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# FLORASCAN-Plant Disease Diagnosis

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**A B S T R A C T :**

Agriculture is a fundamental sector in India, and timely plant disease detection is crucial for maintaining crop yield. FloraScan is a web-based deep learning solution designed to identify plant diseases from leaf images. The system uses the VGG19 model, trained on 38 plant disease classes, achieving over 95% accuracy. The trained model is integrated into a responsive website that allows users to upload images and receive instant disease predictions along with relevant symptoms and remedies. The system is lightweight, user-friendly, and supports multilingual content to help farmers understand the diagnosis.

FloraScan bridges the gap between AI research and practical field application, empowering farmers with real-time decision-making tools. The model's scalability and modular design make it adaptable for future expansions such as pest detection and offline support. By leveraging cloud infrastructure, the website ensures fast processing and easy accessibility across devices. Ultimately, FloraScan aims to contribute towards sustainable agriculture by minimizing crop losses and promoting informed farming practices.

**Keywords**: Plant disease detection, deep learning, VGG19, image classification, web application, crop health, sustainable farming.

## INTRODUCTION

FloraScan is an AI-powered web application designed to identify and diagnose plant diseases quickly and accurately using image analysis. By allowing users to upload pictures of plant leaves, the system automatically detects the specific disease affecting the plant and provides detailed information on symptoms and remedies. This tool aims to support farmers, gardeners, and agricultural experts by offering an accessible, cost-effective method for disease diagnosis, reducing dependence on expert inspection. Plant disease detection is the process of identifying abnormalities caused by pathogens such as fungi, bacteria, viruses, and pests. Early identification is critical to prevent the spread of diseases that can severely impact crop yield and cause economic losses. Traditionally, disease detection relies on manual inspection by specialists, which can be time-consuming, expensive, and inaccessible to many farmers, especially in remote areas. FloraScan addresses these challenges by employing advanced deep learning models and computer vision techniques to automate disease identification. The system analyzes visual features such as color changes, spots, and leaf deformation to classify diseases with high accuracy. After diagnosis, it presents comprehensive information on the disease, including symptoms and suggested treatments, empowering users to take timely and appropriate action. The benefits of FloraScan extend beyond mere detection. It promotes sustainable agricultural practices by enabling early intervention, thereby reducing the excessive use of harmful pesticides and chemicals. This not only protects the environment but also improves crop health and productivity. Additionally, the platform's user-friendly design makes it accessible to individuals with varied levels of agricultural knowledge, contributing to better food security by helping prevent crop losses. By integrating cutting-edge AI technology with practical agricultural needs, FloraScan offers a valuable solution to modern farming challenges. This innovation supports the advancement of precision agriculture and fosters sustainable crop management, ultimately contributing to enhanced agricultural efficiency and resilience.

## LITERATURE REVIEW

**a)** Plant disease detection has been an active area of research, with numerous studies leveraging machine learning and deep learning techniques to automate and improve the accuracy of diagnosis. Traditional methods often relied on manual inspection by experts, which is time-consuming and prone to error. The advent of computer vision and deep learning has paved the way for faster and more accurate plant disease identification.

**b)** Hughes and Salathé (2015) created the PlantVillage dataset, which has become a benchmark for many researchers in this domain. The dataset includes a vast number of images of healthy and diseased plant leaves, enabling the development of various classification models. Several studies have used this dataset to train convolutional neural networks (CNNs) due to their high performance in image recognition tasks.

**c)** Early deep learning models like AlexNet, VGG, and ResNet have shown promising results in plant disease classification. However, these models often require significant computational resources, limiting their deployment on mobile or low-power devices. To address this, newer architectures such as MobileNet and EfficientNet have been proposed. Tan and Le (2019) introduced EfficientNet, a model that balances accuracy and efficiency by optimizing model scaling, making it suitable for real-time applications on mobile devices.

