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SMART MEDPLANT: A HYBRID DEEP LEARNING AND RANDOM FOREST MODEL FOR GEOTAGGED MEDICINAL PLANT DETECTION

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ABSTRACT

Accurate and scalable medicinal plant identification is critical for biodiversity conservation, pharmaceutical development, and ethnobotanical research. Traditional methods, reliant on expert knowledge and manual morphological analysis, are often labor-intensive, error-prone, and limited in scope. To overcome this issue, our research work introduces a hybrid model, TLBR101RF(Transfer Learning Based ResNet101 with Random Forest), to find the medicinal plants from it leaf image with high accuracy. The model employs ResNets's deep residual blocks for effective hierarchical feature extraction and Random forest is used for classifying the result based on robustness against over-fitting and promote generalization on imbalanced datasets. The process consist of data acquisition , data augmentation by GAN , segmentation by LeGrNet and further involved in Classification of leaf image. TLBR101RF achieves a high classification accuracy of 98.69%, when compared with CNN models like VGG16, MobileNet and Inception. The incorporation of geolocation metadata improves classification accuracy by accounting for regional morphological changes influenced by environmental factors. A GPS-enabled web application was developed for real-time species identification, relevant to conservation, agriculture and pharmaceutical research. In TLBR101RF, Deep learning and Artificial Intelligence are combine to form best solution for identifying medicinal plants accurately. The results indicate that TLBR101RF effectively categories medicinal plants with high accuracy of 98.61%, while comparing with CNN models like MobileNet (97.7%), ResNet50(97%), VGG16(96.5%) creating an effective application for identifying correct medicinal valued plants from it localization by achieving high accuracy of 98% by using ResNet101 and Random Forest algorithms.

Keywords: *Pharamaceuticals, Transfer Learning, ResNet101, Random Forest, localization*

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1. INTRODUCTION

Plants play vital role of maintaining life of all living beings on Earth. Especially Medicinal plants are essential for making medications, supporting health and providing natural remedies for various health issues. The identification of medicinal valued plants is quite difficult for most the people due to lack of expert knowledge in medicinal properties, which may sometimes leads to errors in plant identification [1]. Exact plants identification is crucial for medicinal, agricultural, pharmaceutical and various fields. Traditional way of identification techniques requires manual examination which rely on labour power, that is inefficient as well as not known extract location of plants. By considering this difficulties, an automated plant classification tool is implemented by using CNN(Convolutional Neural Network) and image processing techniques[2]. By using this techniques, the image identification and classification is done with great effectiveness for large datasets. Raw plant images are collected, then needs to perform preprocessing, then carried out for segmentation of image[3], followed with feature extraction by ResNet101 and Random Forest for further classification. To perform this method, Transfer Learning Based ResNet101 and Random Forest (TLBR101RF) has executed for medicinal plant classification. To pullout high level features from the images, the deep CNN model ResNet101 familiar for its residual connection is used. After that, these extracted features are classified by using Random Forest, which is the robust machine learning algorithms having ability to handle complex, non-linear datasets. By Combining ResNet101 and Random Forest, the proposed method improves classification accuracy, reduce over-fitting and efficiently processes on datasets. This outcomes highlights TLBR101RF identifies the medicinal plants with high accuracy in various scientific and agricultural applications. The main contribution of this paper are centered around as follows,

i) The Segmentation have done using Leaf_Net and Graph_Cut , which helps to accurately extracts leaf region and eliminates background noise.

ii) For classification ResNet101 and Random Forest are combined to improve roburtness and interpretability.

iii) Final results produced along with Geo-tagged location of the identified leaf image

The paper work composed of detailed literature review was stated in section 2, followed by the main methodology in section 3. The section 4 describes the classification of the leaf image, while section 5 addresses the results and discussion. Finally section 6 concludes the paper with the conclusion and future work

2. LITERATURE REVIEW

The automated detection of medicinal plants has widely increased in recent years, especially due to its usage in ethnobotany, Pharmacology, biodiversity conservation and for healthy agriculture. Traditional ways of medicinal plants identification depends on morphological examination, experts knowledge in plant life, manually needs to differentiate each and every plants, which are time consuming, labor-intensive and high chances of errors to occurs, particularly when plant species are rare or similar in visual appearance. As the the result of these issues, by using Deep Learning technique like CNN (Convolutional Neural Networks), is used to overcome the challenges of classifying medicinal plants through image processing.

[4] chetial, et.al rectifies resemblance between many plant species, by implementing CNN architecture with max-pooling, dense layers, and six convolutional layers is introduced. The Indian Medicinal Leaves Image Dataset, MED117, and a self-compiled dataset by the authors were used to evaluate the model. The Adam, RMSprop, and SGD with momentum optimizers attained accuracies of 99.5%, 98.4%, and 99.7%, respectively. [5] Pushpa, et.al has implemented plants identification from various challenging factors like complex background, uneven lightening, leaf orientation and etc. Forthat the author combines VGG16 and MobileNet deep learning models makes it easy to transfer features from the first model. The second model employs MobileNet and ResNet50 for feature extraction, which a deep learning classifier identifies with an accuracy of 88%. The third model uses MobileNetV2 coupled with SE layers for classification. Upon calibration, hybrid model 3 beats the other two by 94.2.

[6]Gowthaman et.al, integrated WSN and MobileNetV2, whereas WSN filters capture texture patterns without the necessity of learning, and cost-effective is also minimum for limited datasets. The deep layers of MobileNetV2 extracts brief features like the outline and shape of plant species. PCA classifier improve features like the outline and the shape of plant species. Which improves feature perception and remove redundancy that provides accuracy of 98.7%. [7] Sharma et.al, implements AELGNet, which identifies appearances of plants leaf using deep learning. The MBConv modules in AELGNet captures basic properties into sequences of non-overlapping patches to extract local features. Inorder to highlights the medicinal plants or leaf information, they used residual channel-wise and spatial observation to each patch and global feature, which provides accuracy as 99.71%.

