A Robust Approach to Medicinal Plant Classification through the ResNet50 Model

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ABSTRACT:

Medicinal plants have long been integral to traditional medicine valued for their therapeutic properties. Ensuring accurate identification of these plants is paramount for their safe and effective utilization. This work introduces a vigorous approach to the classification of medicinal plant employing the ResNet50 model. By harnessing its deep convolutional layers, Resnet50 is trained on a comprehensive dataset of medicinal leaf images, enabling it to discern intricate features crucial for classification. Through transfer learning, the model adapts its knowledge to proficiently categorize diverse medicinal plants with high precision. It also demonstrates promising potential in revolutionizing the above said classification, thereby making significant contributions to the realms of botany, pharmaceuticals, and ecological conservation. By leveraging cutting-edge technology, this approach not only streamlines the identification process but also enhances accuracy, minimizing the risk of misidentification and consequent adverse effects.

Key Words: Deep learning, ResNet50, Medicinal Plant, Transfer learning.

I.INTRODUCTION

Medicinal plants have been utilized for centuries across various traditional systems, prominently in Ayurveda, as well as modern medicine. These plants contain a plethora of bioactive compounds such as alkaloids, flavonoids which contribute to their therapeutic properties.

Ayurveda, an ancient Indian system of medicine, views medicinal plants as fundamental to maintaining health and treating ailments. In India, Ayurvedic medicines are widely used for their perceived safety and effectiveness. However, the sustainability of Ayurveda relies on medicinal plants, many of which have dwindled in recent years. Recognizing these plants quickly and easily is crucial, yet traditional methods often require intervention. Various characteristics such as shape, color and texture can aid in plant classification. Ayurvedic practitioners believe that medicinal plants not only address symptoms but also restore balance to the body's energies.

In modern science, there's a growing interest in medicinal plants due to their potential therapeutic effects and lower risk Of side effects compared to synthetic drugs. Many have their origins in plant compounds or are directly derived from them. For instance, the anti-malarial drug quinine originates from cinchona tree, while the pain reliever aspirin is derived from willow bark. Moreover, plant-based medicines are being extensively researched for their efficacy in treating various conditions such as cancer, diabetes, and cardiovascular diseases.

Technological innovations like Deep learning and Machine learning have simplified the process for machines to carry out human-like-jobs. But as usage grows and the pool of experts shrinks, the requirement for a plant recognition system grows as well. It would affect daily use, teaching, and research if the proposed technology could identify medicinal plants from a picture of a single leaf, the leaf has one of the most important features while studying plant properties. The knowledge gap between Ayurvedic practitioners and the general public would be closed by this system, benefiting the medical, botanical, and Ayurvedic fields.

II.RELATED WORK

The advancement of deep learning architectures has significantly influenced the field of medicinal plant classification. Among these architectures, ResNet50 stands out for its exceptional performance and innovative design, addressing key challenges encountered by traditional convolutional neural network (CNN) models. ResNet50, a part of ResNet family was unveiled by Microsoft Research in 2015. Unlike earlier CNN models, ResNet50 incorporates residual connections, allowing for the training of exceptionally deep networks with over 50 layers. This addresses the vanishing gradient problem, enabling effective learning of intricate features from medicinal plant images without degradation in performance. The residual connections facilitate the flow of gradient during back propagation, thus promoting better convergence and preventing the loss of information as the network depth increases.

Additionally, resNet50 balances computational economy with model complexity, which makes it a good choice for real-world uses like classification of medicinal plants. Its depth makes it possible to extract subtle visual characteristics that are essential for correctly identifying medicinal plants.

III.EXISTING SYSTEM

The existing system employs deep learning techniques, specifically convolutional neural networks (CNNs) and pre-trained models like VGG16 and VGG19, for the identification of indigenous ayurvedic medicinal plant species. CNN architecture consists of three convolutional layers followed by max-pooling, while VGG16 and VGG19 leverage pre-trained weights for feature extraction and classification. Through comparative analysis, VGG16 demonstrates superior classification accuracy, in aiding the identification of medicinal plants, with potential applications in medical research and environmental conservation.

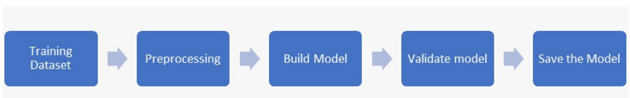


Fig.1. Existing System

IV. PROPOSED SYSTEM

The automation of medicinal plant classification has advanced significantly with the inclusion of the ResNet50 model. ResNet50 is highly effective at extracting complex botanical properties from plant photos by utilizing its deep architecture and residual learning techniques. This allows it can detect minute differences in textures, forms, and vein patterns with a high degree of accuracy. After being trained on a carefully selected dataset of images of medicinal leaves, ResNet50 shows remarkable accuracy in differentiating between various plant species.

