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# SPICE LEAF DISEASE DETECTION USING CNN

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**ABSTRACT:** Spice leaves, such as Bay Leaf, hold multifaceted importance in daily life, serving as essential ingredients in cooking and, notably, emerging as potential remedies during the COVID-19 pandemic. However, challenges arise in spice leaf farming due to manual cultivation methods, hindering disease detection. To tackle this, a survey employing transfer learning with InceptionV3 architecture for image classification was conducted, distinguishing between healthy and diseased leaves. This innovative approach facilitates efficient disease identification, aiding farmers in maintaining crop quality and yield. By leveraging advanced technologies like convolutional neural networks, farmers can swiftly detect and address diseases, ensuring the continued availability of high-quality spice leaves for culinary and medicinal purposes.

KEYWORDS: InceptionV3 architecture, Spice leaves, transfer learning, detection, convolutional neural networks.

## I. Introduction:

Agriculture is one of the important factor of country's economy. It has advanced significance with the automated diagnosis of plant diseases using plant leaves [3]. Spice plants have provided a wealth of information on treating and preventing sickness since the dawn of civilization. Spice plants not only been used for adding colour and flavour to our food but also has been prove to be useful in curing people during covid pandemic. The Spice plants provide is very useful for humans and all organisms, Spices can derive from any section of the plant. Still, knowledge of plant species is required for a variety of tasks, including discovering new or uncommon species, balancing the ecosystem, using plants for medicine, developing the agricultural economy, etc. Spice leaf disease detection is very important and helps farmers for growing healthy plants.

Plant illnesses is a dangerous problem to human existence since they are likely
to lead to droughts and starvations

Early detection is the basis for effective prevention and control of plant diseases, and they play a vital role in the management and decision making of agricultural production[7].

The InceptionV3 architecture is used as the base model for image classification. InceptionV3 is a convolutional neural network (CNN) architecture that has proven to be effective for various computer vision tasks, including image classification.

The InceptionV3 model is loaded with weights pre-trained on the ImageNet dataset.

The top layer of the InceptionV3 model (which includes the final classification layer) is removed by setting include_top=False.

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The remaining layers are set to non-trainable to use the pre-trained weights.
A fresh model is developed by incorporating several layers: a Global Average Pooling layer, a Dense layer with ReLU activation, a Dropout layer to aid in regularization, and a final Dense layer with softmax activation for binary classification, distinguishing between healthy and unhealthy outcomes.
Following that, the model is compiled using the Adam optimizer and categorical crossentropy loss, with accuracy serving as the metric. This configuration renders the model well-suited for binary image classification endeavors.

**Related Work:**

Transfer learning is a well-established technique in deep learning, particularly in computer vision tasks. It involves applying knowledge gained from solving one problem to a related problem. For instance, in [12], researchers utilized SVM classifiers with various kernels to identify diseases in tomato-leaf images by extracting geometric and histogram-based features from diseased portions. Similarly, in [13], S.Kaur et al. employed color and texture features to distinguish three soybean diseases. P Babu et al. [14] used a feed-forward neural network and backpropagation to classify plant leaves and their diseases. Another approach by S. S. Chouhan et al. [15] utilized a bacterial-foraging-optimization-based radial-basis function neural network (BRBFNN) to detect leaves and fungal diseases in plants. They employed a region-growing algorithm to extract features from leaves based on seed points with similar attributes, enhancing classification accuracy and speeding up network performance through bacterial-foraging optimization.