[8] Sekharamantry et.al, discovered PSR-LeafNet neural network design, that learn leaf attributes from P-Net, S-Net and R-Net in MRMR. PSR-LN includes leaf morphology, colors, veins and texture. SVM indentifies PSR network output as PSR-LN-SVM, with 97.12% accuracy.[9] Lapkovskis et.al, introduced novel multimodel deep learning-based plant classification system with automatic modality fusion to use flower, leaf, fruit and stem images inorder to develop a single model via multimodel fusion architectural search. Over 979 Multimodel-plantCLEF classes with 82.61% accuracy.

[10] Musyaffa, et.al, categorizes Indonesian flora utilizing CNN transfer learning, their research utilized an extensive dataset of carefully curated images of Indonesian medicinal plants. Preprocessed and categorized data via transfer learning with ResNet, DenseNet, VGG, ConvNeXt, and Swin Transformer got accuracy with 92.5 %. [11] Qureshi et.al, used CNN and Computer Vision technology for figure out tomato leaves related diseases. This proposed work trained and tested using the plant village database, which contains healthy and diseased leaf images. They used modified CNN architecture with hyperparameter

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tuning and transfer learning methods and got accuracy as 92%.

[12] Salsabila et.al, have used Deep Learning Pre-trained models like MobilNet, VGG16, DenseNet121, ResNet50V2 and NASNetMobile to identify medicinal plants by its leaves. By combinations like 80:10:10 and 70:20:10 are examined with augmented and non-augmented data, whereas MobileNet has highest accuracy of 98.86%. [13] Pushpa et.al, proposed system to identify ayurvedic plant species with Ayur-PlantNet, an impartial lightweight deep CNN model evaluating with pre-trained models like ResNet34, ResNet50, VGG16, MobileNetV3_Large, EfficientNet_B4, and DenseNet121, Whereas Ayur-PlantNet attains 92.27% of accuracy.

[14] Hajam et.al, have ensembled VGG16,VGG19 and DenseNet201 to identify medicinal plants, by extracting its features from blooms, leaves and roots, for 34,123 images. that are reflecting its history. Whereas leaf images are frequently used, for its accessibility. The developed models were evaluated by using Mendeley Medicinal leaf dataset. The combination of VGG19 and DenseNet201 has achieved accuracy of 99.12% by identifying medicinal plants. [15] Abou Bakary et.at, have collected 7,543 plants images for traing, testing and validating datasets, whereas MobileNet, VGG19, InceptionV3 and ResNet101 achieved accuracies as 82.80%, 84.40%, 85.53%, and 85.80%, respectively. Among these pre-trained model ResNet101achieved as accuracy of 85.80%.

[16] Akter et.al, discovered an automated method for identifying medicinals plants by classifying their images especially found in Bangladesh. Three-layer Convolutional neural networks as well as data augmentation for finding advanced characteristics of plants to perform classification. By this method, they achieved 71.3% as accuracy

Table 1 : Literature survey

S/NO	Ref	Year	Methodology	Plant's Part	Pros	Cons	Accuracy
1	[4]	2025	CNN-based deep learning	Leaf	High precision in classification, extracts intricate details	Limited generalization to unseen samples	97.7%
2	[5]	2025	Hybrid deep learning (VGG16 + MobileNet, MobileNet + ResNet50, MobileNetV2 + SE layers)	Leaf	High classification accuracy, feature recalibration	Challenges with varying lighting and backgrounds	85.85 % - 94.24 %
3	[6]	2025	Wavelet Scattering Networks (WSNs) + MobileNetV2 with PCA	Leaf	Effective for small datasets, texture and structural feature extraction	Requires feature fusion, computationally intensive	98.75 % - 98.7%
4	[7]	2025	AELGNet with MBConv modules & residual attention	Plant & Leaf	Outperforms 14 models, improved generalizability	Requires high computation	97.71 %
6	[8]	2024	PSR-LeafNet (P-Net, S-Net, R-Net) + SVM	Leaf	Captures multiple features, surpasses existing methods	High computational cost	95.88 % - 98.10 %

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7	[9]	2024	Multimodal deep learning (optical, spectral, texture)	Leaf	Improved classification robustness	High preprocessing and computational cost	83.5%
8	[10]	2024	Transfer Learning with ConvNeXt	Leaf	Reduces training time, good generalization	Requires high computational power	92.5%
9	[11]	2024	15-layer CNN	Leaf	Effective in differentiating species	Limited dataset scope	90%
10	[12]	2024	Transfer Learning (MobileNet, VGG16, DenseNet121, ResNet50V2, NASNetMobile)	Leaf	MobileNet performs best, high classification accuracy	Dependent on dataset quality	98.86 %
11	[13]	2023	Image Processing (Color segmentation, edge detection, texture analysis)	Leaf	Low computational power, real-time efficiency	Affected by lighting, lacks adaptability	88%
12	[14]	2023	Transfer Learning with CNN (VGG16, VGG19, DenseNet201 ensemble)	Leaf	Ensemble learning improves accuracy	Requires large datasets	97.92 %
14	[15]	2022	CNN (DenseNet-121, InceptionV3, VGG19, MobileNet, ResNet101)	Leaf	Preprocessing improves accuracy	Computationall y expensive	83.47 % - 85.80 %
15	[16]	2020	3-layer CNN with Data Augmentation	Leaf	Feasible for plant identification	Low accuracy compared to newer methods	71.3%

Table 1, describes the overall literature survey on medicinal plants detection by using various CNN algorithms.

