

AYURVEDIC PLANT IDENTIFICATION USING DEEP LEARNING

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Abstract—This project aims to leverage the capabilities of Deep Learning (DL), specifically ResNet50 and VGG19 models, to address the complex task of classifying medicinal plants. Conventional methods of plant identification often fall short in providing real-time, precise, and comprehensive information about these invaluable botanical resources. The DL-based system developed here aims to accurately classify medicinal plants based on images, offering users detailed information on their medicinal properties. Incorporating factors like age restrictions, gender-specific considerations, and pregnancy restrictions, the model provides essential guidelines for safe and effective plant utilization. Additionally, it offers insights into usage methods and recommended dosages for each identified medicinal plant. By merging advanced DL techniques with botanical expertise, this project aims to create a robust tool for precise plant identification and informed utilization, promoting a more accessible and knowledgeable approach to natural healthcare.

Keywords—Deep Learning Neural Network, Convolutional Neural Network, SVK, Random Algorithm, Probabilistic Neural Network

I. INTRODUCTION

In a world where the healing properties of medicinal plants play a vital role in natural healthcare, the accurate identification and understanding of these botanical treasures are essential. Deep Learning (DL), a subset of Artificial Intelligence (AI), offers a cutting-edge solution to the challenge of classifying medicinal plants. In this project, we leverage the power of DL models, specifically ResNet50 and VGG19, to create a sophisticated system that not only identifies medicinal plants with precision but also provides in-depth information on their medicinal contents, age restrictions, gender specific considerations, pregnancy restrictions, mode of use, and recommended dosage. [1.1] The Problem: The vast array of medicinal plants poses a formidable challenge in precise identification and comprehensive information retrieval. Conventional methods often lack the accuracy and efficiency required for real-time and detailed analysis, hindering the widespread and informed use of these invaluable botanical resources for healthcare purposes. Innovative Approach: We propose an innovative approach solely based on Deep Learning, utilizing state-of-the-art models ResNet50 and VGG19. By

training these DL models on extensive datasets containing images of various medicinal plants, our goal is to create a powerful system that accurately classifies plants and provides a wealth of information on their medicinal attributes. [1.2] Key Objectives: • Plant Identification: Implement ResNet50 and VGG19 DL models to achieve precise and efficient classification of medicinal plants based solely on images, ensuring reliability in identification. • Medicinal Content Analysis: Extract and present detailed information on the medicinal contents of each identified plant, offering insights into their therapeutic benefits. • Guidelines for Use: Incorporate age restrictions, gender-specific considerations, and pregnancy restrictions into the DL model, providing users with essential information for the safe and effective use of medicinal plants. • Mode and Dosage Recommendations: Utilize DL to offer insights into the recommended modes of use and appropriate dosage for each detected medicinal plant, ensuring adherence to best practices for optimal health outcomes. [1.3] Impact: This pioneering project aims to revolutionize the identification and utilization of medicinal plants by relying solely on the power of Deep Learning. Through this innovative approach, we seek to empower individuals and healthcare professionals alike, enabling them to harness the healing potential of medicinal plants with precision and confidence, thus contributing to a healthier and more informed society.

II. LITERATURE REVIEW

1. Real-Time Identification of Medicinal Plants using Machine Learning Techniques

C. Sivaranjani, L. Kalinathan, R. Amutha, R. S. Kathavarayan and K. J. Jegadish Kumar et.al. This research tackles lighting variability in plant leaf segmentation for species identification by employing an enhanced vegetation index, ExG-ExR. Unlike traditional methods relying on fixed thresholds, ExG-ExR's inherent zero threshold adapts to diverse lighting backgrounds, effectively isolating plant regions. Leveraging color and texture features, a Logistic Regression classifier achieves 93.3% accuracy in species classification. This innovative strategy exhibits robust performance, overcoming challenges posed by lighting variations in plant identification.

2. Automatic Classification of Medicinal Plant Species Based on Color and Texture Features

L. D. S. Pacifico, L. F. S. Britto, E. G. Oliveira and T. B. Ludermir, et.al. This study addresses the challenges in accurately identifying medicinal plant species for traditional medicine purposes using machine learning and computer vision. Despite the widespread use of traditional medicine, existing recognition systems often lack accuracy. The research introduces a new medicinal plant dataset and proposes a comprehensive automatic recognition system employing five machine learning classifiers. Results show classifiers achieve over 97% accuracy, indicating the efficacy of the approach in precise medicinal plant species identification.