## 2. Proposed Work Plan:

2.1 Flow Chart of the Overall System:

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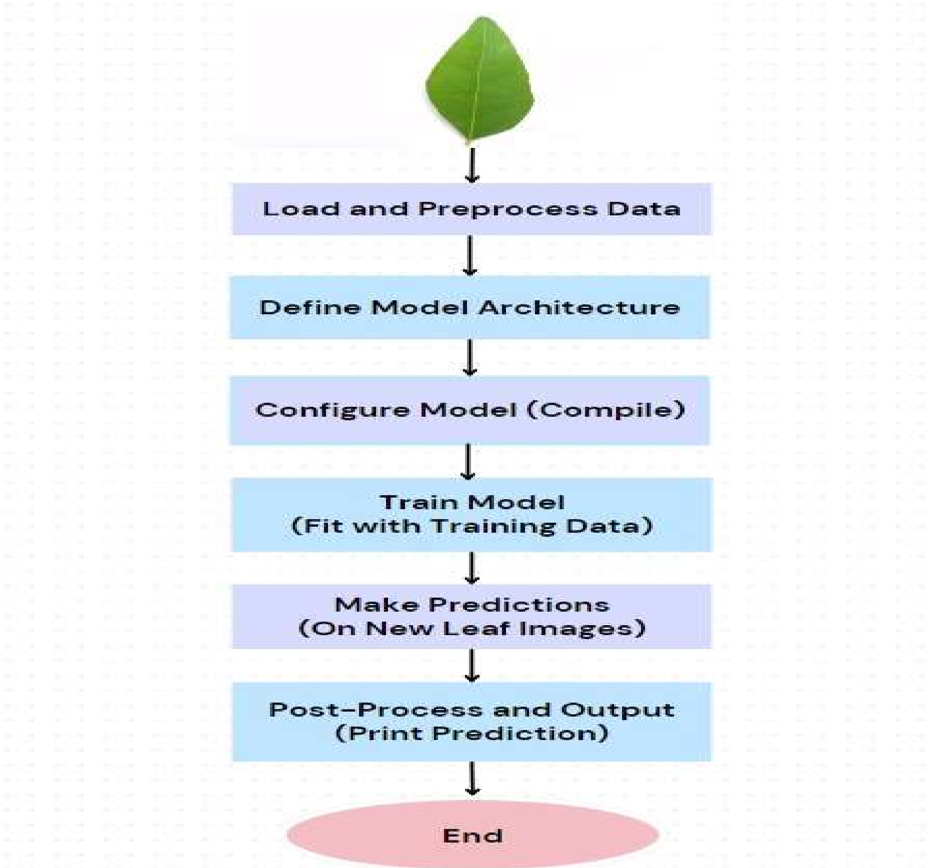


**2.2 Description of Various Modules of the System**

**1. Data Management Module:**
The Data Management Module is responsible for handling the plant leaf image dataset throughout its lifecycle. It encompasses tasks ranging from the acquisition of raw data to the preprocessing required for effective model training.
Functions:
**Dataset Acquisition:** Involves the collection of plant leaf images from various sources, ensuring diversity and representativeness.
**Data Preprocessing:** Includes tasks such as labelling images with corresponding classes, adjusting images to a consistent resolution.
**Data Augmentation:** Data augmentation involves employing methods to artificially expand the variety within the training dataset, which is essential for improving the model's capacity to generalize across various situations. Dataset splitting entails dividing the dataset into training and validation subsets, allowing for distinct sets for training the model and assessing its performance.
**2. Model Development Module:**
The Model Development Module focuses on the creation and training of the machine learning model tailored for plant leaf disease classification. It leverages pre-trained convolutional neural networks (CNNs) as a foundation and adapts them to the specific requirements of the classification task.

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**Functions:**

Model Selection: Involves choosing a suitable pre-trained CNN architecture (e.g., InceptionV3, ResNet) that serves as the base model.

**Model Customization:** Customizes the base model by adding additional layers, such as global average pooling, dense layers, and dropout, to adapt it for the specific classification needs.

**Data Augmentation Implementation:** Integrates data augmentation techniques into the model to improve its ability to handle variations in the input data.

**Training of Model and Evaluation:** It trains using the preprocessed dataset and evaluates its performance on the validation set.

**3. Fine-tuning and Optimization Module:**

The Fine-tuning and Optimization Module is dedicated to refining the model's parameters and addressing any issues identified during the evaluation phase. It aims to enhance the model's performance and adapt it to specific challenges.

Functions:

**Model Fine-tuning:** Adjusts the model's parameters based on the evaluation results, aiming to improve overall performance.

**Hyperparameter Adjustments:** Fine-tunes hyperparameters, including learning rates and regularization parameters, to optimize the model's learning process.

**Class Imbalance Handling:** Implements strategies to address class imbalances in the dataset, ensuring fair representation and preventing biased model outcomes.

**4. Integration and User Interface Module:**

The Integration and User Interface Module is responsible for connecting the trained model with a user-friendly interface. This allows end-users to interact with the system, input new plant leaf images, and receive classification predictions.

