Diagnosing Medicinal Plants and their Fungal Diseases Using Deep Learning Models

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***Abstract*— Today, with the development of technology, most manual methods have been replaced by automated computer systems for human convenience. Plant identification and disease classification are two major areas of agricultural research and are aimed at introducing computerized systems instead of manual methods. Millions of plant species are in the world and play a significant role in human life. Among all the types of plants, medicinal plants play an essential role in the traditional medical field because herbal plants can heal humans. Currently, there is a reactivation of interest in herbal medicines at the global level, and conventional medicine is now accepting the use of medicines and their products once they have been scientifically validated. To achieve this goal, we evaluated the performance of two common pre-trained deep learning models (VGG19 and ResNet50) and compared their accuracy levels Finally, the system can estimate some performance metrics such as accuracy and error rate for both algorithms and compare the algorithms based on accuracy in the form of graph. These results are promising, as they show that machine-learning techniques could be used for the early identification of medicinal plants. Our algorithm has been able to achieve a high level of accuracy in the classification of medicinal plants in training and test sets, making it a potentially valuable tool for fast and accurate diagnosis in clinical environments.**

Keywords—VGG19, ResNet50, Traditional medicine, Medicinal Plant Identification and Disease Classification

I. INTRODUCTION

Millions of plant species are in the world and play a significant role in human life. Among all the types of plants, medicinal plants play an essential role in the traditional medical field because herbal plants can heal humans. Recently, WHO (World Health Organization) mentioned that 80% of people use herbal medicines to fill their health requirements, and approximately there are 21000 medicinal plants worldwide. Apart from medicinal uses, herbs can be used in drug development, cosmetology, natural dye, pest control, perfume, tea, and so on. Among Asian countries, Sri Lanka has 3000 years of a huge history of conventional medicine. In Sri Lanka, the traditional medicine system contains four types: Ayurveda, Siddha, Unani, and Deshiya Chikitsa (or Indigenous medicine). Indigenous medicine is the endemic medicinal system of Sri Lankans. Thus, it is called "Sinhala wedakama" or "Helawedakama", related to Sinhala culture, Sinhala language, and Buddhism. The combination of Ayurveda and Indigenous medicine introduces the "Sri Lankan Ayurveda" system. Sri Lanka has a rich biodiversity with many plant resources, especially medicinal plants. Today, around 60- 70% of the Sri Lankan population uses medicinal plants for their primary healthcare needs.

The term “herbal treatment” has been used in many different countries with many names such as traditional therapy, complementary therapy, or natural therapy. The first records of herbal therapy were found in Mesopotamia in 5000 BC and it was determined that 250 herbal medicines were obtained from medicinal and aromatic plants, as generally dried and sometimes fresh, whole, shredded, or cut plants or parts of plants, as are. According to the World Health Organization (WHO), traditional medicine is used to prevent physical and mental illnesses, diagnose, heal or treat them, and maintain health. Furthermore, all knowledge, skills, and practices are explained based on theories, beliefs, and experiences specific to different cultures (WHO, 2017).

The therapeutic use of plants varies depending on the level of development of the country. In developing countries, 80 percent of the population uses herbal products for medical purposes. Although this figure is up to 95 percent in some Asian, African, and Middle Eastern countries, it is lower in developed countries (40–50 percent in Germany, 42 percent in the United States, 48 percent in Australia, and 49 percent in France). However, the most important medical plant trade centers are in Germany, the United States, Japan, and England. The World Health Organization predicts that herb treatment will increase worldwide in the coming years. According to the World Health Organization, 25% of drugs currently used are made from plants and 30% of drugs sold worldwide contain compounds derived from plant materials (FAO, 2005).

In countries where traditional medical treatments are applied, the use of herbal medicines varies according to the recommendations or experiences of people practicing traditional/alternative medicine. In addition, training is provided in universities related to complementary medicine in some countries. For example, many universities in the Western African Economic Community, such as the Democratic Republic of the Congo, South Africa, and Tanzania, have complementary medical courses in pharmacy and medical studies (WHO, 2014). In some African countries, complementary medicine is considered to be a primary medical service. For example, the ratio of traditional healers to the population of Africa is 1/40.000, while the ratio of physicians is 1/500.

Medicinal and aromatic plants are plants that have many uses, such as foods, drugs, cosmetics, and spices and have been used for similar purposes since the beginning of human history. Some of these plants come from nature, while others are cultivated and produced. However, most of the herbs used for therapeutic purposes come from nature. The most prominent and studied characteristics of medicinal and aromatic plants are their therapeutic uses. The extracts of these plants in water and alcohol are also used for the protection of pests and plant diseases because of their biological effects. Aromatic parts of aromatic plants are used to extract therapeutic oils/essential oils containing economic-value allelochemical aroma.