3. AI Based Indigenous Medicinal Plant Identification

A. Paulson and S. Ravishankar et.al. This research employs Convolutional Neural Networks (CNN), including pretrained models VGG16 and VGG19, to identify indigenous ayurvedic medicinal plant species, addressing concerns for healthcare professionals, government, and the public. Its applications extend to medical research, particularly in identifying rare plant species, and remote areas where drones capture plant images. With a dataset featuring leaf images of 64 medicinal plants from Kerala, CNN achieves 95.79% accuracy, while VGG16 and VGG19 outperform basic CNN, achieving 97.8% and 97.6% accuracies respectively, demonstrating the efficacy of pretrained models in leaf identification.

4. Medicinal Plant Species Detection using Deep Learning

K. Kavitha, P. Sharma, S. Gupta and R. V. S. Lalitha, et.al. This research employs Convolutional Neural Networks (CNN), including pretrained models VGG16 and VGG19, to identify indigenous ayurvedic medicinal plant species, addressing concerns for healthcare professionals, government, and the public. Its applications extend to medical research, particularly in identifying rare plant species, and remote areas where drones capture plant images. With a dataset featuring leaf images of 64 medicinal plants from Kerala, CNN achieves 95.79% accuracy, while VGG16 and VGG19 outperform basic CNN, achieving 97.8% and 97.6% accuracies respectively, demonstrating the efficacy of pretrained models in leaf identification..

5. Identification of selected medicinal plant leaves using image features and ANN

R. Janani and A. Gopal, et.al. The proposed method addresses the challenge of proper medicinal plant identification and the urgency to protect endangered species. By focusing on leaf images, shape, color, and texture features are extracted for training an Artificial Neural Network (ANN) classifier. The key emphasis lies in selecting efficient input features to achieve high accuracy

with minimal computational complexity. Through testing various combinations of image features on 63 leaf images, the method achieves an impressive accuracy of 94.4% with just eight input features. This approach offers a promising solution for leaf identification systems requiring minimal input and computational time. The implementation utilizes MATLAB's image processing and neural network toolboxes.

6. Medicinal Plant Species Classification Using Neural Network Classifier

A. P. Saikia, P. V. Hmangaihzuala, S. Datta, S. Gope, S. Deb and K. R. Singh, et.al. The paper addresses the crucial need for accurate classification of medicinal plants, crucial for various applications. Utilizing morphological, color, and texture features, the study discusses the classification of six medicinal plant species. The dataset comprises 90 leaf images from Assam, India. Features were evaluated both individually and in combination for classification using a Back Propagation Neural Network (BPNN) classifier. Remarkably, the proposed method achieves a high accuracy of 98.88% across the six plant varieties, demonstrating its effectiveness in identifying leaves with diverse features.

7. Medicinal plant leaf information extraction using deep features

S. Prasad and P. P. Singh, et.al. In this paper, we propose a novel approach for medicinal plant species identification using deep convolutional neural networks (DCNNs). By transferring knowledge from object identification, raw plant leaf images are transformed into deep features, leading to improved recognition accuracy. The method incorporates an efficient leaf acquisition technique and utilizes device-independent color spaces for feature computation, followed by PCA subspace projection for optimization. Experimental results on two different plant leaf datasets demonstrate the robustness and efficacy of the proposed approach.

8. Ayurvedic Plants Identification based on Machine Learning and Deep Learning Technologies

R. S and V. M.N, et.al. The plant kingdom is essential for human life, providing oxygen, food, medicine, and more. Recognizing medicinal plants is crucial for preserving their benefits for future generations. Leaves and flowers are key features in identifying medicinal plants, as they contain potent medicinal properties. This study focuses on classifying local medicinal plants using leaf images. Experimentation involves 100 species, each with 15 different species, totaling 1500 images. The proposed algorithm achieves an impressive accuracy of 98.7%, showcasing its effectiveness in medicinal plant classification.