**Functions:**

**Model Integration with User Interface:** Integrates the trained model into a user interface, creating a seamless connection between the backend model and the frontend interface.

User Input Handling: Manages the user input process, ensuring that users can easily input new plant leaf images into the system.

**Displaying Predictions to Users:** Presents classification predictions to users in a comprehensible format, offering insights into the health status of plant leaves.

**5. Deployment Module:**

The Deployment Module manages the transition of the plant leaf disease classification system from the development environment to a production environment. It ensures a smooth deployment process.

Functions:

**System Deployment:** Transfers the system to a server or cloud platform, making it accessible to end-users.

Configuration for Production Environment: Configures the system to operate optimally in a production environment, considering factors such as scalability and reliability.

**6. Monitoring and Maintenance Module:**

The Monitoring and Maintenance Module is used for ongoing monitoring of the system's performance in a real-world environment. It addresses issues promptly, updates the model as needed, and ensures continuous

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system health.

**Functions:**

**System Monitoring:** Monitors the system in real-time, tracking performance metrics and identifying potential issues.

**Issue Resolution:** Addresses any issues or challenges that arise during system operation, preventing disruptions.

**Model Updates and Maintenance:** Updates the model as necessary to adapt to changing conditions or to improve performance based on new data.

These modules collectively contribute to the development, deployment, and maintenance of an effective plant leaf disease classification system. The modular design facilitates organization, collaboration, and scalability for future enhancements.

### 2.3 Algorithm of the Various Modules of the System

Plant Leaf Disease Classification Algorithm: Load Pre-trained Base Model: Load a pre-trained convolutional neural network (CNN) model. Common choices include InceptionV3, ResNet, or MobileNet.

Customize Model Architecture: Customize the loaded base model for the plant leaf disease classification task. Add additional layers to the model, including global average pooling, dense layers, and dropout for regularization.

Compile the Model: Compile the model with appropriate configurations for the training process. Specify the optimizer (e.g., Adam), loss function (categorical crossentropy for multi-class classification), and evaluation metric (accuracy).

Train the Model: Train the model using the preprocessed training dataset. Monitor training progress with validation on a separate dataset.

Evaluate Model Performance: Analyze the confusion matrix to understand class-wise performance.

Fine-tuning (Optional): Optionally fine-tune the model based on evaluation results. Adjust hyperparameters or unlock specific layers for further training.

Prediction on New Leaf Image: Preprocess a new plant leaf image using the same preprocessing steps applied during training. Use the trained model to predict the probability of each class for the new image.

Post-process Prediction: Determine the predicted class based on the highest probability. Optionally, set a threshold for binary classification.

Display Prediction Result: Display or communicate the prediction result, indicating whether the spice leaf is healthy or diseased. Optionally, provide additional information such as disease type.

End:

The algorithm concludes after making predictions on the new leaf image.

This algorithm outlines the key steps involved in training the model and making predictions on new plant leaf images. It assumes a multi-class classification task where the model distinguishes between different types of plant diseases. The algorithm can be further customized based on the specific requirements of the project.

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## 3. Experimental Result Analysis:

### 3.1 Description of data set used:

During this we have collected the dataset of fresh and infair Bay Leaf, Murraya Koenigii (Curry Leaves) and Ajwain Leaves. The dataset of Bay Leaf consist of both fresh and infair eighty three (83) leaves whereas the dataset of Curry leaves consist of twenty five (25) leaves and same of the Ajwain. For training and testing we have collected the live dataset. The images of spice leaves were separated into two distinct sets: one for training purposes and another for validation. To assess performance effectively, the leaf images were divided into three separate sets.