More than 6000 species of medicinal plants from different tropical regions have been identified, more than 1,000 of which are classified as aromatic. Climate change, intensive cultivation practices, and market-based cultivation management have led to an increase in pests and diseases. These problems in medicines and aromatics have gradually increased. Damage caused by pests or diseases can reduce their biomass and oil content. In addition to changes in climatic conditions, the large-scale indiscriminate, and unplanned cultivation of medicinal and aromatic plants to meet the growing demand of the pharmaceutical industry leads to an increase in the incidence and severity of diseases. Losses caused by plant diseases reduce not only the production of secondary plant metabolites but also the quality of raw materials.

II. LITERATURE REVIEW

A. *Plant Identification Technique*

To identify plants, there are two types of techniques available, Molecular Technology and Morphological Technology. Molecular technologies mean that DNA barcoding, PCR-based methods, and DNA sequencing have become common tools for accurate identification of medicinal plants. Morphological techniques mean that traditional methods such as leaf morphology, flower structure, and other physical characteristics are still used, especially in field studies. Pulicherla Siva Prasad (2023) discusses the importance of plant predictions and the challenges associated with them. The following information describes various image acquisition techniques and data sets commonly used in this field and highlights their strengths and limitations. Jana Waldchen's (2018) paper is the first systematic review of the literature with the aim of thorough analysis and comparison of primary studies on computer vision approaches to the identification of plant species. Ghorbani (2017) proposed a comprehensive review of traditional and modern plant identification techniques, discussed their effects, and recommended recommendations. Ragupathy's (2016) paper focuses mainly on the integration of ethnobotanical knowledge with DNA barcoding techniques for effective plant identification. Chase (2016) presents an overview of recent advances in DNA-based coding technology for identifying plant species.

B. *Medicinal plant Authentication*

Ensuring the authenticity of medicinal plants is crucial. Studies often focus on developing methods to detect adulteration and substitution. It includes Authentication techniques including chemical fingerprinting, chromatography, and spectroscopy.

Vina Ayumi (2021) aims to conduct a systematic literature review on the recognition of medicinal leaves published in the last two years (2019–2020) by IEEE, Springer, and Science Direct. We have obtained 15 studies on the recognition of leaves of medicinal plants using artificial intelligence. The data sets used to recognize medicinal plant leaves are mostly private data sets, however, there are public data sets called Leaf, Flavia, and Swedish data sets. Qi-Qing Cheng's (2021) review provides a historical perspective on the current situation of genomes in medicinal plant biology, highlights the use of the rapidly developing sequencing technologies, and conducts a comprehensive summary of how the genomes apply to solve the practical problems in medicinal plants, like genomics-assisted herb breeding, evolution history revelation, herbal synthetic biology study, and geothermal research.

Alexandra Jitareanu (2022) focuses on presenting the current strategies and techniques used and recommended by regulatory authorities to investigate the authenticity and toxicity of pharmaceutical herbal products. Kalanithi Pushpa Nathan (2020) presents a variety of effective and reliable machine-learning algorithms for plant classification using leaf images that have been used in recent years. The review includes the methods of image processing used to detect and extract important leaf features for some machine-learning classifiers. These machine learning classifiers are classified according to their performance when classifying leaf images based on typical plant characteristics, i.e. shape, veins, texture, and a combination of multiple characteristics.

C. *Fungal Disease in Medicinal Plants*

To analyze fungal disease in the medicinal plant there are 2 types of survey. they are Common Fungal Pathogens and Pathogenicity Studies. Common Fungal Pathogenesis Identification and characterization of fungi causing diseases in medicinal plants, e.g., rusts, smuts, mildews, and various types of fungi affecting roots, stems, and leaves. Pathogenicity Studies are Understanding the mechanisms through which fungi affect medicinal plants and the impact on the quality and quantity of bioactive compounds.

Mansoor A Malik's (2022) current research acts as a basic platform and summarizes a detailed account of various severe diseases along with their causal organisms. Therefore, the study will help the researchers to combat these multiple illnesses by following proper management strategies.