Moreover, transfer learning improves ResNet50's performance by utilizing pre-trained weight knowledge, which helps it to generalize to a variety of medicinal plant species even in the absence of a large amount of training data, Hence, by automating medicinal plant classification and decreasing the requirement for human annotation and categorization, the identification process and provides a reliable and scalable solution.

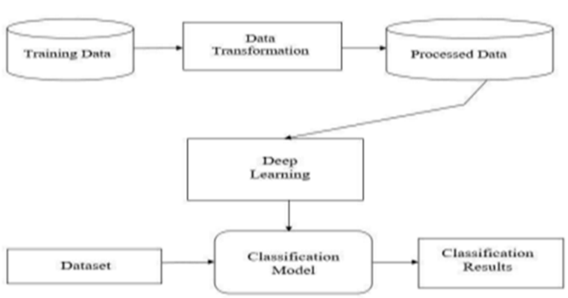


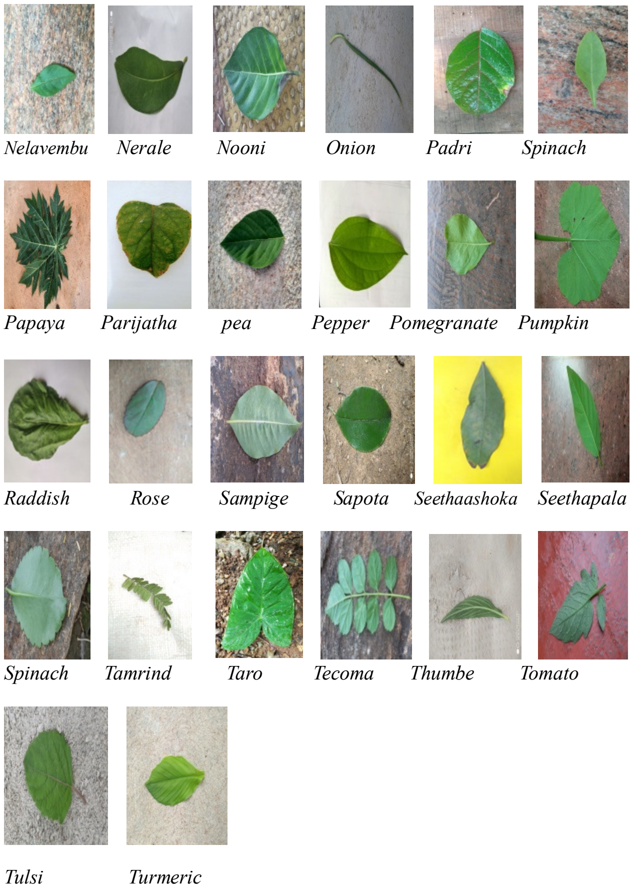
Fig-2.Proposed System

V.DATASET USED

The "Indian Medicinal Leaves Image Datasets" is a compilation of images showcasing medicinal plants, primarily emphasizing their leaves. This dataset serves the purpose of supporting research in medicinal plant studies and associate fields.

It encompasses images taken in diverse settings, encompassing various backgrounds, without any particular limitations regarding the environmental conditions during capture.

Leaf Images in Dataset:



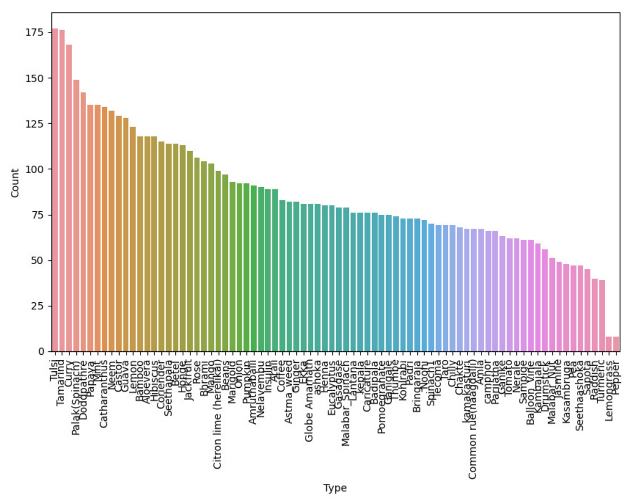


Fig-2.Graph diagram of number of leaves of each class

These leaves are used for training the model and the model extracts intricate features from the images. By learning these features the model classifies the medicinal plants efficiently.