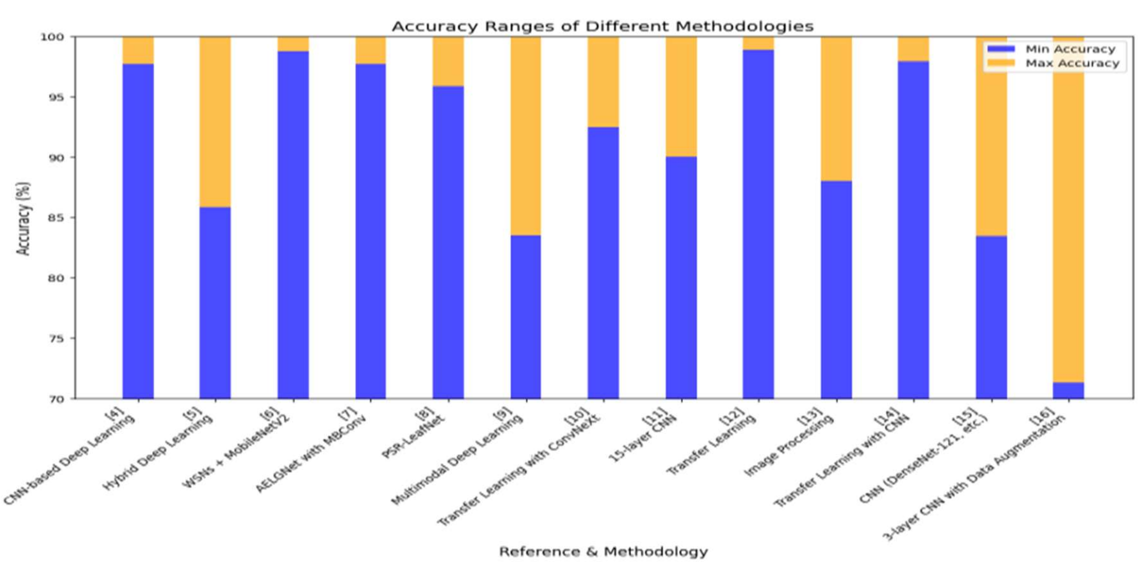

Figure 1: Literature Survey

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3. PROPOSED FRAMEWORK

3.1 Materials and Methods:

The Proposed work describes the systematic framework developed for the classification of medicinal plant species with a hybrid deep learning and ensemble model, TLBR101RF (Transfer Learning–Based ResNet101 with Random Forest). The implemented pipeline comprises five critical phases: data collecting, preprocessing and image segmentation, data augmentation, feature extraction, and classification, culminating in deployment with geotagging support.

3.2 System Architecture Overview

Figure 2, the architecture of the TLBR101RF framework, which is composed of four closely integrated modules: (i) the User Interface Layer, (ii) Model Training and Testing, (iii) Model Deployment, and (iv) Central Data Repository. A GPS-enabled web application provides an interface that enables users to upload plant leaf images. During the capture process, geo-tagged metadata (latitude and longitude) is included with the images, which makes it easier to map the geographic location and track ecological trends. The images are first preprocessed by denoising, normalising, and resizing before they are routed to the model pipeline. Predicted species, medicinal usage, and geographic location are included in the final output. By storing the results, the users can access them for retraining at a later time, enabling continuous learning.

