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An AI Doctor For Leaf Disease Detection

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Abstract: The prompt accurate identification of leaf diseases are crucial for enhancing agricultural productivity and mitigating crop losses. This study introduces a model based on Convolutional Neural Networks (CNN) that utilizes transfer learning through EfficientNet-B0 for the intelligent detection of plant leaf diseases. The model was trained and validated using a carefully curated dataset comprising over 10,000 images across various disease categories. We conducted a comparative analysis with three advanced models: Vision Transformer (ViT), ResNet-50. The experimental findings indicate that our proposed model achieved a remarkable classification accuracy of 97.8%, surpassing ViT's 94.2%, ResNet-50's 92.6%. The system's precision, recall, and F1-score were recorded at 98.1%, 97.5%, and 97.8%, respectively. Additionally, the model demonstrates quicker inference times and lower computational requirements. This research presents an effective and scalable solution for real-time implementation in smart agriculture applications, suitable for mobile or embedded systems.

KEYWORDS: Convolutional Neural Networks (CNN), Leaf Disease Detection, EfficientNet-B0, Transfer Learning, Smart Agriculture, Deep Learning.

I. INTRODUCTION:

Agriculture is fundamental to ensuring food security and sustaining economic stability in both developing and developed countries. Within the many challenges confronting the agricultural sector, crop diseases pose a significant threat, frequently leading to considerable yield losses and financial strain for farmers. Leaf diseases, in particular, are key early signs of declining crop health. Conventional techniques for disease identification, which depend on manual observation and consultations with experts, are often time-intensive, subjective, and susceptible to human error, particularly in remote or resource-limited areas.

Recent developments in Artificial Intelligence (AI) and Machine Learning (ML) have paved the way for enhanced automation in plant disease detection, achieving remarkable accuracy and speed. Research from Too et al. (2019), Ferentinos (2018), and, more recently, Chen et al. (2023), has showcased the potential of deep learning techniques such as CNNs and Transformers in classifying plant diseases. Nonetheless, many current methods encounter challenges, including significant computational demands, difficulties in generalizing across diverse datasets, and less-than-ideal performance under real-world conditions, such as varying lighting, background noise, or partial obstruction.

This research tackles existing gaps by introducing a lightweight and precise AI-driven system for identifying and classifying plant leaf diseases. Our model utilizes a transfer learning approach based on EfficientNet-B0, making it suitable for deployment on mobile and edge devices. It has been trained on a comprehensive dataset comprising over 10,000 labeled leaf images and has been evaluated against three contemporary models: Vision Transformer (ViT), ResNet-50. The proposed system surpasses these models in accuracy, inference speed, and resilience to noise and variability.

The main goals of this research are:

1. To create a highly efficient and precise model for automated detection of leaf diseases.
2. To evaluate the performance of the proposed method against current models using quantitative measures.
3. To develop the system with real-world applicability in mind, particularly for low-resource farming settings.

This study advances the field by connecting leading-edge AI research with real-world agricultural applications. Its goal is to equip farmers with an intelligent, user-friendly tool that facilitates early diagnosis and timely interventions, ultimately improving crop health management and food security.

II. RELATEDWORK

The methodology for identifying plant diseases automatically has seen substantial progress, transitioning from traditional machine learning to more powerful deep learning frameworks. Initial efforts in this area often depended on conventional techniques like Support Vector Machines (SVMs). However, these earlier methods were constrained by their reliance on manual feature engineering and their limited performance in the unpredictable conditions of real-world agricultural environments.

A significant breakthrough came with the application of Convolutional Neural Networks (CNNs). Foundational CNNs, such as AlexNet and ResNet, achieved remarkable accuracy levels, with some studies reporting success rates over 99% under controlled laboratory conditions. Despite this success, these models frequently encountered issues with overfitting and struggled to generalize effectively when deployed in actual fields, where variables like inconsistent lighting and background clutter are prevalent.

To further enhance detection accuracy, subsequent research has investigated more modern architectures. Vision Transformers (ViT), which have proven to be highly effective for general image recognition tasks, were adapted for agricultural applications. Nevertheless, ViT and other complex models present considerable practical challenges; they are computationally demanding, require vast amounts of data for training, and necessitate powerful hardware, which makes them unsuitable for real-time, on-farm implementation.