Reema Devi's (2023) review highlights the endophytic fungi population influenced by host genotype, environment, and the endophytic fungi species of the host plant. The effects of endophytic fungi are discussed in detail, influencing the commercial properties of plants. Endophytes also have an impact on plant productivity by increasing parameters such as nutrient recycling and Phyto stimulation. Studies focused on mechanisms to regulate the reduction of secondary metabolite production in EF would provide a much-needed impulsive mechanism for ensuring the continued production of bioactive molecules from an indubitable source. Kanika Chowdhary's (2015) paper explores the diversity and ant phytopathogenic activity of the endophytic myco population isolated from India's Queen of Herbs Tulsi.

Swetha's (2022) research presents a detailed review of previously reported as well as current investigations of fungal diseases, etiologic, symptoms, and their management in selected 10 medicinal plants surveyed in Karnataka, India.

D. Disease Diagnosis and Detection

To diagnose the disease and detect there are 2 types of techniques available. They are Advanced Imaging Techniques and Biochemical Markers. Advanced Imaging Techniques use technologies like hyperspectral imaging and infrared spectroscopy for non-destructive disease detection. The Biochemical Markers Identifying specific biochemical markers associated with fungal infections in medicinal plants.

Sk Mahmudul Hassan (2022) presents an inclusive review of the various research everything completed activities engaged in plant ailment discovery utilizing two together state-of-cunning, made-by-hand visage- and deep-education-located methods. Raman Jot (2023) examined some of the existing methods for data collection, preprocessing, feature extraction, data enhancement, and models used to detect and classify diseases that affect a plant, how image quality has been improved, and how model overfitting is reduced or accurate. Jun Liu (2021) discusses how deep learning technology can be used to study plant diseases and pest identification. It defines plant diseases and pest detection problems and compares them with traditional plant diseases and pest detection methods.

Srividya Attaluri (2023) projected focal points various direct and roundabout habits of detecting plant diseases like Something which incites activity-connected immunosorbent assay, Lateral flow assays, Polymerase chemical reaction, spectroscopic methods, and biosensors. Olushola Olawuyi (2023) provides a thorough investigation, and review of deep transfer learning and deep coevolutionary neural networks (CNNs). The focus of this research work was to implement a pre-trained model (Resnet50) for the detection and classification of plant diseases using ImageNet.

E. Plant-Fungus Interactions

Ensuring the authenticity of medicinal plants is To Understand the molecular and biochemical aspects of the interaction between medicinal plants and pathogenic fungi. The Role of Secondary Metabolite is to Investigate how secondary metabolites in medicinal plants act as defense mechanisms against fungal diseases. Nigora Rustamova (2020 discusses the phytochemistry and medicinal chemistry of plant-associated natural compounds produced by endophytic fungi. Reema Devi's (2023) review focuses on the biodiversity of endophytic fungi in plants and their role in enhancing various properties of plants such as antimicrobial, antimycobacterial, antioxidant, cytotoxic, anticancer, and biological activity of secondary metabolites produced by various fungal endophytes in host plants from 1994 to 2021.

Natalia Vaou (2021) explores the antimicrobial activity of plant-derived components, their possible mechanisms of action, and their chemical potential. The authors discuss the current challenges and future perspectives surrounding medicinal plants' antimicrobial activity. Prajhjot Singla (2023) This paper discusses the events occurring during plant–fungus interaction, unfolding a process of unexpected complexity. It provides insights into the various defense mechanisms plants have to counteract the harmful effects of fungi. Raffaella Balestrini (2021) This paper discusses the mechanisms involved in both pathogenic and mutualistic interactions, as well as the subtle differences that lead to the different results.

III. METHODOLOGIES

A. Image Processing

Digital image processing is the class of methods that deal with manipulating digital images through the use of computer algorithms. It is an essential preprocessing step in many applications, such as face recognition, object detection, and image compression.

There are several types of image processing techniques, including image enhancement, restoration, and others. Here are some examples of typical image-processing operations:

1. **Visualization**: Find objects that are not visible in the image.
2. **Recognition**: Distinguish or detect objects in the image.
3. **Sharpening and Restoration**: Create an enhanced image from the original image.
4. **Pattern Recognition**: Measure the various patterns around the objects in the image.
5. **Retrieval**: Browse and search images from a large database of digital images that are similar to the original image.

B. How does Image Processing work?

In the below figure (1), an image has been captured by a camera and has been sent to a digital system to remove all the other details, and just focus on the water drop by zooming it in such a way that the quality of the image remains the same.