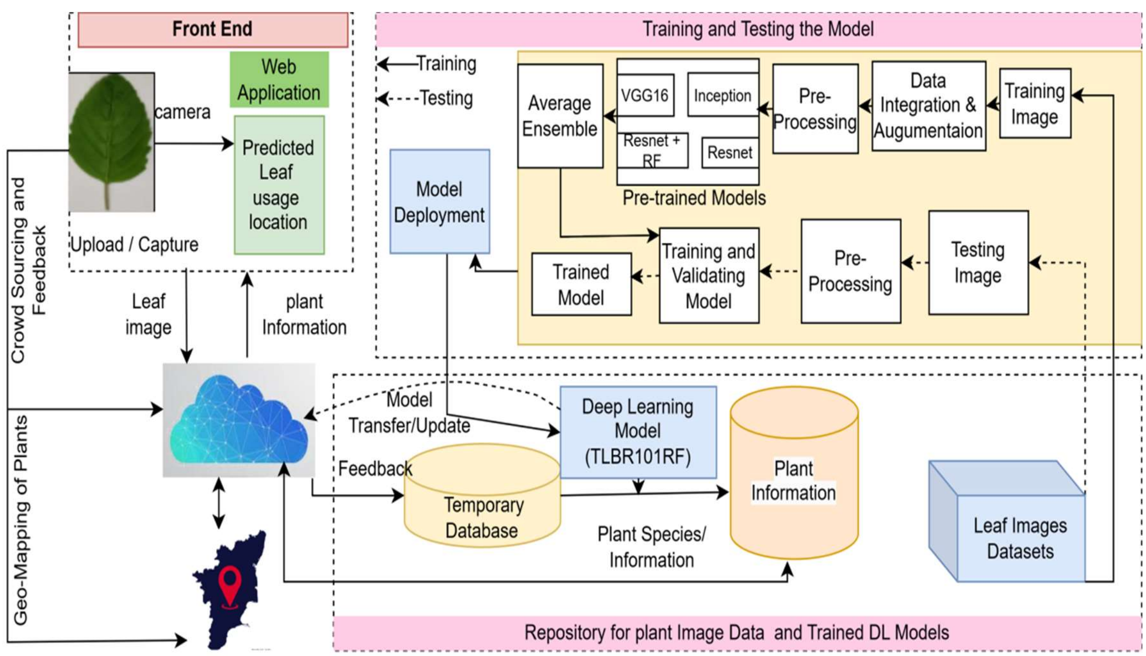

Figure 2:Architecture of TLBR101RF Model

The proposed work is comprehensive system for plant image recognition and classification using deep learning techniques. The system is structured into four interconnected components: Front End, Model Training and Testing, Model Deployment, and Data Repository. The Front End includes a web-based interface where users can upload plant images captured using a camera. These images are initially processed to discover leaf features and geographic information before being sent to a cloud-based repository for further analysis. The technology incorporates geo-mapping to associate plants with its available location, facilitating real-time data collecting and feedback. During the model training and testing phase, the uploaded images undergoes preprocessing and augmentation to enhance the data quality prior to fed as input into deep learning model (TLBR101RF) such as VGG16, ResNet, Inception along with ensemble models which combines with ResNet and Random Forest. These models are carried out for extreme training on datasets to enhance the image classification performance. Once the training part is over, then the model are tested on separate datasets to improve their performance before deployment. At the time of model deployment, the trained deep learning model (TLBR101RF) classify the plants and extract plant relevant details. A temporary database is adapted to store user feedback to enable continous model updates and improvements. The identified plant species and related information are stores in a sturctures plant information related database, that acts as a reference for future classification tasks. The plant date repository serves as a centralized storage system, maintaining large-scale plant image datasets along with trained deep learning models. This repository supports continuous learning by incorporating new data, and enhances model accuracy and classification efficiency. The entire system is developed to be adaptive, continuously evolving through user feedback, model refinements and advancements in deep learning, ensures a strong and efficient solution for plant species identification.

3.3 Processing on Datasets:

To perform medicinal leaf datasets compilation,the high-resolution leaf images are gathered from Botanical gardens, Herbariums and field surveys under proper lightening effect to maintain uniformity among images. Each images are labeled as precise annotations to facilitate accurate classification. To expand the dataset and improve model robustness, data augmentation processes like angle rotation, scaling, and flipping are applied[17]. Datasets are thoroughly structured for coherent retrieval and analysis. A complete datasets of frequently used medicinal plants and herbs with medicinal values is compiled for model training. The datasets comprises over 15GB of leaf images, having more than 150 species of medicinal plants. For model evaluation, a separate set of 6,784 images from 70 plant species are collected as both front and back view of leaf images. To perform training and testing phase , the datasets are splitted as 80:20 ratio for the balanced training. Then it is carried out for pre-processing techniques lie noise reduction using specialized filters, background segmentation to isolate the leaf and resize it for maintaining the uniformity of dimensions among the datasets. For highlighting key features of leaf image, color enhancement technique is applied, to focuses on identifying leaf shape, texture, and venation patterns. Segmentation techniques like edge detection, watershed algorithms, and morphological operations are adapted for further refine feature boundaries[18]. These paces ensure accurate identification of complicated leaf structures, such as veins and lobes, eventually improving the accuracy and reliability of the classification model.

3.4 Segmentated Image:

Segmentation of leaf image is implemented by ensemble segmentation method LeGr_Net starts by loading the pre-trained Leaf_Net_model inorder to provide required dimensions of leaf image[19]. In this method, initially segementation mask (initial_mask) was generated for the preprocessed image. To maintain evenness, this mask is resizes to match the dimensions of the original image[20]. A cost function (C(I, initial mask) is defined to refine the segmentation process. For each pixel pair(p1,p2) in the image, the cost function assess two key components like data term(D_data(P1,P2) to determines how well the segmentation line-up the actual image data, and the smoothness term(D_smoothing(p1,P2) to ensures spatial coherence among neighboring pixels. By these cost terms, a graph structure is created where nodes represent image pixels and edges are added based on initial_mask to comprise the segmentation predictions generated by the Leaf_Net _model. The Graph Cut algorithm is then applied to compute the optimal segmentation by deciding the maximum flow and corresponding minimum cut in a graph. This process effectually partitions the image into different regions, then the final segmentation mask(refined_mask), is extracted from the Graph Cut results, providing a more accurate and refined output.

3.5 Augmentation using GAN:

GAN (Generative Adversarial Network) is used in plant leaf image for augmentation to generated realistic synthetic leaf images, to increase datasets and improves model performance.These networks can create multiple variations in leaf structure, texture, color and environmental background. By training a GAN on an existing datasets of leaf images, the generator learns to produce new leaf structure, visually authentic images, while the discriminator ensures quality by distinguishing between real and synthetic images. The inclusion of these artificial leaf images helps in replicate rare conditions, plant disease and environmental variations, making GAN a valuable tool for expanding datasets in plant pathology and image segmentation applications[21].

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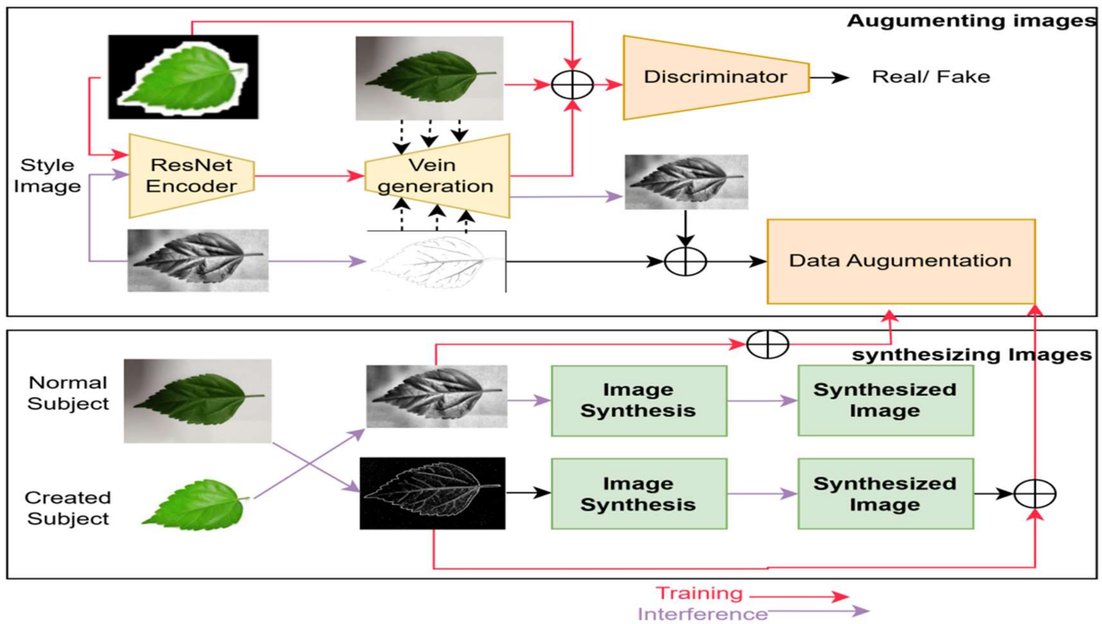