9. Identification of Medicinal Plants by Visual Characteristics of Leaves and Flowers

A. D. A. D. S. Jayalath, T. G. A. G. D. Amarawanshaline, D. P. Nawinna, P. V. D. Nadeeshan and H. P. Jayasuriya, et.al Correct identification of medicinal plants is crucial in Ayurveda medicine to prevent adverse effects. Human experts traditionally rely on visual features and aroma for plant identification. Automating this process using image processing and machine learning can enhance accuracy. This paper demonstrates high accuracy in identifying rare medicinal plants through a database of scanned images, including both front and back sides of leaves and flowers. Unique feature combinations are used for leaf classification, resulting in identification rates of up to 98% across 10 tested plants

10. Medicinal Plant identification in the wild by using CNN

T. Nguyen Quoc and V. Truong Hoang, et.al Plant identification based on deep learning received many attention and effort from the research community with many promising results. It becomes an active trend in the recent years. We apply Convolutional Neural Network (CNN) to recognize Vietnamese medicinal plant images in this paper. Different frameworks are evaluated such as: VGG16, Resnet50, InceptionV3, DenseNet121, Xception and MobileNet. The highest accuracy reached by Xception with 88.26%. We might think this approach will greatly contribute to the discovery and conservation of valuable medicinal plants.

A Smart Study on Medicinal Plants Identification and Classification using Image Processing.	Probabilistic Neural Network, Convolutional Neural Network.	Focuses on different existing models for plant classification. Comparison of Classification Method.	No identification and classification model were purposed for medicinal plant detection.
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III. SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

This research addresses the issue of lighting variability in plant leaf segmentation for species identification through the utilization of an enhanced vegetation index called ExG-ExR. Unlike traditional methods that rely on fixed thresholds, ExG-ExR's zero threshold adapts to diverse lighting backgrounds, effectively isolating plant regions. By leveraging color and texture features, a Logistic Regression classifier achieves an impressive accuracy of 93.3% in species classification. This innovative strategy demonstrates robust performance, successfully overcoming challenges posed by lighting variations in plant identification.

3.2 DISADVANTAGES

1. Complex Implementation: Implementing the ExG-ExR index and the Logistic Regression classifier may increase the complexity of the system. This complexity could require additional resources, expertise, and time for development and deployment.

2. Resource Intensive: The computational requirements of computing the ExG-ExR index and processing color and texture features may be demanding, particularly for real-time applications or when dealing with large datasets. This could limit the system's efficiency, especially on devices with limited processing power.

3. Sensitivity to Environmental Conditions: While the ExG-ExR index is designed to adapt to diverse lighting backgrounds, extreme environmental conditions such as extreme shadows or glare might still pose challenges for accurate plant segmentation and species identification.

4. Limited Generalization: The system may struggle to generalize well to new environments or species not adequately represented in the training data. This limitation could reduce the applicability of the system across different geographical regions or botanical contexts.

5. Maintenance and Updates: Keeping the system up-to-date with new species or environmental changes may

COMPARITIVE STUDY OF ALGORITHMS

Title of the Paper	Methodology	Findings	Research Gap
Study On Identification and Classification Of Medicinal Plants	SVK, Random Algorithm	Used different Algorithms like SVK, KNN, and Random Forest	Slow training of Datasets.
Identification Ayurvedic Medicinal Plants by Image Processing of Leaf Samples.	Deep Learning Neural Network, CNN	Comparing various Machine Learning algorithms to find the best accuracy.	They heavily on the internet and are unable to function effectively without it.
Identification Of Medicinal Plants and Their Usage by Using Deep Learning	Deep Learning Neural Network, CNN	Created a model MNN (Medicinal Neural Networks) which is trained with the dataset, and collected manually.	Leaves sample tested were 8259 out of which 1010 leaves samples were not identified

require continuous efforts in data collection, model retraining, and software updates, adding to the overall maintenance overhead.

3.3 PROPOSED SYSTEM

The proposed system leverages Deep Learning (DL) techniques, specifically ResNet50 models, for the classification of medicinal plants. It addresses the limitations of conventional methods by providing real-time, precise, and comprehensive information about medicinal plants based on image analysis. The system aims to accurately classify medicinal plants and offer detailed information on their medicinal properties, including factors such as age restrictions, gender-specific considerations, and pregnancy restrictions. It provides essential guidelines for safe and effective plant utilization, including insights into usage methods and recommended dosages for each identified medicinal plant. By merging advanced DL techniques with botanical expertise, the system aims to create a robust tool for precise plant identification and informed utilization, promoting a more accessible and knowledgeable approach to natural healthcare.

3.4 ADVANTAGES

1. **Real-time and Precise Identification:** The DL-based system offers real time and precise identification of medicinal plants, overcoming the limitations of conventional methods which may be time-consuming and less accurate.

2. **Comprehensive Information:** Users are provided with comprehensive information about medicinal plants, including their medicinal properties, age restrictions, gender-specific considerations, and pregnancy restrictions. This ensures safe and effective plant utilization.

