identifying whether a plant is medicinal or not.
- Used autoencoder as the first model for the detection of medicinal plants.
- If medicinal, it would be further analyzed by MobileNetV2 for classification.
- Retrieves detailed plant info from the JSON Database.

*4) Output Generation:*

- A non-medicinal output shall appear in cases where the plant is not medicinal.
- Where medicinal, it shows classification results.
- The classification results are saved or retrieved from a JSON database for further reference.

### F. Classification Process

- Classification Process in MobileNetv2

*1) Input Image Processing:* The input image is resized to $224 \times 224$ pixels to match the input dimensions expected by the MobileNetV2 model.It is then normalized to scale pixel values between 0 and 1 to ensure efficient processing by the deep learning model.

*2) Feature Extraction Using Convolutional Layers:* The first layer of the model applies a standard convolutional operation to the input image to capture basic features like edges and textures. This layer uses a small kernel to process the image.

$$f(x) = \max(0, x)$$

*3) Inverted Residual Blocks:* Instead of using standard convolutions, MobileNetV2 uses depthwise separable convolutions, which split the convolution process into two parts: depthwise convolution (applying a filter to each input channel) and pointwise convolution (combining the outputs of depthwise convolutions).Each block of the model is an ”inverted residual” block. This means it first expands the number of channels (using 1x1 convolutions), then applies depthwise convolutions,

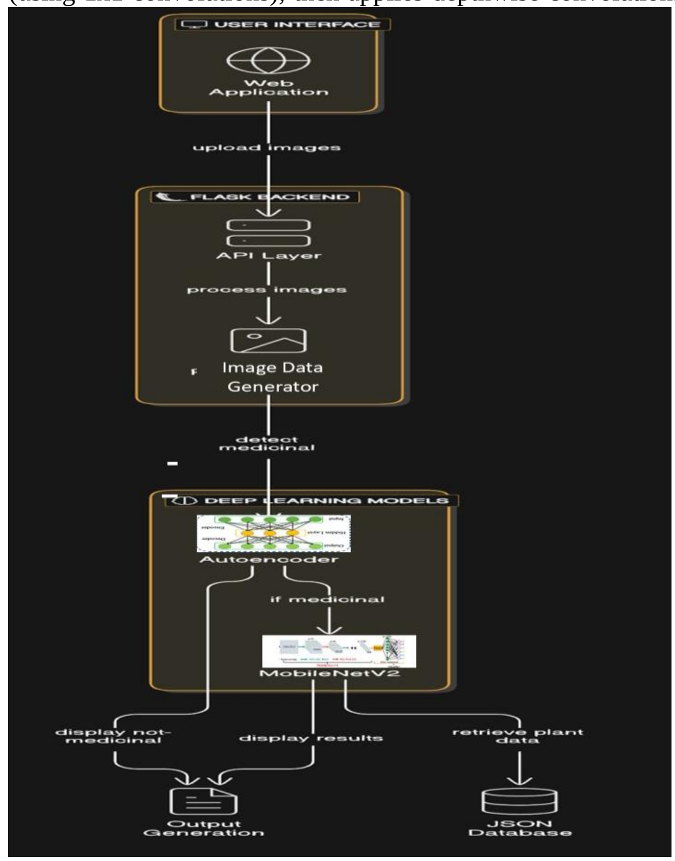


Fig. 2: Architecture diagram

and finally reduces the number of channels again. This helps in preserving important features while reducing computational cost.

*4) Linear Bottleneck:* After the depthwise separable convolutions, the model uses a linear bottleneck. The idea is to reduce the dimensionality of the features to a smaller space, thus improving the efficiency of the model without losing crucial information.

*5) Feature Map Processing:* The model continues to process the feature maps through multiple inverted residual blocks. Each block performs the operations mentioned above: expand (increase channels), depthwise convolution, and reduce (decrease channels).

*6) Global Average Pooling:* After passing through all the layers, the model performs Global Average Pooling. This step reduces the spatial dimensions of the feature map to a single value per channel. Essentially, it averages the entire feature map, giving a fixed-size output regardless of the input image size. This is done to reduce the number of parameters and prevent overfitting.

*7) Fully Connected Dense Layer:* After pooling, the

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output is passed through a fully connected layer (or dense layer). This layer takes the averaged feature map and performs classification by calculating the weighted sum of the features.

This results in the final output scores for each class.