Figure 3: Design of GAN-based Image Segmentation

Figure 3 demonstrates augmenting and synthesizing of plant leaf images, by the features of vein structure, utilizing a deep learning-based Generative Adversarial Network(GAN) architecture.The procedure have carried out with three essential components[22].

i)**Feature Encoding and Vein Generation:** ResNet encoder extracts features from the original leaf image, then processed to form vein patterns. Data augmentation improves the training datasets. A discriminator assesses the generated outputs to differentiate between real and fake images.

ii)Image Synthesis Module: This module generates images by amalgamating vein structures with original leaf textures. Numerous synthesis stages enhance the generated output, iterating through the pipeline to yield high-quality Synthesized images.

iii)**Training and Inference Workflow:** The training phase emphasizes the optimization of the model for the development of realistic leaf images. The inference phase entails utilizing the trained model to produce vein-detailed leaf pictures from the input data.

3.6 Extraction of Leaf features:

Extracting the various features of Leaf is most imporatant characteristics in Image Processing. CNN yields superior in identifying and classifying using patterns of an image. Consequently, some of the Pre-trained CNN models are adapated for feature extraction. VGG16, ResNet 101, MobileNet, Inception, and Xception are used, among these, Resnet101 model demonstrating superior performance compared to the other techniques. Then the result was carried to Randon Forest for performing classification. The implemented work integrates Resnet101 with RF algorithms. Whereas features of the plant leaf are extracted by ResNet 101 and further it was classified by Random Forest.

3.6.1 VGG16: VGG16(Visual Geometric Group 16) is convolution neural network , which is known for its 16 layers, specifically used for image classification and feature extraction. It consist of 3X3 convolutional filters, ReLU-activation, Max pooling [23]. These specialized models can differentiate among several visual categories, including distinct objects such as domestic animals, birds, shapes etc. The architecture of VGG16 utilizing small convolution filters measuring 3 × 3, which exhibits notable results as cutting_edge conditions[24].

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3.6.2 Mobile_Net: The Mobile_Net is a lightweigted CNN model, used for mobile related applications. It uses depth_wise separable convolutions inorder to reduce the computional complexities for accuracy. The sole exception to this rule is the resultant fully-connected layer, which contains no nonlinearities and directly inputs into a softmax layer for further classification. Each alternating layer is followed by batch normalization and ReLU activation functions[25].

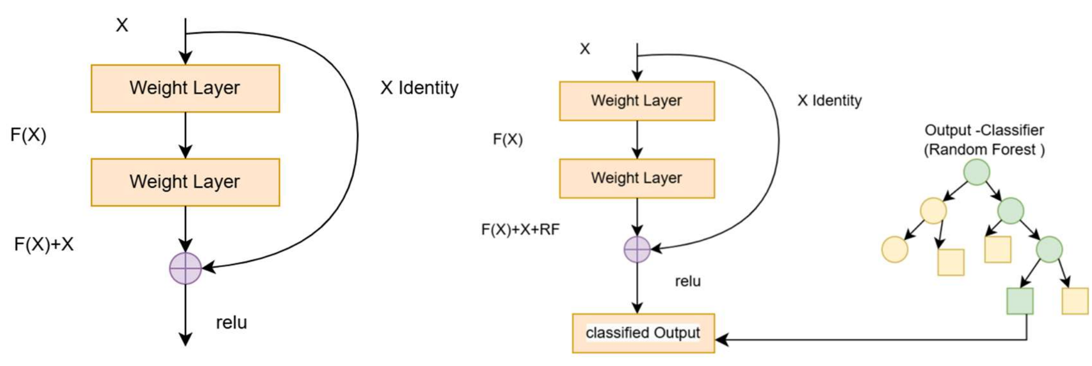
3.6.3 ResNet101: ResNet101 is a residual network comprising 101 layers. It closely resembles VGG-16, except that ResNet101 includes an enhanced capability for identification mapping[26]. ResNet can precisely predict the adjustment required to get the final output when transitioning from one layer to the subsequent layer[27].

3.6.4 Inception: Inception is also called as Google_Net, was trained by segmented manner, allowing an entire model to be retained in memory. This enabled the memory to retain the model in its entirety. During the training process, this indicated that each replica was divided into several distinct, more manageable networks[28]. Residual connections, in contrast to filter concatenation, are employed in networks such as Inception-ResNet-v2.Inception modules, present in convolutional neural networks, are described as a transitional phase between depthwise separable convolution operations and standard convolution[29].

3.6.5 Xception: Xception is the extreme inception by improving the depth-wise separable convolution, which enhance the computational efficacy inorder to maintain high accuracy [30]. The network incoporates residual connections, which allows better gradient flow and faster convergence[31].