3. **Guidelines for Usage:** The system offers essential guidelines for the safe and effective utilization of medicinal plants, including insights into usage methods and recommended dosages. This helps users make informed decisions about plant-based healthcare.

4. **Integration of Botanical Expertise:** By merging DL techniques with botanical expertise, the system combines the strengths of both fields to create a robust tool for plant identification and utilization. This ensures the accuracy and reliability of the information provided.

5. **Promotion of Natural Healthcare:** The system promotes a more accessible and knowledgeable approach to natural healthcare by empowering users with accurate information about medicinal plants and their usage.

IV. SYSTEM DESIGN

4.1 Architecture of ResNet50

Input layer: The input layer of ResNet50 takes an image of size 224 x 224 x 3 as input. The 3 represents the RGB color channels of the image.

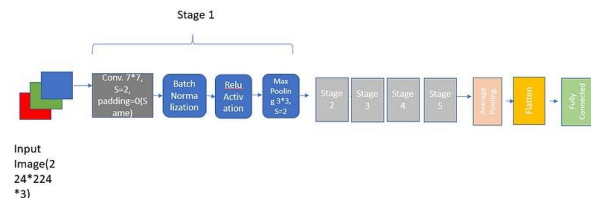


Figure 4.1 Architecture

Components used in this architecture:

1. **Convolutional layers:** Convolutional layers are the building blocks of convolutional neural networks (CNNs), a type of deep learning algorithm that is commonly used for image processing tasks. Convolutional layers are designed to extract features from the input image by applying a series of convolutional filters to the image. Each convolutional filter is a small matrix of weights that is applied to a local region of the input image. The filter slides over the entire image, producing a feature map that highlights patterns and edges in the image. The weights of the filter are learned during the training process, allowing the network to automatically learn the best set of filters for the given task. By applying a series of convolutional filters to the input image, convolutional layers are able to extract features from the image and produce a set of feature maps that can be used as input to the next layer of the network.

2. **Batch Normalization:** Batch normalization is typically applied after the convolutional or fully connected layers in a neural network but before the activation function. It is a widely used technique in deep learning and has been shown to improve the performance of many types of neural networks. Faster convergence, Improved generalization, and Regularization are some benefits of batch normalization.

3. **Relu Activation:** It is an activation function commonly used in neural networks. It is a simple and effective way to introduce nonlinearity into the output of a neuron. The function is defined as: $ReLU(x) = \max(0, x)$. In other words, the output of the ReLU activation function is equal to the input if the input is positive, and 0 if the input is negative.

4. **Max Pooling:** It is used to reduce the spatial dimensions of the feature maps produced by the convolutional layers while retaining the most important information. Which can help to reduce the computational cost of the network and prevent overfitting. By selecting

the maximum value in each window, the operation retains the most important features in the input feature map, while reducing the noise and the effect of small variations.

5. *Flatten layers*: The layer converts the output of the previous layer into a 1D vector, which is then fed into the fully connected layer

6. *Fully Connected Layers*: Also known as dense layers are a type of neural network layer where all neurons in the layer are connected to every neuron in the previous layer. These layers are typically used as the final layers in a neural network and are responsible for making the final predictions, where each neuron in the layer receives inputs from all neurons in the previous layer. The output of 24 each neuron is then computed as a weighted sum of these inputs, followed by an activation function.

7. *Identity Block*: An identity block is the basic building block of the ResNet50 architecture, and it is used to maintain the same dimension of the input and output. An identity block consists of three convolutional layers, each followed by batch normalization and ReLU activation functions. The input is added to the output of the third convolutional layer.

8. *Global Average Pooling*: Reduce the spatial dimensions of the output tensor to a vector by applying global average pooling. This operation computes the average of each feature map, resulting in a feature vector with the same number of channels as the number of filters in the last convolutional layer.

9. *Projection block*: A projection block is used when the input and output dimensions are different. This block includes a convolutional layer with a stride of (2, 2) to down sample the input, and a convolutional layer with a (1, 1) filter size to change the depth of the input to match the output.

V. SYSTEM IMPLEMENTATION

5.1 MODULE DESCRIPTION

5.1.1 Data Collection:

Creating a comprehensive data collection module for identifying Ayurvedic plants involves gathering detailed information across multiple domains to ensure accuracy, usefulness, and ethical integrity. Firstly, botanical information forms the foundation, requiring meticulous documentation of each plant's scientific classification, including genus, species, and any subspecies or varieties, along with common names in various languages. Morphological characteristics such as leaf shape, flower color, and stem type aid in accurate plant identification. Medicinal properties are of paramount importance, necessitating the identification and cataloging of active compounds and chemicals present in each plant.