- **d)** Data augmentation techniques have also played a vital role in improving model generalization by artificially increasing the diversity of training images through transformations such as rotation, flipping, and color adjustments (Shorten & Khoshgoftaar, 2019). This approach helps overcome the limitations of small or imbalanced datasets, which are common challenges in plant disease detection.
- **e)** In addition to CNN architectures, transfer learning has become a popular strategy. Pretrained models on large datasets like ImageNet are fine-tuned on plant disease datasets to leverage learned features and reduce training time (Gunasekaran & Dhinesh Babu, 2020). This approach has demonstrated higher accuracy with fewer data and computational resources.
- **f)** Despite these advancements, many existing systems lack easy accessibility and user-friendly interfaces for farmers and agricultural professionals. Web-based applications, like the one developed in this FloraScan project, offer a practical solution by providing remote, real-time disease diagnosis without the need for specialized hardware. Flask and other lightweight web frameworks facilitate the deployment of such AI models in an accessible manner.
- **g)** In summary, previous research has made significant progress in applying deep learning to plant disease detection. However, challenges remain in deploying these models effectively for end-users. The FloraScan project aims to bridge this gap by combining a high-accuracy EfficientNet-based model with a web platform, providing an accessible and efficient tool for plant health monitoring.

## METHOLOGY

The development of FloraScan involves several key stages: data collection and preprocessing, model selection and training, web application development, and deployment.

**1. Data Collection and Preprocessing**

The first step in the methodology was acquiring a comprehensive dataset consisting of high-quality images of healthy and diseased plant leaves. The dataset used includes 38 classes of common plant diseases, covering multiple crops and leaf conditions. Each image was labeled according to the disease it represents. Before feeding the images into the model, preprocessing was performed to enhance model accuracy and training efficiency. This involved resizing images to a uniform resolution of 224x224 pixels, normalization of pixel values, and data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment. Data augmentation helps improve the model's ability to generalize and perform accurately on new, unseen images.

**2. Model Selection and Training**

For disease classification, the VGG19 convolutional neural network architecture was chosen due to its balance of high accuracy and computational efficiency. The model was pre-trained on the ImageNet dataset, allowing transfer learning to leverage existing learned features. The training process consisted of two phases: initially freezing the base layers to train only the classification head, followed by fine-tuning selected layers of the base model for improved performance. Categorical cross-entropy was used as the loss function, with Adam optimizer to update model weights. Early stopping and model checkpoint callbacks were employed to prevent overfitting and save the best-performing model. After training, the model achieved an accuracy exceeding 95% on validation data, confirming its reliability for disease classification.

**3. Web Application Development**

The FloraScan web app was developed using the Flask framework in Python to serve as the backend. Flask handles image uploads, runs the disease classification model on the uploaded image, and returns prediction results. The frontend was built with HTML, CSS, and JavaScript to provide a responsive and user-friendly interface. Users can easily upload images of plant leaves, and the app displays the predicted disease name along with detailed symptoms and suggested remedies on the results page.

**4. Deployment**

The Flask application is hosted on a cloud platform, enabling users to access FloraScan through a web browser without the need for software installation. The deployment ensures scalability, allowing multiple users to use the service simultaneously.

The system's modular design supports easy updates to the model and user interface, facilitating continuous improvements based on user feedback and new research findings.

## SOFTWARE USED

- **A. Python** : Python served as the primary programming language for developing the FloraScan system. Its simplicity, vast library ecosystem, and strong support for machine learning and image processing made it an ideal choice for both backend development and model implementation. Additionally, Python's compatibility with various platforms and frameworks enabled smooth integration across different components of the project. Its readability and community support further contributed to efficient development and debugging. Moreover, Python's support for object-oriented programming enhanced modularity and maintainability in the application design.
- **B. TensorFlow (with Keras API)** :TensorFlow, an open-source deep learning framework developed by Google, was utilized to design, train, and evaluate the Convolutional Neural Network (CNN) model used in FloraScan. The Keras API within TensorFlow offered a user-friendly interface for building and experimenting with neural networks, significantly reducing development time. TensorFlow's scalability and support for both CPU

and GPU processing were particularly beneficial in handling the large dataset of plant images efficiently. Its ability to export models in a portable format also facilitated smooth deployment into the Flask-based web environment.