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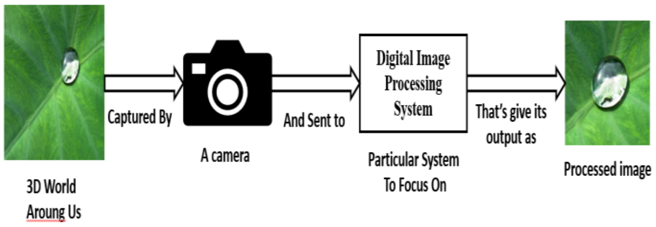

FIGURE 1: Process of Image Processing

C. Object Detection

1. Object Detection algorithms act as a combination of image classification and object localization.
2. It takes an image as input and produces one or more bounding boxes with the class label attached to each bounding box.
3. These algorithms are capable enough to deal with multi-class classification and localization as well as to deal with objects with multiple occurrences.
4. In object detection, the bounding boxes are always rectangular. So, it does not help with determining the shape of objects if the object contains the curvature part.
5. Object detection cannot accurately estimate some measurements such as the area of an object, perimeter of an object from an image

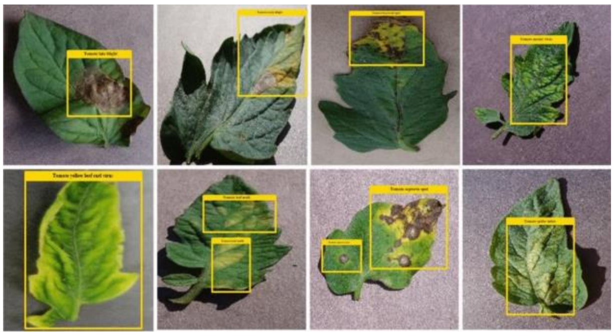

FIGURE 2: Object Detection

D. Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a type of deep learning algorithm that is particularly well-suited for image recognition and processing tasks. It is made up of multiple layers, including convolutional layers, pooling layers, and fully connected layers.

The convolutional layers are the key component of a CNN, where filters are applied to the input image to extract features such as edges, textures, and shapes. The output of the convolutional layers is then passed through pooling layers, which are used to down-sample the feature maps, reducing the spatial dimensions while retaining the most important information. The output of the pooling layers is then passed through one or more fully connected layers, which are used to make a prediction or classify the image.

CNNs contain a combination of layers which transform an image into output the model can understand.

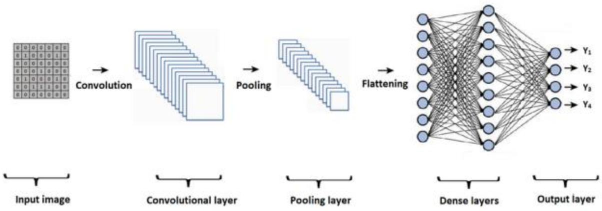

FIGURE 3: CNN Architecture

1. Convolutional layer: creates a feature map by applying a filter that scans the image several pixels at a time
2. Pooling layer: scales down the information generated by the convolutional layer to effectively store it
3. Fully connected input layer: flattens the outputs into a single vector
4. Fully connected layer: applies weights over the inputs generated by the feature analysis
5. Fully connected output layer: generates final probabilities to determine the image class

a) Process of CNN

Forward and backward propagation iterate through all of the training samples in the network until the optimal weights are determined and only the most powerful and predictive neurons are activated to make a prediction

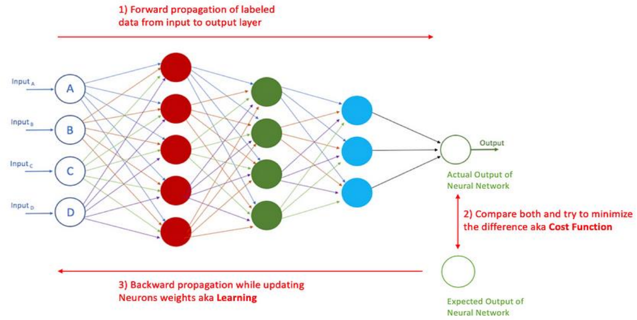

FIGURE 4: Process of CNN

1. The model trains throughout many epochs by taking one forward and one backward pass of all training samples each time.
2. Forward propagation calculates the loss and cost functions by comparing the difference between the actual and predicted target for each labelled image.
3. Backward propagation uses gradient descent to update the weights and bias for each neuron, attributing more impact on the neurons which have the most predictive power, until it arrives to an optimal activation combination.
4. As the model sees more examples, it learns to better predict the target causing the loss measure to decrease.
5. The cost function takes the average loss across all samples indicating overall performance.