Understanding the therapeutic properties, such as anti-inflammatory, antioxidant, or antimicrobial effects, is crucial. Traditional uses in Ayurveda and other indigenous medicinal systems must be meticulously documented, including historical and cultural significance, traditional preparation methods, and conditions or ailments treated using the plant. Geographical distribution data is essential for understanding the natural habitats and ecological requirements of each plant species. Information on native regions, climatic preferences, and ecological factors influencing growth helps in assessing cultivation feasibility and conservation strategies. Insights into cultivation and harvesting techniques are vital for sustainable utilization of Ayurvedic plants. This includes information on growth habits (annual, perennial), propagation methods (seeds, cuttings), ideal soil and environmental conditions, and appropriate harvesting techniques and timing. Safety considerations are paramount, given the potential toxicity or side effects associated with some plants. Integration of findings from scientific research and clinical trials provides empirical validation of traditional knowledge and helps bridge the gap between ancient wisdom and modern evidence-based medicine. This involves cataloging relevant research studies supporting medicinal claims and clinical trials evaluating efficacy and safety. Organizing the data in a structured manner, implementing user-friendly interfaces, and ensuring regular updates are essential for accessibility and relevance. Ethical considerations, including respecting intellectual property rights, obtaining necessary permissions for data usage, and adhering to legal frameworks governing plant identification and usage, must underpin the entire process. In summary, developing a data collection module for identifying Ayurvedic plants requires a multidisciplinary approach that synthesizes botanical expertise, medicinal insights, cultural heritage, and technological innovation while upholding ethical principles and legal standards.

5.1.2 Preprocessing

In the Ayurvedic plant identification project, the application of Residual Neural Networks (ResNet) stands as a pivotal approach to enhancing the precision and efficacy of plant recognition endeavors. However, before the data can be effectively utilized by the ResNet model, it undergoes a series of preprocessing steps aimed at refining its quality and suitability. The initial phase involves the meticulous collection of a diverse array of Ayurvedic plant images, capturing variations in lighting conditions, backgrounds, orientations, and sizes to ensure the dataset's representativeness. Subsequently, this dataset is meticulously partitioned into distinct subsets for training, validation, and testing, ensuring the model's performance is rigorously evaluated across different data splits. Following this, the images are uniformly resized to a predetermined resolution, typically 224x224 pixels, using interpolation techniques like bilinear or bicubic interpolation to ensure compatibility with the ResNet

architecture. Moreover, normalization techniques are applied to standardize the pixel values across the dataset, often involving the subtraction of mean values and division by standard deviations. This normalization process enhances the model's stability and convergence during training by reducing the impact of variations in pixel intensity. Furthermore, the categorical labels associated with each image, denoting the Ayurvedic plant species, are encoded into numerical representations using techniques such as one-hot encoding or label encoding. One-hot encoding transforms categorical labels into binary vectors, while label encoding assigns unique integer identifiers to each category. Overall, the data preprocessing pipeline orchestrates a systematic sequence of transformations tailored to optimize the data's compatibility with ResNet architectures, thereby laying a robust foundation for subsequent model training and evaluation in Ayurvedic plant identification tasks.

5.1.3 Development and training of a CNN ResNet model:

The utilization of Convolutional Neural Networks (CNNs) and specifically Residual Neural Networks (ResNet) holds immense potential in the field of Ayurvedic plant identification. This module outlines the development and training process of a CNN ResNet model tailored for accurately identifying Ayurvedic plants based on their images. **Model Architecture Selection:** The choice of ResNet architecture is based on its proven effectiveness in handling deep networks while mitigating the vanishing gradient problem. ResNet's residual connections facilitate the training of deeper networks by allowing the gradient to flow directly through the network, enabling the model to learn more complex features. **Data Preparation:** The dataset curated for training the CNN ResNet model comprises images of Ayurvedic plants collected from various sources. These images are preprocessed as per the established pipeline, including resizing, normalization, data augmentation, and label encoding. The resulting dataset is divided into training, validation, and test sets to facilitate model evaluation. **Model Deployment:** The trained CNN ResNet model is deployed for real-world applications, where it can be integrated into mobile apps, web platforms, or embedded systems for on-device inference. Deployment considerations include model optimization for inference speed and memory footprint, as well as ensuring robustness to variations in input images and environmental conditions. The development and training of a CNN ResNet model for Ayurvedic plant identification represent a significant advancement in leveraging deep learning for botanical research and healthcare applications. By harnessing the power of CNNs and ResNet architectures, this module facilitates accurate and efficient identification of Ayurvedic plants, contributing to the preservation of traditional knowledge and the advancement of herbal medicine.