(Bay leaf)

(Curry leaf)

(Ajwain Leaf)

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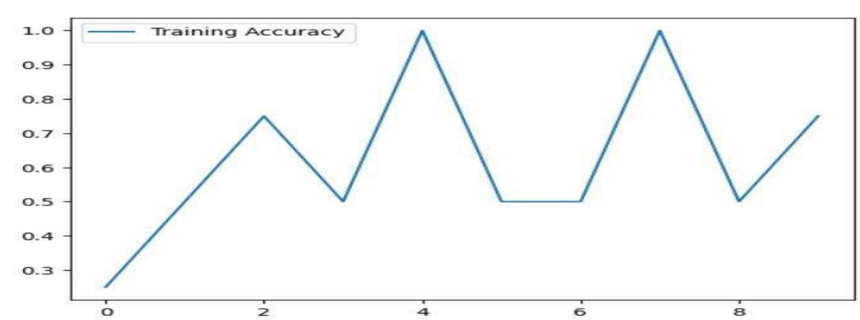
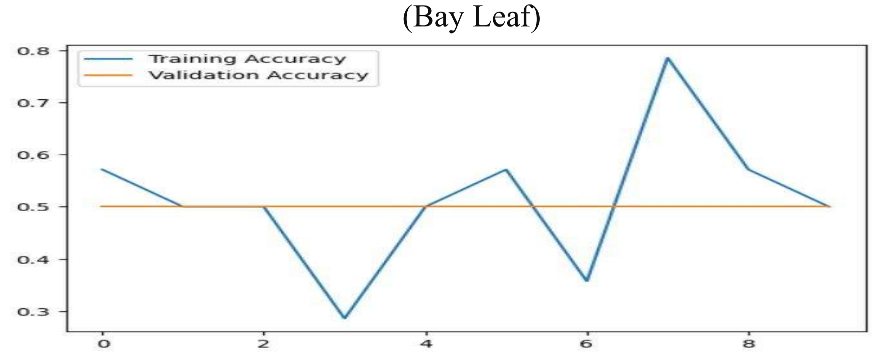
| Class | Plant Name | Disease Name | Cause of Disease |
|---|---|---|---|
| C1 | Ajwain | Aphid | Over fertilization |
| C2 | Ajwain | Whiteflies | Warm temperature |
| C3 | Ajwain | Thrips | Poor soil condition |
| C4 | Curry leaf | Caterpillars | Environmental conditions |
| C5 | Curry leaf | Spider Mites | Low humidity |
| C6 | Curry leaf | Mealybugs | Over watering |
| C7 | Bay leaf | Scale Insects | Poor Plant Hygiene |
| C8 | Bay leaf | Brown Spot | Water logged roots |
| C9 | Bay leaf | Shot Hole | Fungus |

3.2 Calculate the efficiency or accuracy of the designed system according to the parameter used to evaluate the system




(Bay Leaf)




(CurryLeaf)

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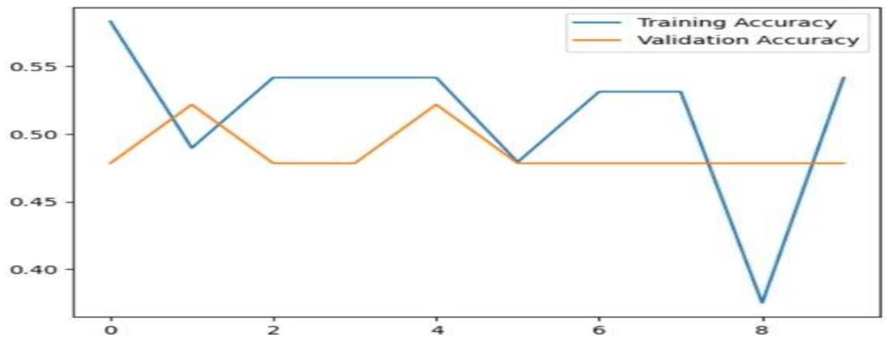


(AjwainLeaf)

**Result:**

The output we get from the code is divided into two that is healthy and unhealthy. In the above figure clearly it is shown spice leaf is healthy or unhealthy.