4. CLASSIFICATION:

Classification of segmentated leaf image is carried out to find out the healthy and unhealthy plant leaf for futher process of identifying its medicinal values using Resnet based Transfer learning. Whereas, the input plant leaf image feature extraction was carried out by ResNet 101. Then the result is given classification to Random Forest Classifier.



(a) **(b)**

Figure 4. (a) resnet Module (b) Transfer Learning Based resnet101 + Random Forest(TLBR101RF)

Figure 4(b), which combines a Random Forest classifier for ultimate decision-making with a Residual Block. The input X is converted into F(X) via the residual block's two weight layers. Bypassing the transformation layers and adding directly to F(X), a skip connection creates a residual connection from the original input X. After that, the summation F(X)+X is run through a ReLU activation function, which aids in introducing non-linearity in deep networks while preserving gradient flow. A Random Forest classifier (RF), which uses tree-based decision rules to produce the final prediction after transforming the output, further improves the processed features.

$$Y = \mathrm{ReLU}(F(X) + X) \rightarrow \text{Random Forest Classifier}(Y)\text{---->}(1)$$

Whereas, X is input data, F(X) is Transformed representation of X after Passing through two weight layers, X+F(X) is Residual connection that preserves information and improves training efficiency.ReLU is Activation function applied to the residual output. Random Forest Classifier processes Y and provides the final Classification.

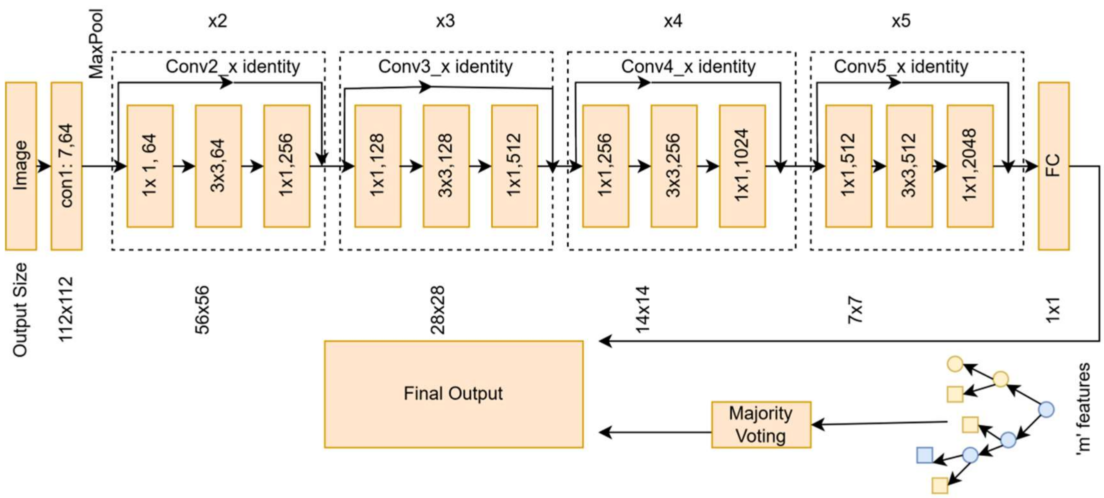


Figure 5:Transfer Learning Based resnet101 + Random Forest(TLBR101RF)

Figure 5 demonstrates, Transfer Learning based Resnet101 and Random Forest(TLBR101RF) used for plant classification from leaf images, combining a machine learning classifier (Random Forest) with deep learning-based feature extraction. A deep learning-based Residual Block is used to process an input leaf image at the start of the procedure. Using a skip connection to maintain the original information, this block's weight layers convert the image into feature representations. A ReLU activation is used to the residual output to guarantee non-linearity and enhanced gradient flow. After that, the collected features are passed into a Random Forest classifier, which classifies the leaf into various plant species using tree-based decision rules. ResNet-101 is a deep convolutional neural network (CNN) with 101 layers, commonly used for image classification tasks. Transfer learning involves using a pre-trained ResNet-101 model and fine-tuning it for a new task.

Given,

A Source Domain, $\mathrm{Domain\_S} = \{X_{Source}, P(X_{Source})\}$ ----->(2)

with learning task, $T_{source} = \{Y_{Source}, P(Y_{Source}|X_{Source})\}$ ----->(3)

A Target Domain, $\mathrm{Domain\_T} = \{X_{Target}, P(X_{Target})\}$ ----->(4)

with learning task, $T_{Target} = \{Y_{Target}, P(Y_{Target}|X_{Target})\}$ ----->(5)

A Pre-trained ResNet-101 model with parameters θ_{Source} Optimized for T_{source}.

A new dataset X_{Target} with the different but related label distribution $P(Y_{Target}|X_{Target})$.The goal is to adapt θ_{Source} for the new task:

$$\theta^{*}_{Target} = arg\ min_{\mathrm{Target}} \sum_{i=1}^{N_{Target}} L(f(X^{i}_{Target}; \theta_{Target}), Y^{i}_{Target}) \text{ ----->(6)}$$

Whereas, $f(X^{i}_{Target})$ is the prediction of the model with updated parameters θ_{Target} , L is the Loss function, N_{Target} is number of samples in the target dataset. If fine-tuning , we update the parameters, θ_{Target} using propagation, while in feature extraction, we freeze early layers and train only the final classification layers.A Random Forest is an ensemble of decision trees used for classification or regression.Given a feature representation Z extracted from the fine-tuned ResNet-101, the random forest is trained on the extracted features. Each decision tree in the Random Forest makes a prediction.

$$h_m(Z),\ m = 1,2,\ldots,M \text{------>(7)}$$

Where as, $h_m(Z)$ is the prediction from the m-tree, M is the number of trees.The final output is obtained through classification or regression.

$$Y = \mathrm{argmax} \sum_{m=1}^{M} 1(h_m(Z) = y \text{----->(8)}$$

for classification, where 1(.) is the indicator function.The Random Forest consists of MMM decision trees. Each tree h_m predicts a class for the test feature Z. The final classification decision is made using majority voting, where the predicted class 'y' with the highest number of votes is selected.