5.1.4 Model Evaluation and Deployment Module:

The Model Evaluation and Deployment Module in the Ayurvedic plant identification project involves two critical stages: evaluation of the trained CNN ResNet model and its subsequent deployment for real-world applications. Evaluation begins with meticulous assessment of the model's performance using a separate test dataset, computing metrics like accuracy, precision, recall, and F1-score, alongside analyzing confusion matrices to identify classification errors. Visual inspection of misclassified images provides additional insights into the model's weaknesses. Following rigorous evaluation, the model is deployed across various platforms such as mobile apps, web applications, or embedded systems, enabling on-device inference. Deployment considerations include optimization for inference speed and memory usage, compatibility with different hardware platforms, and mechanisms for model updates and maintenance. Continuous monitoring and feedback mechanisms are established to ensure the model's reliability and effectiveness in real-world scenarios, contributing to the advancement of Ayurvedic medicine and botanical research while preserving traditional knowledge.

5.2 ALGORITHM

5.2.1 CNN Architecture

CNN is a deep learning model which can be used for processing data that has a grid. It is a mathematical construct that is composed of three types of layers. The first two layers' convolution and pooling layers perform the 10-feature extraction whereas the third, the fully connected layer maps the extracted features into the final output. The convolutional layer is composed of a stack of mathematical operations, such as convolution which is a special type of linear operation. In digital images, the pixel values are stored in 2D format and the kernel is used as the optimizable feature extractor that can be applied to each image position. The kernel can be optimized in such a way that the difference between outputs and actual outputs can be minimum, and backpropagation and gradient descent can be used for it. CNN is a highly efficient algorithm at present that can be used for image processing. CNN works by extracting features from the images. Any CNN consists of the following:

- a. The input layer which is a grayscale image.
- b. The Output layer which is a binary or multi-class labels.
- c. Hidden layers consisting of convolution layers, RLU (rectified linear unit) layers, the pooling layers, and a fully connected Neural Network.

5.2.2 Convolution Layer

This layer is the first layer that is used to extract the various features 30 from the input images. In this layer, the mathematical operation of convolution is performed between the input image and a filter of a particular size $M \times M$. By sliding the filter over the input image, the dot product is taken between the filter and the parts of the input image with respect to the size of the filter ($M \times M$). A convolutional layer is the main building block of a CNN. It contains a set of filters (or kernels), parameters of which are to be learned throughout the training. The size of the filters is usually smaller than the actual image. Each filter convolves with the image and creates an activation map. The primary purpose of Convolution in the case of CNN is to extract features from the input image.

5.2.3 Pooling Layer:

In most cases, a Convolutional Layer is followed by a Pooling Layer. The primary aim of this layer is to decrease the size of the convolved feature map to reduce computational costs. This is performed by decreasing the connections between layers and independently operating on each feature map. Depending upon the method used, there are several types of Pooling operations. In Max Pooling, the largest element is taken from the feature map. Average Pooling calculates the average of the elements in a predefined-sized Image section. The total sum of the elements in the predefined section is computed in Sum Pooling. The Pooling Layer usually serves as a bridge between the Convolutional Layer and the FC Layer.

5.2.4 Max Pooling:

Max pooling is a pooling operation that selects the maximum element from the region of the feature map covered by the filter. Thus, the output after the max-pooling layer would be a feature map containing the most prominent features of the previous feature map



Figure 5.1 Max Pooling Layer

5.2.5 Fully Connected Layer:

The Fully Connected (FC) layer consists of the weights and biases along with the neurons and is used to connect the neurons between two different layers. These layers are usually placed before the output layer and form the last

few layers of a CNN Architecture. In this, the input image from the previous layers is flattened and fed to the FC layer. The flattened vector then undergoes a few more FC layers where the mathematical function's operations usually take place. In this stage, the classification process begins to take place.