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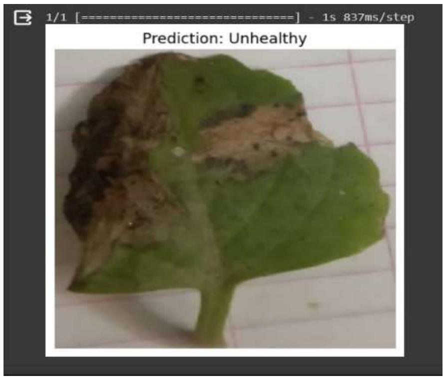



After this one more output is shown if the leaf is found to be healthy it will show written 'healthy' otherwise if found unhealthy it will show diseases such as pest infestation or fungus disease

**Conclusion:**

The presented research introduces a robust plant leaf disease classification system, addressing crucial challenges in early disease detection and management. Leveraging advanced machine learning techniques, particularly convolutional neural networks (CNNs), the system achieves highly accurate analysis and classification of spice leaf images. Its modular architecture, spanning data management, model development, fine-tuning, user interface integration, testing, documentation, deployment, and ongoing monitoring, ensures scalability, maintainability, and collaborative potential. Notably, the system's data management module ensures the acquisition and preprocessing of high-quality datasets, crucial for effective model training, while the model development module demonstrates adaptability through pre-trained CNN architectures. Integration with a user-friendly interface enhances accessibility, enabling broader user adoption. Rigorous testing and debugging procedures ensure reliability and functionality, while thorough documentation facilitates transparency and knowledge transfer. The system's successful deployment and ongoing monitoring guarantee sustained performance, as demonstrated by experimental results showcasing its efficiency in accurately classifying healthy and diseased plant leaves. With agriculture facing increasing challenges, this classification system emerges as a valuable tool for stakeholders, empowering them with timely information for enhanced crop management practices and agricultural sustainability.

**REFERNCES:**

1. Rajiv, K., et al. "Accuracy evaluation of plant leaf disease detection and classification using GLCM and multiclass SVM classifier." Congress on Intelligent Systems. Singapore: Springer Singapore, 2020.
2. Patel, Venus, Noopur Srivastava, and Manish Khare. "Plant disease detection using image processing and machine learning." Futuristic Trends in Networks and Computing Technologies: Select Proceedings of Fourth International Conference on FTNCT 2021. Singapore: Springer Nature Singapore, 2022.
3. Fulari, Utkarsha N., Rajveer K. Shastri, and Anuj N. Fulari. "Leaf disease detection using machine learning." J. Seybold Rep 1533 (2020): 9211.

**CAHIERS MAGELLANES-NS**
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http://magellanes.com/

4. Kumar, Sandeep, et al. "Leaf disease detection and classification based on machine learning." 2020 International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE). IEEE, 2020.
5. Rinu, R., and S. H. Manjula. "Plant disease detection and classification using CNN." International Journal of Recent Technology and Engineering (IJRTE) 10.3 (2021): 152-156.
6. A SURVEY ON LEAF DISEASE DETECTION USING IMAGE PROCESSING TECHNIQUES
7. Saleem, Muhammad Hammad, Johan Potgieter, and Khalid Mahmood Arif. "Plant disease detection and
8. Rajendran, Rajesh Kanna, and Mohana Priya Thiruvengadam. ORPN Algorithm to Diagnosis and Detect Plant Diseases Based on Image Segmentation Using Machine Learning Techniques. No. 9760. EasyChair, 2023.
9. Shetkar, Vishal, et al. "LEAF DISEASE DETECTION IN PLANTS USING AI-ML AND IMAGE PREPROCESSING TECHNIQUES."
10. Chohan, Murk, et al. "Plant disease detection using deep learning." International Journal of Recent Technology and Engineering 9.1 (2020): 909-914.
11. Identification of Plant-Leaf Diseases Using CNN and Transfer-Learning Approach Mokhtar, U.; Ali, M.A.; Hassanien, A.E.; Hefny, H. Identifying two of tomatoes leaf viruses using support vector machine. In Information Systems Design and Intelligent Applications; Springer: Berlin/Heidelberg, Germany, 2015; pp. 771–782.
12. Kaur, S.; Pandey, S.; Goel, S. Semi-automatic Leaf Disease Detection and Classification System for Soybean Culture. IET Image Process. 2018, 12, 1038–1048.
13. Babu, M.P.; Rao, B.S. Leaves recognition using back propagation neural network-advice for pest and disease control on crops. Available online: https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.110.3632&rep=rep1&type=pdf (accessed on 1 May 2021).
14. Chouhan, S.S.; Kaul, A.; Singh, U.P.; Jain, S. Bacterial foraging optimization based radial basis function neural network (BRBFNN) for identification and classification of plant leaf diseases: An automatic approach towards plant pathology. IEEE Access 2018