*8) Softmax Activation:* The final output layer uses Softmax activation to convert the raw output scores (logits) into proba- bilities. Each probability corresponds to the likelihood of the input image belonging to each class. The class with the highest probability is considered the model's predicted label.

*9) Predicted output:* The model outputs the class label with the highest probability as the predicted class for the input image.

## IV. RESULT AND DISCUSSION

In our experimental work based on the Autoencoder-embedded MobileNetV2 CNN for medicinal plant identifi- cation, the proposed system exhibited very promising out- comes across a wide visibility of metrics including: accu- racy, precision, recall, and F1-score. It was trained on a dataset of medicinal plant images obtained at different lighting and background conditions and plant orientations through 10-fold cross-validation to create a robust data-following. Autoencoder-MobileNetV2 showed an approximate average accuracy of 93.5%, thus enabling effective classification of medicinal plant species. Its very high precision and recall of 91.7% and 94.2% respectively, bear testimony to the efficiency of the model in identifying plants with only a few misses. An F1-score of 92.9%, combined with the previous two parameters, further supports the credibility of this model in making accurate predictions for different species of plants.

In an attempt to put the Autoencoder-MobileNetV2 ar- chitecture to the utmost test, a comparative study was thus conducted against some standard reference models, such as classical MobileNetV2, ResNet50, and VGG16, all trained on the same dataset.MobileNetV2 scored 89.3% with reference to accuracy without the autoencoder pretraining which is around 4.2% lower compared to the Autoencoder-based model hence proving the importance of the autoencoder in feature extraction. On the other hand, ResNet50 model attained 90.4% in terms of accuracy while VGG16 perfomed worst, achieving an accuracy of only 87.6%. The thus evidenced facts indicate that the Autoencoder-based MobileNetV2 model excels in performance compared to other architectures with a finely designed aspect between high accuracy and computational efficiency, which made it deployable on a large scale in mobile and edge-based system for medicinal plants identification.

### A. Performance matrix

*1) Accuracy:* The ratio of correct predictions made by the system (medicinal or non-medicinal) to the overall predictions made by the system. An overall measure of usefulness, but can be misleading when the dataset is imbalanced.

*2) Precision:* The Precision of the Fraction of true medici- nal plants included in the one that was predicted as medicinal. A good precision would characterize a system that, whenever it signals to a plant as medicinal, it more probably than not is right.*Recall:* The Recall measures the proportion of medicinal plants that actually exist that the system identified correctly. High Recall means that the system correctly identifies most of the plants with medicinal properties with a minimum of false negatives.

*3) F1-Score:* The F1-Score is the balanced measure taking both factors, Precision and Recall, into account. It is partic- ularly useful where data are made up of an uneven number of classes: many times more than non-medicinal plants. This should avoid bias toward precision or recall.