**C.** **Flask** :Flask, a lightweight and flexible web framework for Python, was employed to create the web-based user interface of FloraScan. It facilitated seamless integration between the trained machine learning model and the front-end interface, enabling users to upload images and receive real-time predictions. Flask's modular structure allowed for a clear separation of concerns, including routing, backend logic, and template rendering. The framework also supports easy deployment and extension, which made it an ideal choice for a scalable web-based system.

**D.** **Google Colab** :Google Colaboratory (Colab) was used as the primary cloud-based development environment for training and validating the model. It provided free access to powerful hardware accelerators, including GPUs and TPUs, which significantly improved the speed of model training. Google Colab also supported real-time collaboration among team members, enabling shared access to code, output, and results. Furthermore, integration with Google Drive made data storage and access more convenient, eliminating the need for local setup and hardware dependence.

**E.** **Pandas and NumPy** :Pandas and NumPy were fundamental tools for data manipulation and numerical computation within the project. Pandas enabled efficient handling of structured data, such as image labels and dataset metadata, while NumPy provided the necessary tools for performing matrix operations and array transformations required for image preprocessing. These libraries played a critical role during the data cleaning, augmentation, and preparation stages, ensuring that the input data was accurately formatted and optimized for training the deep learning model.

## RESULTS

The FloraScan model was rigorously trained and evaluated on a publicly available dataset comprising 38 distinct plant disease categories. The dataset was preprocessed with advanced augmentation techniques to enhance generalization and avoid overfitting. The final classification model was based on VGG19, which was fine-tuned to suit the specific task of plant disease identification. During training, the model achieved a high training accuracy of 98.2% and a validation accuracy of 95.4%, indicating strong performance and effective generalization to unseen data.

In addition to accuracy, other performance metrics such as precision, recall, and F1-score were computed. These metrics provided a more holistic view of the model's performance across various disease classes. The average precision and recall were 95.6% and 95.3%, respectively, resulting in an average F1-score of 95.4%, reflecting balanced classification quality. The model was successfully converted into .h5 and .tflite formats to enable seamless deployment on web platforms.

To ensure user accessibility and practical utility, the model was integrated into a fully functional web application using Flask. The app allows users to upload an image of a plant leaf and receive real-time predictions along with disease symptoms and recommended remedies. The inference time was found to be under one second per image, making the model efficient for practical use.

| *Metric* | **Score(%)** |
|---|---|
| Accuracy | 95.3 |
| Precision | 95.7 |
| Recall | 94.9 |
| F1 Score | 95.3 |

## CONCLUSIONS

The FloraScan project successfully demonstrates the integration of deep learning techniques into the agricultural domain for effective plant disease detection. By leveraging a pre-trained convolutional neural network (such as VGG19), the system achieved high accuracy in classifying 38 different plant diseases from leaf images. The results confirm that with proper preprocessing, augmentation, and model fine-tuning, the FloraScan model can reliably assist in early disease diagnosis. The system not only identifies the disease but also provides farmers and agricultural workers with relevant symptoms and remedies, making it a comprehensive tool for field application. By offering a web-based interface, FloraScan ensures accessibility to a wider user base without the need for expensive hardware or mobile app installation. This solution contributes to reducing crop loss, minimizing misdiagnosis, and enhancing productivity by enabling timely and accurate disease management. It empowers users to take informed decisions based on model predictions and improve yield quality. In addition, the lightweight design of the model ensures faster predictions and smoother integration into low-resource environments, making it scalable and adaptable. Future work can explore integrating satellite data, voice input for illiterate farmers, and chatbot support to enhance the user experience and functionality. By bridging the gap between artificial intelligence and sustainable agriculture, FloraScan holds the potential to transform how plant health is monitored and managed on a global scale.

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