4.1 Transfer Learning pipeline (ResNet-101 + Random Forest):

i) Extract deep features using the pre-trained ResNet-101:

$$Z = \text{ResNet101}(X_{\text{Target}};\theta_{\text{Target}}) \text{------}(9)$$

Given an input image I, the pre-trained ResNet-101 model R extracts a feature vector Z. This vector represents high-level features such as texture, shape, and structure, which are useful for classification.

ii) Train a Random Forest classifier on these extracted features:

$$Y = RF(Z) \text{----->}(10)$$

The extracted feature vectors Z are used to train a Random Forest classifier RF. The training dataset (Z,Ytrain) consists of the feature vectors and their corresponding labels Ytrain, allowing the model to learn classification rules.Where, RF is the trained Random Forest model.

Thus the overall function for predicting Y_{Target} is

$$Y_{\text{Target}} = RF(\text{ResNet101}(X_{\text{Target}};\theta_{\text{Target}})) \text{----->}(11)$$

Feature Extraction will be done by ResNet101 and Random Forest (RF) is used for Classification.

Algorithm: Proposed Transfer Learning Based Resnet101 + Random Forest (TLBR101RF)

```
Initialize images_list ← [ ], labels_list ← [ ]
FOR each image I in dataset D^T Do
   Resize I into [244,244]
   Pixel values normalize into (1,0)
   Append processed I to images_list
   Assign corresponding label to labels_list
END FOR
X ← images_list, Y ← labels_list
(X_training, Y_training), (X_testing, Y_testing) ← training_testing_split(X, Y, test_size=0.2)
Load R with ImageNet weights (include_top = False)
Freeze early layers of R
Replace classification head with Global Average Pooling (GAP) layer
Initialize features_train ← [ ]
FOR each image I in X_train DO
   Extract feature vector Z ← R(I)
   Append Z to features_train
END FOR
Initialize Random Forest model RF
Train RF using (features_train, Y_train)
Load test image I_test
Resize I_test into[224,224]
Pixel values normalize into (1,0)
Extract feature vector Z_test ← R(I_test)
IF Z_test is valid THEN
   Predict label Ŷ_test ← RF(Z_test)
ELSE
   RETURN "Error: Feature extraction failed"
END IF
IF GPS metadata exists in I_test THEN
      Extract latitude and longitude (lat, lon)
      Convert coordinates using systematic transformation
END IF
```

The procedure commences with data acquisition, involving the collection of images of medicinal plants along with their geo-tagged metadata. Then images are augmented for producing larger number of datasets. Afterthat, the images are subsequently pre-processed by scaling image values into [224,224] and normalize into (1,0) for consistency. During the feature extraction step, a pre-trained ResNet101 model is employed to convert images into deep feature representations, which act as input for classification. The collected features are utilized to train a Random Forest Classifier (RFC), which acquires the ability to distinguish among distinct plant species. In the prediction phase, a new leaf picture is analyzed using ResNet101 to extract features, which are subsequently classified by the trained RFC model. The anticipated plant species is compared with a database to obtain its local name, botanical name, and therapeutic use. Concurrently, geotagged metadata is retrieved from the image to ascertain the plant's position. The results, encompassing the anticipated plant species, therapeutic relevance, and geolocation, are presented via a web-based application. This systematic method guarantees precise identification and facilitates location-based tracking, supporting study, conservation, and sustainable use of medicinal plants.

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4.2 PREDICITON BY WEB APPLICATION:

The TLBR101RF model can be deployed as a web application to offer a smooth interface for identifying medicinal plants from their majorly available location. It provides a efficient and user-friendly to identify medicinal plants from leaf images. Users can upload an image, which is then classified using a Random Forest classifier to identify the type of plant after being processed through ResNet101 for deep feature extraction. Once found, the application offers important information about the plant's traditional and pharmacological medical benefits, such as treating skin illnesses, digestive problems, or respiratory ailments. Subsequently, application also furnish geotagged location information of the identified plant, that was already feeded in the model based on the analysis. The functionality enables the creation of a geospatial distribution like longitude and latitude map location for the plants, aiding researcher, conservationist, and herbalists to track the presence and natural habitats of medicinal plant species.The interactive platform displays the plant's name. Medicinal properties and a mapped visualization of its location. By combining deep learning ResNet101 for feature extraction, machine learning Random Forest technique for classification and geospatial mapping for biodiverstiy analysis, the system works as a crucial tool for medicinal research, ecological conservation and the sustainable utilization of the plant resources.