E. Objective of the project

To identify medicinal plant and its fungal disease, we evaluated the performance of two common pretrained deep learning models (VGG19 and ResNet50) and compared their

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accuracy levels. Finally, the system can estimate some performance metrics such as accuracy and error rate for both algorithms and compare the algorithms based on accuracy in the form of graph.

a) VGG19 (Visual Geometry Group 19)

VGG19 is a convolutional neural network (CNN) architecture that was introduced by the Visual Geometry Group at the University of Oxford. It is named "19" because it has 19 layers, including 16 convolutional layers and 3 fully connected layers is known for its simplicity and uniformity. It uses small 3x3 convolutional filters throughout the network, with max-pooling layers in between. The use of small filters helps in learning complex patterns. Despite its simplicity, VGG has been widely used and has served as a baseline architecture for many computer vision tasks.

VGG are based on the most essential features of convolutional neural networks (CNN). The (Figure 3) shows the basic concept of how a CNN works: The VGG network is constructed with very small convolutional filters. The VGG-16 consists of 13 convolutional layers and three fully connected layers

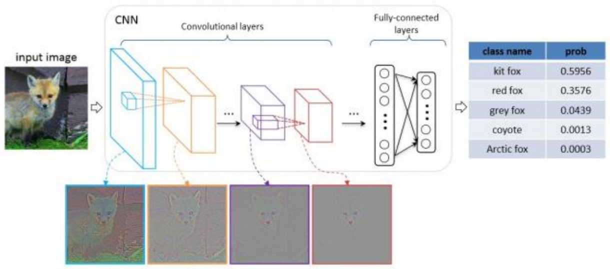

FIGURE 5: VGG Architecture

Let's take a brief look at the architecture of VGG:

1. **Input:** The VGG19 takes in an image input size of 224×224. For the ImageNet competition, the creators of the model cropped out the center 224×224 patch in each image to keep the input size of the image consistent.
2. **Convolutional Layers:** VGG's convolutional layers leverage a minimal receptive field, i.e., 3×3, the smallest possible size that still captures up/down and left/right. Moreover, there are also 1×1 convolution filters acting as a linear transformation of the input. This is followed by a ReLU unit, which is a huge innovation from Alex Net that reduces training time
3. **Hidden Layers:** All the hidden layers in the VGG network use ReLU. VGG does not usually leverage Local Response Normalization (LRN) as it increases memory consumption and training time. Moreover, it makes no improvements to overall accuracy.
4. **Fully-Connected Layers:** The VGG19 has three fully connected layers. Out of the three layers, the first two have 4096 channels each, and the third has 1000 channels,1foreach class.

b) RestNet50 (Residual Network With 50 Layers)

ResNet-50 is based on a deep residual learning framework that allows for the training of very deep networks with hundreds of layers. The ResNet architecture was developed in response to a surprising observation in deep learning research: adding more layers to a neural network was not always improving the results. This was unexpected because adding a layer to a network should allow it to learn at least what the previous network learned, plus additional information.

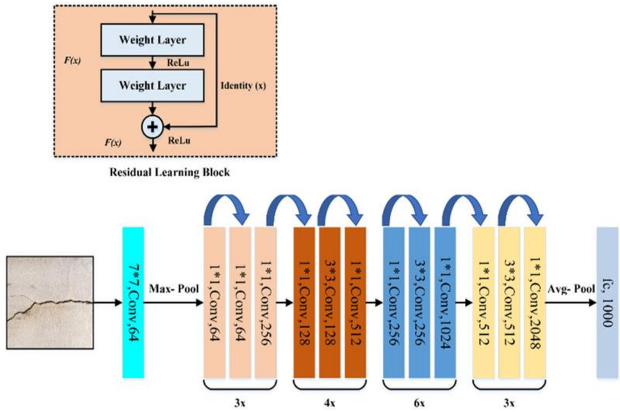

FIGURE 6: RESTNET Architecture

Let's take a look at the architecture of RESNET:

1. Convolutional Layers: The first layer of the network is a convolutional layer that performs convolution on the input image. This is followed by a max-pooling layer that down samples the output of the convolutional layer. The output of the max-pooling layer is then passed through a series of residual blocks.

2. Residual Blocks: Each residual block consists of two convolutional layers, each followed by a batch normalization layer and a rectified linear unit (ReLU) activation function. The output of the second convolutional layer is then added to the input of the residual block, which is then passed through another ReLU activation function. The output of the residual block is then passed on to the next block.

3. Fully Connected Layer: The final layer of the network is a fully connected layer that takes the output of the last residual block and maps it to the output classes. The number of neurons in the fully connected layer is equal to the number of output classes.