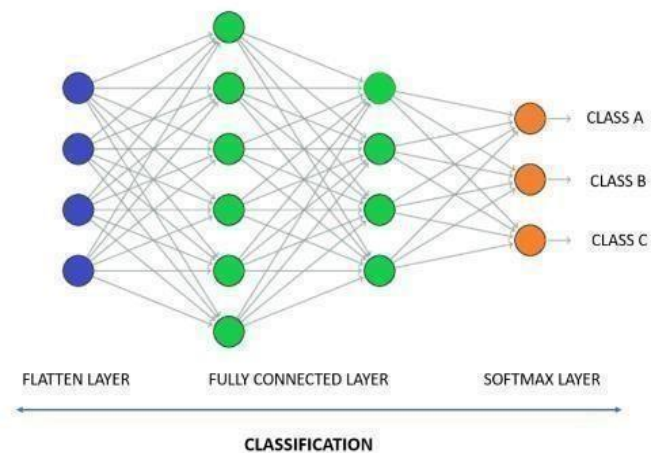


Figure 5.2 Fully Connected Layer

5.2.6 Dropout:

Usually, when all the features are connected to the FC layer, it can cause over fitting in the training dataset. Over fitting occurs when a particular model works so well on the training data causing a negative impact on the model's performance when used on new data. To overcome this problem, a dropout layer is utilized wherein a few neurons are dropped from the neural network during the training process resulting in a reduced size of the model.

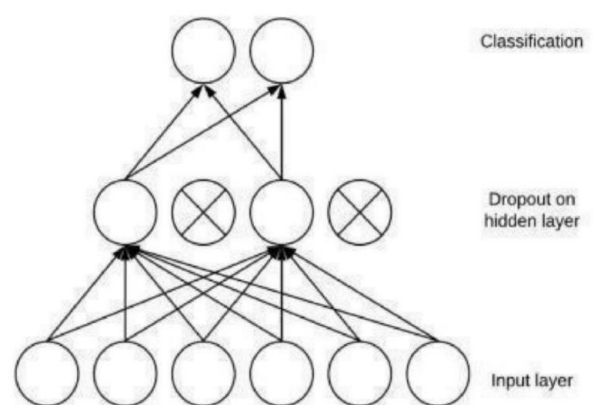


Figure 5.3 Dropout

5.2.7 RESNET 50:

ResNet stands for Residual Network and is a specific type of convolutional neural network (CNN). ResNet-50 is a 50-layer convolutional neural network (48 convolutional layers, one MaxPool layer, and one

average pool layer). Residual neural networks are a type of artificial neural network (ANN) that forms networks by stacking residual blocks.

1. Architecture:

ResNet-50 is a deep convolutional neural network architecture composed of 50 layers, hence the name. It consists of convolutional layers along with one MaxPool layer and one average pooling layer. The architecture includes skip connections or residual connections, which allow the gradient to propagate more effectively during training.

2. Residual Blocks:

ResNet-50 is constructed using residual blocks, each of which contains multiple convolutional layers. These residual blocks enable the network to learn residual functions instead of directly learning underlying functions, making training easier.

3. Skip Connections:

Skip connections allow the gradient to bypass certain layers, helping to mitigate the vanishing gradient problem. In ResNet-50, these connections add the input of a layer to its output before applying a nonlinearity (e.g., ReLU activation function).

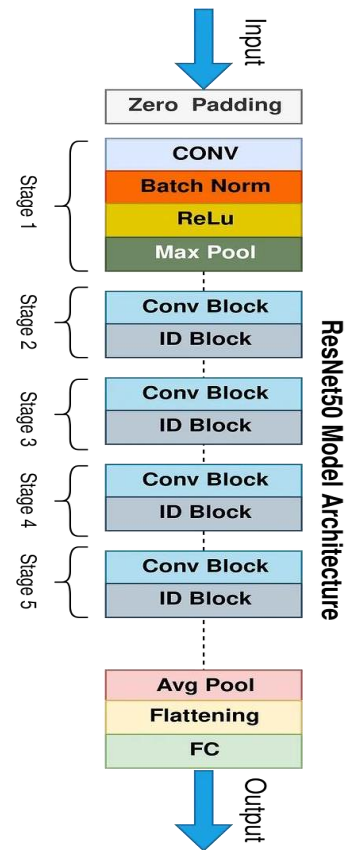
4. Training:

ResNet-50 is typically trained using mini-batch gradient descent, a variant of stochastic gradient descent. During training, the network's weights are updated using backpropagation, where the gradient of the loss function with respect to the network weights is calculated and used to adjust the parameters. Hyperparameters such as learning rate are tuned using techniques like grid search to optimize model performance.