VI.ALGORITHM USED

ResNet50 (RESIDUAL NETWORK WITH 50 LAYERS):

ResNet50 is a convolutional neural network architecture renowned for Image classification. It consists of 50 layers, including convolution layers, pooling layers, and fully connected layers. The innovation lies in the introduction of residual connections, which mitigate the vanishing gradient problem encountered in deep networks. These connections allow for the direct flow of information from one layer to another, enabling the network to learn more complex features effectively. ResNet50 employs a bottleneck architecture, where 1x1 convolutions reduce dimensions before more computationally intensive 3x3 convolutions. It utilizes skip connections, where inputs are added to outputs via shortcut connections, facilitating easier optimization. This architecture achieves remarkable accuracy on various image classification tasks while maintaining manageable computational complexity.

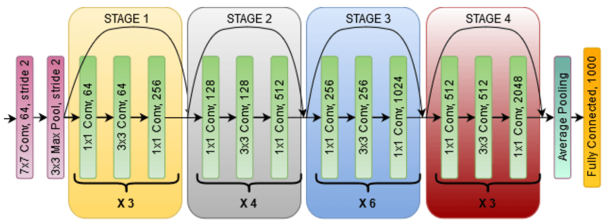


Fig-4: ResNet50

[https://open-instruction.com/dl-algorithms/overview-of-residual-neural-network-resnet/]

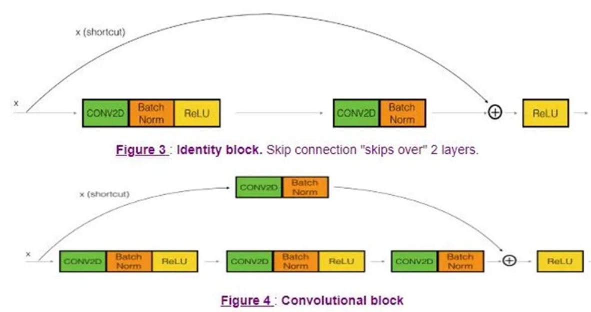


Fig-5: Operation of Residual Blocks

[https://blog.devgenius.io/resnet50-6b42934db431]

1. Input Layer:

The Input layer receives the raw image data as input. In ResNet50, the input images are typically resized to a fixed size before being fed into the network.

2. Convolutional Layers:

The convolutional layers perform feature extraction by applying a series of convolutional filters to the Input image. These filters detect patterns such as edges, textures, and shapes in the image.

3. Residual Blocks:

The key innovation of ResNet50 lies in its use of residual blocks. Each residual block contains multiple convolutional layers along with skip connections that bypass one or more layers. These skip connections allow the network to learn residual functions, making it easier to train deeper networks without suffering from vanishing gradients.

4. Identity Blocks:

In addition to the residual blocks, ResNet50 also includes identity blocks, which are similar to residual blocks but have a simpler structure without any additional convolutional layers. Identity blocks are used to maintain the spatial dimensions of the feature maps while increasing the depth of the network.

5.Activation Functions:

The Rectified Linear Unit(ReLU) activation function is a piecewise linear function commonly used in neural networks.

Mathematically ReLU is defines as,

F(x) = max(0,x)

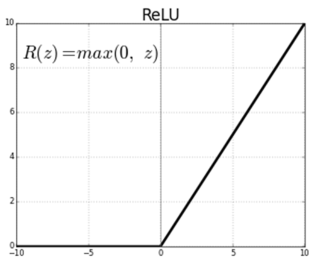


Fig-6 ReLu function

The other activation function is softmax. It is a mathematical function commonly used in neural networks, particularly in the output layer of classification models. The softmax function exponentiated each score and normalizes them by dividing by the sum of all exponentiated scores.

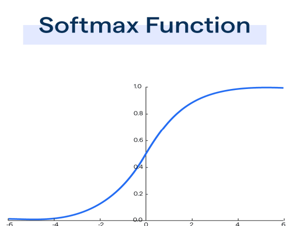


Fig-7.Sigmoid function

Mathematically it can be represented as:

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

6.Pooling Layer:

Pooling layers reduce the spatial dimensions of the feature maps, effectively downsampling the feature representations to capture the most salient features.

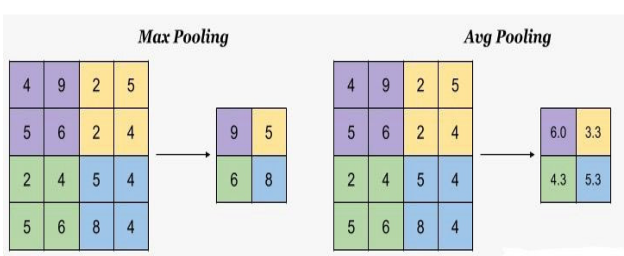


Fig-8 Pooling Layer

7.Fully Connected Layer:

The fully connected layers at the end of the network aggregate the extracted features and perform classification based on these features. In ResNet50, these layers are typically followed by a softmax activation function to produce class probabilities.

$$y_{jk}(x) = f\left(\sum_{i=1}^{n_H} w_{jk}x_i + w_{j0}\right)$$

VII.METHODOLOGY

This technique makes use of ResNet50, a deep learning model specifically designed for the classification of medicinal plants, to extract complex information from leaf images.