F. Usefulness/Relevance to the Society

Medicinal plant identification and fungal disease detection in plants are both highly relevant to society for several reasons:

Medicinal plants have been used for centuries in traditional medicine practices around the world. Accurate identification of these plants is crucial for determining their medicinal properties and potential applications. Incorrect identification can lead to unexpected side effects in human beings. Therefore, automatic identification and classification of medicinal plants is needed for greater benefit to humankind. Fungal afflictions in plants pose meaningful threats to worldwide farming and gardening labor.

These destructive pathogens can ransack crops, chief to lowered yields, financial misfortunes, and even cooking shortages. The swift labeling of fungal diseases by prompt acknowledgment of their manifestations is an active management practice and grant permission helps control and hamper their spread and progress.

Many valuable plant species are immediately dead and are destroyed on account of determinants in the way that global warming is up, growing people, professional concealment, lack of Government support for research actions, and lack of knowledge about curative plants. Therefore, the preservation of these plants is also crucial for maintaining biodiversity.

The study of medicinal plants and plant diseases contributes to our understanding of plant biology and ecology. This knowledge can be used to develop new drugs and treatments, improve agricultural practices, and inform conservation efforts.

G. Problem Definition

In existing system proposes a Long Short Term Memory neural network algorithm to accomplish the leaf disease classification task. Plant disease recognition is an interesting and practical topic. However, this problem has not been sufficiently explored due to the lack of systematic investigation and large-scale datasets. The most challenging step in constructing such a dataset is providing a reasonable structure from both the agriculture and image processing perspectives.

The *Disadvantages* are It converts the images as a data frame and predicts using data mining techniques. LSTMs are prone to overfitting and it is difficult to apply the dropout algorithm to curb this issue. Dropout is a regularization method where input and recurrent connections to LSTM units are probabilistically excluded from activation and weight updates while training a network.

H. Proposed System

In the proposed system, the input image is taken from the dataset repository. In pre-processing, we can resize the original image and grayscale conversion, which means converting RGB to a B/W image. After that, we can extract the features from pre-processed images such as Local Binary Pattern (LBP) and Mean Median Variance. We can split the images into test images used for prediction and train images used for evaluation or training the model. Then, we can implement the different transfer learning algorithms such as Resnet- 50 and VGG -19 for classifying whether the input image is affected by or not. Finally, the system can estimate some performance metrics such as accuracy and error rate. The influence of the projected method was habitual by equating accuracy bettering.

The Advantage is, that it is efficient for a large number of datasets. The experimental result is high when compared with the existing system. Time consumption is low.

I. System Architecture

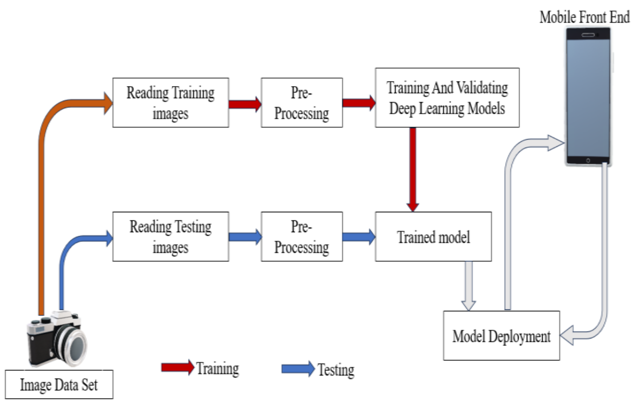

FIGURE 7: System Architecture

IV. MODULE DESCRIPTION

There are 6 modules. They are

A. Image Selection

The dataset, Medicinal fungal disease Image disease dataset is implemented as input. The dataset is taken from the dataset repository. The input dataset is in the format '.png, '.jpg. In this step, we have to read or load the input image by using the imread () function. In our process, we used the tkinter file dialogue box for selecting the input image.

B. Image Preprocessing

In this process, we have to resize the image and convert the image into grayscale. To resize an image, you call the resize () method on it, passing in a two-integer tuple argument representing the width and height of the resized image. The function doesn't modify the used image; it instead returns another Image with the new dimensions. Convert an Image to Grayscale in Python Using the Conversion Formula and the Matplotlib Library. We can also convert an image to grayscale using the standard RGB to grayscale conversion formula which is imgGray = 0.2989 * R + 0.5870 * G + 0.1140 * B.