5. Application:

ResNet-50 has been widely adopted for image classification tasks due to its superior performance. It has been applied in various domains including object detection, image segmentation, and medical image analysis. In the context of medicinal plant classification based on leaf images, ResNet-50 can accurately classify plant species by analyzing input images and producing probability distributions over different plant classes. 6. Impact: ResNet-50's introduction marked a significant advancement in deep learning, enabling the training of much deeper neural networks with improved performance. Its success has inspired further research in deep neural network architectures, leading to the development of more sophisticated models for various tasks in computer vision and beyond. The ResNet-50 architecture can be broken down into 6 parts:

1. Input Pre-processing
2. Cfg[0] blocks
3. Cfg[1] blocks
4. Cfg[2] blocks
5. Cfg[3] blocks
6. Fully-connected layer



VI. SYSTEM TESTING

System testing and implementation is actually a series of different tests whose primary objective is to fully exercise the computer-based system. Each test is having its own purpose, and all work should verify that all system elements have been properly integrated and perform allocated functions. This helps us to rectify a problem if occurs in our project. This helps us to do various testing depending upon the project such as security testing, validation testing, integration testing, unit testing etc...

Testing methodologies

By verifying the system one can verify the proper function of the system. The primary purpose is to fully exercise the computer based system. Although each test has different purpose, all the work should verify that all the system elements have been properly integrated and perform the allocated function. The types of some tests are listed below.

White box testing:

This method that uses the control structure of the procedural design to derive test cases. With this white box testing it is able to test all the independent paths are examined or exercised with their true and false. It also uses the external data structure to ensure their validity.

Black Box Testing:

This testing method focus on the functional requirements of the software. This tests the fully functional conditions of the program. This is used likely uncover the errors than the white box testing. It finds the errors in the following parts: Incorrect of missing functions, Interface errors, Errors in data structures or external database access.

Comparison Testing:

This is a method that a way of alternate software exactly as the existing one is developed by another team and this will be very useful in critical situations. This new software is tested with the identical inputs as the previous one to check whether it satisfies the existing terms and conditions.

Security Testing:

This is used to verify the protection mechanisms built into the system that protect it from illegal penetration. Penetration spans a broad range of activities because of hackers who attempt to penetrate systems for sport and disgruntled employees who want to destroy some details.

Unit Testing:

This test focuses on system individually ensuring that it functions properly as an individual unit according to solve the requirements of the particular module. This enable to correct and detect errors this testing is always a white box oriented one and the process may be in parallel.

Validation Testing:

validation testing succeeds when the software functions in a good manner as expected by the customer.

VII. CONCLUSION & FUTURE WORK

7.1 CONCLUSION

In conclusion, this project represents a significant stride towards bridging the gap between traditional herbal knowledge and modern technology through the application of Deep Learning (DL) methodologies. The utilization of ResNet50 and VGG19 models has proven instrumental in addressing the inherent challenges of classifying medicinal plants. The limitations of conventional methods for identification and information retrieval have been overcome by our DL-based system, providing real time,

accurate, and comprehensive details about these botanical resources. The incorporation of age restrictions, gender-specific considerations, and pregnancy restrictions into the model adds a layer of sophistication, offering users invaluable guidelines for the safe and effective utilization of medicinal plants. This not only enhances user safety but also contributes to the responsible promotion of herbal remedies within diverse demographic contexts. In the broader context, the outcomes of this project hold promise for promoting a more accessible and informed approach to natural healthcare. As we continue to unlock the potential of DL in the realm of medicinal plant classification, we envision a future where the convergence of technology and traditional wisdom leads to a harmonious integration of natural remedies into modern healthcare practices.

7.2 FUTURE WORK

Future endeavors will focus on refining and expanding the capabilities of our module to better serve the needs of researchers and botanists in medicinal plant studies. Efforts will be directed towards enhancing the accuracy and relevance of the module through continuous updates to the training dataset, integration of multimodal data, and development of domain-specific models. Additionally, the deployment of field-ready solutions and collaboration with indigenous communities will be prioritized to ensure practical usability and cultural sensitivity. Exploration of drug discovery applications will also be pursued to unlock the therapeutic potential of medicinal plant compounds identified by the AI module. Through these initiatives, we aim to advance the field of medicinal plant research and contribute to the development of innovative healthcare solutions.



Figure 7.1 Unlock the Power of Nature's Pharmacy



Figure 7.2 User Interface allows user to upload the image



Figure 7.3 Display the User Uploaded Image



Figure 7.4 Displaying Prediction

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