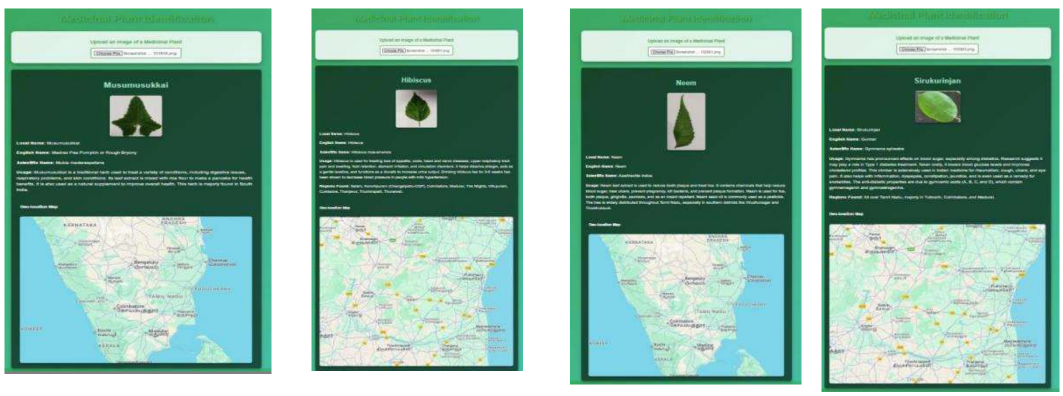

Figure 6: Predicted Output

5. RESULTS AND DISCUSSION:

CNN encompass numerous attributes and are having computational intensive. Fundamental convolution was supplanted with depth-wise separable convolution, hence reducing the number of parameters and computational cost. Table 3 describes the comparision between vaious CNN Classifiers. The performance of the proposed TLBR101RF (Transfer Learning-Based ResNet101 + Random Forest) model was thoroughly assessed through experimental evaluation and comparative analysis with state-of-the-art CNN architectures and their hybrid variants. This section highlights the classification effectiveness, evaluation metrics, and deployment capability of the proposed method in real-world scenarios.

5.1 Comparative Analysis of Classification Accuracy

The primary objective of this study was to enhance medicinal plant identification by leveraging a hybrid deep learning and ensemble-based classification framework. Five pre-trained CNN models VGG16, MobileNet, Inception, Xception, and ResNet101 were evaluated both as standalone classifiers and in hybrid combination with Random Forest (RF).

Table 3: Accuracy Details of Classifier

CNN Models	**Classifier (%)**	**Random Forest(%)**
VGG16	48.28%	93.68%
MOBILENET	45.72%	91.22%
INCEPTION	55.80%	96.77%
EXCEPION	50.35%	94.55%
RESNET	**57.40%**	**98.69%**

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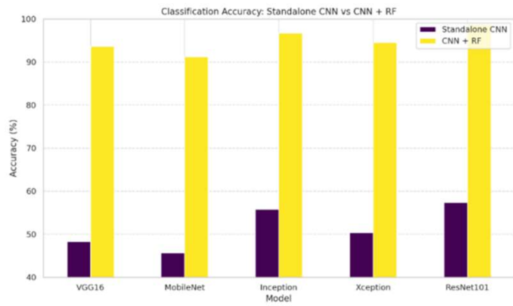

Figure. 5 Bar Chart for Accuracy

As seen in Table 2, standalone CNN classifiers suffer from underfitting when trained on complex botanical data due to limited domain-specific adaptation. Hybrid models significantly outperform their standalone counterparts by introducing non-linear decision boundaries via RF, thus reducing generalization error. The proposed ResNet101 + RF model achieves the highest accuracy of 98.69%, reflecting its superior feature learning and classification synergy.

5.2 Evaluation Metrics: Precision, Recall, and F1-Score

To further validate classification robustness, standard metrics precision, recall, and F1-score were computed across all hybrid models.

Table 4: Evaluation Metrics

Combination of CNN with Random Forest	**F1 Score(%)**	**Precision(%)**	**Recall (%)**
VGG16 +Random Forest	93.60	93.50	93.85
MOBILENET+Random Forest	91.33	91.00	91.36
INCEPTION+Random Forest	96.92	96.67	96.94
EXCEPION +Random Forest	94.75	94.48	94.78
Proposed(RESNET101+Random Forest)	**98.89**	**98.56**	**98.87**

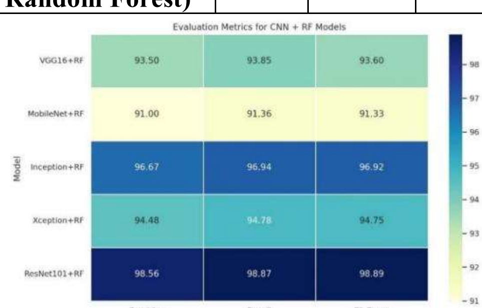

Figure 6: Web Application Output

These metrics reinforce the superiority of TLBR101RF, which achieves an F1-score of 98.89%, indicating balanced precision and recall. Such high metrics suggest effective discrimination between subtle leaf texture and shape variations, crucial in fine-grained botanical classification.

6 CONCLUSION:

The Transfer Learning Based ResNet101 and Randon Forest (TLBR101RF) model, represents a remarkable advancement in medicinal plant identification by combining deep learning ensemble with machine learning techniques. The ResNet101 is specifically known for its residual connections, acts as a powerful feature extractor, capturing complex patterns in leaf image. Whereas , the Random Forest classifier then influences these extracted features to make highly accurate classification decisions. This hybrid approach attains an impressive classification accuracy of 98.61% significantly outperforming traditional deep learning models like VGG16, ResNet50, and MobileNet. This model's better performance can be attributed to its ability to handle high-dimensional feature representations while reducing the risks of overfitting, an usual challenges in deep learning models when working with limited or imbalanced datasets. In addition with that, incorporation of geographical data further enhances the accuracy and reliability of the model, allowing it to recognize medicinal plants based on region-specific variation. Most of the medicinal plants shows morphological differences based on climate, soil consumption and other classification. By considering location-based features, the TLBR101RF model ensures that plants indigenous to specific regions are correctly identified, making it more versatile and effective in real-world applications such as conservation efforts, herbal medicine research and biodiversity monitoring.

7. FUTURE WORK:

Future enhancement focuses on medicinal detection by deploying lightweight models for real-time mobile applications and federated learning can make detection more possible. For more accuracy needs to utitlize deep learning improvements by leveraging advanced architecture such as vision transformers and self-supervise learning. Integrating multimodel data, like comibining image recognition with chemical composition analysis and text-based information, for providing better medicines for chronic diseases by identifying various medicinal valued plants.

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