C. Feature Extraction

In this module, we have to extract the features from the pre-processed image. Standard deviation is the spread of a group of numbers from the mean. The variance measures the average degree to which each point differs from the mean. Local Binary Pattern (LBP) is an effective texture descriptor for images that thresholds the neighboring pixels based on the value of the current pixel. LBP descriptors efficiently capture the local spatial patterns and the grayscale contrast in an image. The technique of extracting the features is useful when you have a large data set and need to reduce the number of resources without losing any important or relevant information. Feature extraction helps to reduce the amount of redundant data from the data set.

D. Image Splitting

During the machine learning process, data are needed so that learning can take place. In addition to the data required for training, test data are needed to evaluate the algorithm's performance to see how well it works. In our process, we considered 70% of the input dataset the training data and the remaining 30% the testing data. Data splitting is the act of partitioning available data into two portions, usually for cross-validator purposes.

E. Classification

In our process, we can implement deep learning algorithms such as VGG-19 and Resnet-50.VGG stands for Visual Geometry Group; it is a standard deep Convolutional Neural Network (CNN) architecture with multiple layers. The “deep” refers to the number of layers with VGG-16 or VGG-19 consisting of 16 and 19 convolutional layers. The VGG architecture is the basis of ground-breaking object recognition models. ResNet-50 is a convolutional neural network that is 50 layers deep. You can load a pre-trained version of the neural network trained on more than a million images from the ImageNet database.

F. Performance Metrics

The Final Result will be generated based on the overall classification and prediction. The performance of this proposed approach is evaluated using some measures like the accuracy of the classifier refers to the ability of the classifier. It predicts the class label correctly and the accuracy of the predictor refers to how well a given predictor can guess the value of a predicted attribute for new data.

AC= (TP+TN)/ (TP+TN+FP+FN)

Then, we can detect or classify whether the input image is affected by disease or not.

V. EXPERIMENTAL ANALYSIS

In this study, the experimental software and hardware configuration are shown in Table 1.

TABLE 1. Software and hardware configuration of the test.

Name	**Model and Parameters**
CPU	Intel Core i7-14700K
OS	Windows 11
GPU	GTX 1080Ti
Development Language	Python
Environment	KIVY

A. Assumptions

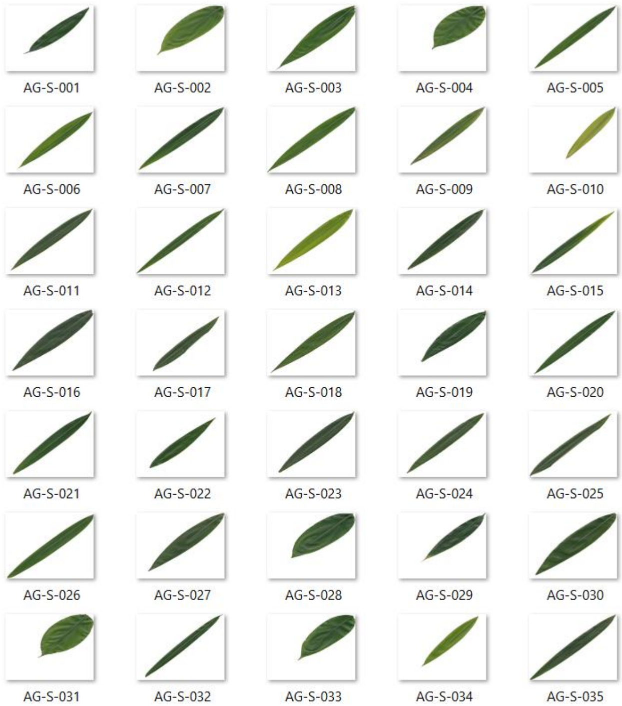

FIGURE 8: Displaying Some of The Training Images

Figure 8 shows some of the training images which we used to train the data models.