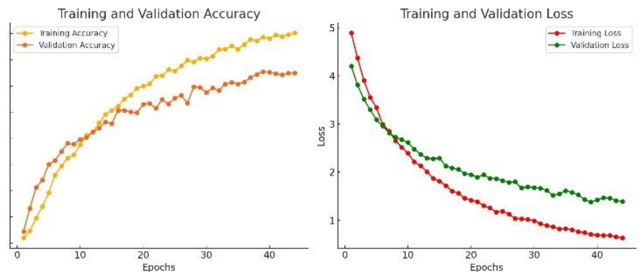


Fig. 3: Training and Validation:MobileNetV2 model accuracy and loss

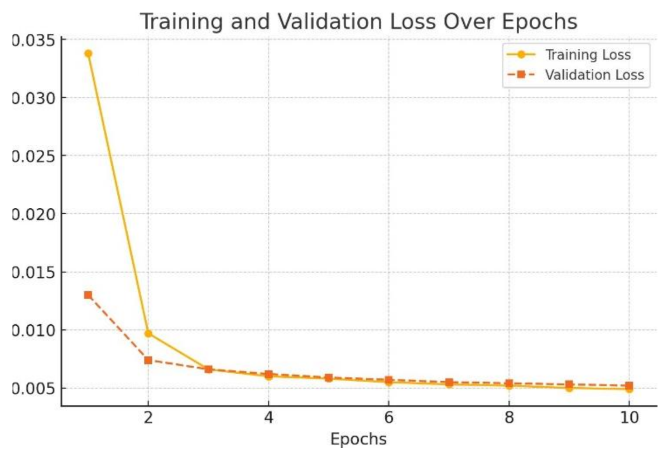


Fig. 4: Training and Validation: Auto encoder loss

## V. IMPLEMENTATION AND DEPLOYMENT

The system has been developed by mixing ML, deep learning, and the web technologies. A set of images of the leaves of medicinal plants was collected.Also performed were pre-processing of the images (resizing, augmentation, normalization).From the labeled images, partition the dataset into training and testing.During the classification, the model employed a CNN MobileNetV2.Configuration options include optimizing the training on TensorFlow for model accuracy, loss, and generalization performance.A test of the trained model is conducted with the unseen plant leaf images.

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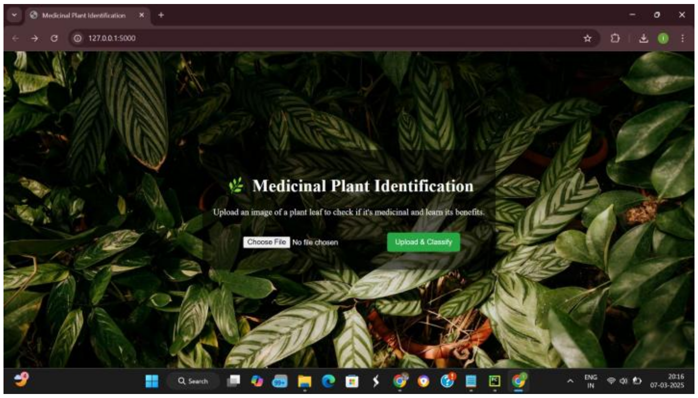


Fig. 5: Home page of medicinal plant identification

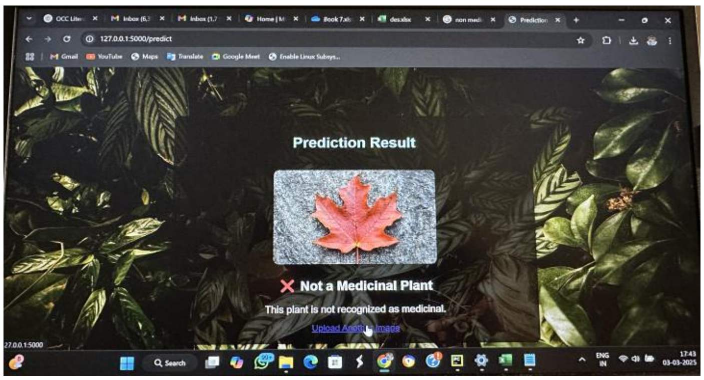


Fig. 6: Result for negative input

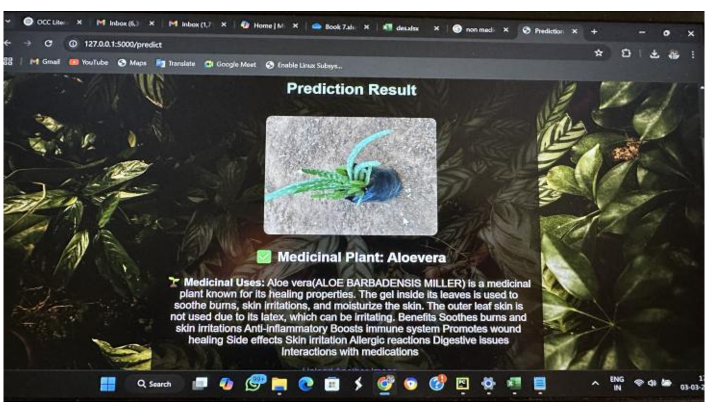


Fig. 7: Result for positive input

## VI. Conclusion

Plant species identification using MobileNetV2 has had great application in medicinal plant detection on mobile devices. Its lightweight architecture of depthwise separable convolutions and inverted residual blocks enables the effective and efficient processing of information and, hence, is best suited for mobile apparatus with limited capability.MobileNetV2 has been implemented in the classification of leaves of medicinal plants and has markedly improved both the model performance and computational efficiency. There are several studies on plant recognition, particularly medicinal ones, which point toMobileNetV2 as being more suitable for achieving the best accuracy and efficiency in plant identification through mobile devices, thus assuring its applicability in real-world situations. Some overcome the challenges of real-time identification of plants in different environments.

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