A. Data Collection

The dataset called "Indian Medicine leaves Image dataset" is used for the classification. This dataset encompasses diverse images of medicinal plants from India, serving as a valuable resource for training and evaluating deep learning model.

B. Data Pre-processing

Pre-processing involves augmentation techniques such as flipping, rotating, and scaling increase dataset variability, aiding model's ability to generalize patterns effectively and the dataset becomes enriched with a wide range of leaf variations, enhancing the model's robustness and accuracy in classifying medicinal plants.

C. Model Training

ResNet50 :

A pre-trained ResNet50 model, initialized with ImageNet weights, is employed as a feature extractor, excluding its fully connected layers. This choice capitalizes on the model's ability to extract high level features from images. The last layers of the ResNet50 model are augmented with densely connected layers to facilitate learning of specific classification patterns related to medicinal plants. The model is compiled with an Adam optimizer and categorical cross-entropy loss function. By fine- tuning only the added classification layers, computational resources are conserved, while still achieving effective classification performance. This approach offers a robust and efficient solution for medicinal plant classification tasks, leveraging the knowledge learned from a diverse set of natural image categories pre-trained on ImageNet.

D. Performance Evaluation

In order to assess the model performance in classifying species of medicinal plants, it is tested on a different test set. To evaluate performance thoroughly, metrics including accuracy, precision, recall, and F1 score are calculated. Confusion matrices also help to identify misclassifications and areas that require development. This extensive evaluation procedure guarantees a solid comprehension of the model's capacity to correctly identify different species of medicinal plants, which is essential for guiding subsequent optimization.

VIII. RESULTS

We utilized the Indian Medicinal leaves Image Dataset for our experiments. This Dataset comprises of leaf images of 80 different medicinal plant species. The model exhibited outstanding performance in classifying medicinal plant species, achieving a remarkable test accuracy of 99.84%. ResNet50 showed a notable improvement above baseline techniques, demonstrating its competence in handling challenging classification problems.

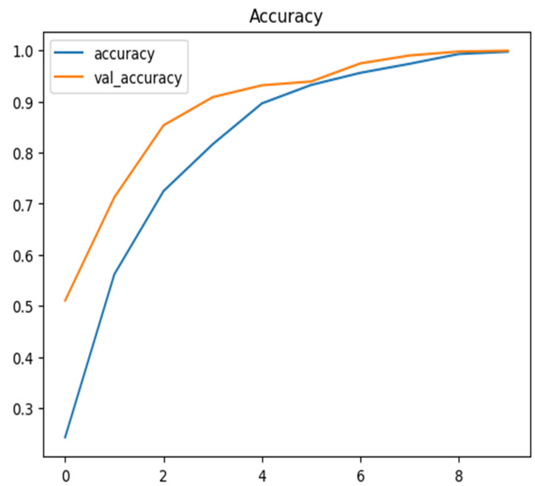


Fig-9 Test Accuracy

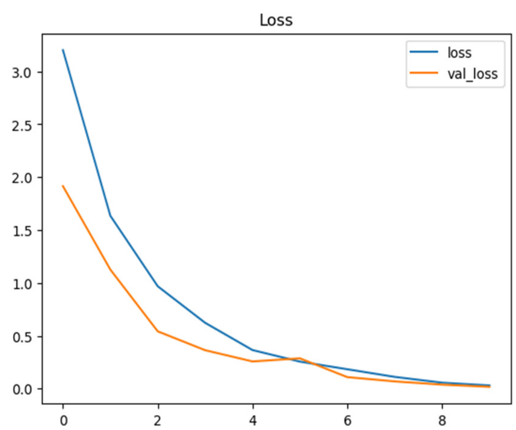


Fig-10 Test Loss

IX. CONCLUSION

It is believed that this work represents a major step forward in the use of Deep Learning techniques to combine ancient herbal knowledge with contemporary technology. Through this, we can successfully tackle problems with medicinal plant classification by using ResNet50 model. The limitations of traditional techniques are eliminated by this DL-based approach which provides accurate, thorough, and real-time information on botanical resources. This study helps close the knowledge gap between modern technology and traditional herbal remedies, opening the door to better understanding and application of medicinal plants in pharmacology, health care, and biodiversity preservation, among other fields.

The comprehensive approach to medicinal plant classification presented here offers a scalable solution for addressing challenges in traditional medicinal knowledge. By harnessing the power of ResNet50, researchers can expedite the identification and cataloging of medicinal plant species, fostering advancements in both scientific understanding and sustainable resource management. Ultimately, this work contributes to the broader goal of harnessing nature's biodiversity for the betterment of human health and ecological balance.

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