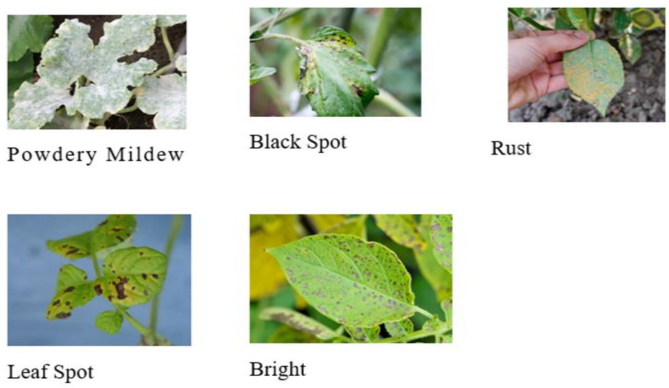

FIGURE 9: Fungal Disease types

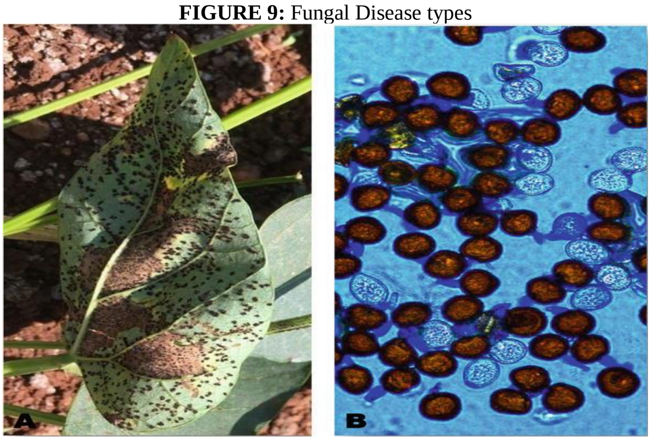

FIGURE 10: Fungal Disease images

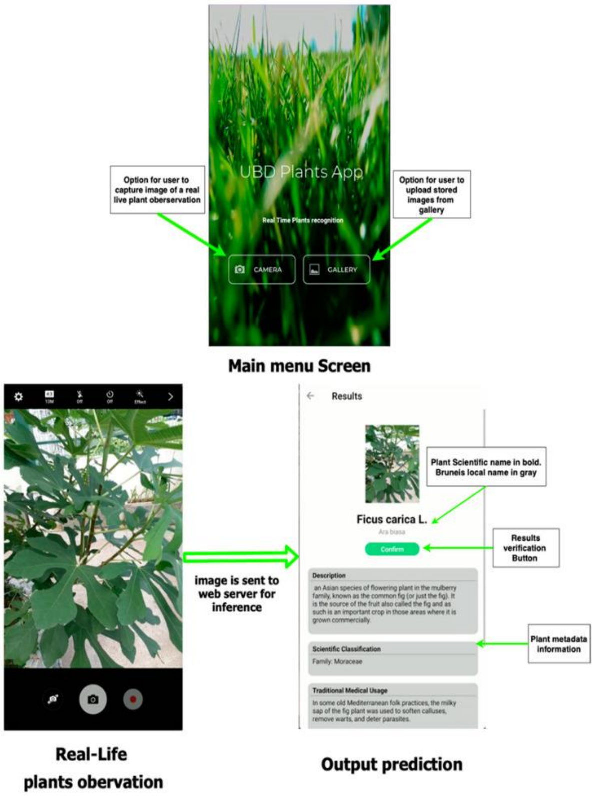

FIGURE 11: Sample App Display

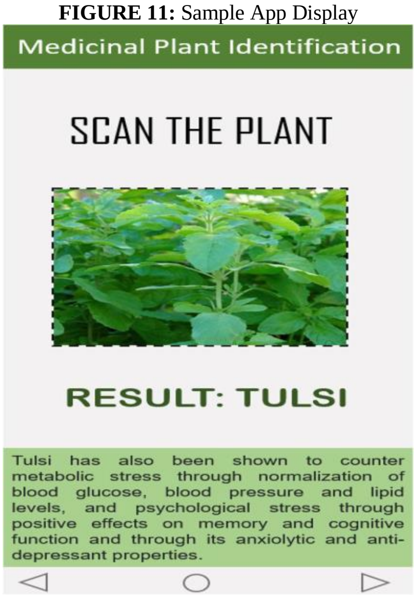

FIGURE 13: Sample App Display

CONCLUSION

We conclude that the fungal medicinal plant disease dataset was collected from the dataset repository as input. The input dataset was mentioned in our research paper. We have implemented the different classification algorithms (i.e.) deep learning algorithms. Then, deep learning algorithms such as VGG-19 and Resnet-50. Finally, the result shows the accuracy and error rate for the above-mentioned algorithm and predicts whether the input image is affected or not.

FUTURE SCOPE

An AI-based approach for medicinal plant identification using Deep CNN based on Global Average Pooling has been proposed. This system achieved more than 99.3% accuracy for all the image definitions, effectively identifying medicinal plants in real-time and capable of replacing traditional methods. Fast and reliable molecular methods to detect fungal pathogens in woody plants have been developed. This review focuses on fast and reliable molecular methods to detect the presence of woody plant pathogens at an early stage of disease development before symptoms occur in the host.

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