A central challenge consistently identified across the literature is the critical trade-off between a model's accuracy and its computational footprint. This has fueled a growing focus on the development of lightweight deep learning models that are optimized for deployment on mobile or edge devices. This research trend aims to make real-time analysis accessible directly in the field. The work presented in this paper contributes directly to this effort by utilizing EfficientNet-B0, an architecture recognized for providing an excellent balance of high performance and low computational requirements, making it a fitting choice for practical agricultural use

III. METHODOLOGY:

a. Research Design: This study adopts a quantitative experimental research design to create and assess an AI-driven model for detecting diseases in plant leaves. The methodology utilizes a supervised machine learning pipeline that leverages a pre-labeled image dataset to train, validate, and test multiple deep learning algorithms. The primary objective is to evaluate the performance of the proposed EfficientNet-B0 model in comparison to three baseline models: Vision Transformer (ViT)

b. Dataset Collection and Preprocessing: The dataset utilized in this research consists of over 10,000 labeled leaf images obtained from Plant Village and other open-source platforms such as Kaggle and the UCI Machine Learning Repository. It features images depicting both healthy and diseased leaves from various crops, including tomatoes, potatoes, grapes, and maize. The images encompass a range of disease categories, such as early blight, late blight, powdery mildew, leaf spot, and rust. The data preprocessing steps included: -

- Resizing the images to dimensions of 224x224 pixels.
- Normalizing pixel values to a range of [0, 1].

- Applying data augmentation techniques (random rotation, zoom, horizontal/vertical flipping) to enhance model generalization.
- Dividing the dataset into training (70%), validation (15%), and testing (15%) sets.

c. Model Architecture and Development: The proposed system employs EfficientNet-B0, a compound-scaled convolutional neural network that has been pre-trained on ImageNet and fine-tuned for multi-class classification. In this setup, the final dense layer has been replaced with a softmax layer tailored to the specific number of disease classes. The architecture was developed using Tensor Flow and Keras frameworks. For comparison, the following baseline models were utilized: - Vision Transformer (ViT):

- A transformer-based model pre-trained on ImageNet-21k.
- ResNet-50: A residual learning architecture featuring 50 convolutional layers.

All models underwent training for 25 to 30 epochs with the following parameters:

- Optimizer: Adam
- Learning rate: 0.001
- Loss function: Categorical Cross-Entropy
- Batch size: 32

d. Evaluation Metrics: The evaluation of model performance was conducted using several metrics, including:

- Accuracy
- Precision
- Recall
- F1-score
- Confusion matrix
- Inference time per image

The EfficientNet-B0 model demonstrated an impressive accuracy of 97.8%, outperforming other models such as ViT at 94.2%, ResNet-50 at 92.6%, it recorded the quickest average inference time of 32 ms per image when run on a GPU system.

e. Ethical Considerations: As the study solely relies on publicly accessible datasets that do not contain any personal or sensitive information, it did not require ethical approval. Nonetheless, all datasets were utilized in accordance with their specific licenses and attribution mandates. The research adheres to the core principles of open research and reproducibility.

f. Reproducibility and Tool chain: To guarantee reproducibility:

- The source code was developed using Python 3.10.
- The following libraries were utilized: Tensor Flow 2.x, Keras, NumPy, Matplotlib, and OpenCV.
- Experiments were performed on a machine equipped with an NVIDIA RTX 3060 GPU and 16 GB of RAM.
- Random seeds were set to ensure consistent results.

Algorithm:

The proposed algorithm is a lightweight and efficient deep learning pipeline designed to accurately classify plant leaf diseases in real-time, overcoming the computational and speed limitations of older models.

The Algorithm Step-by-Step: The core of our approach is a systematic process based on a fine-tuned Convolutional Neural Network (CNN).

1. Data Preparation: The algorithm begins by loading the image dataset. Each image is resized to a standard 224x224 pixels, normalized, and enhanced using data augmentation techniques like rotation and flipping. The prepared dataset is then split into 70% for training, 15% for validation, and 15% for testing.

2. Model Setup: We use transfer learning by loading a pre-trained EfficientNet-B0 model, which is known for its efficiency. We then replace its final classification layer with a new Softmax layer that is tailored to our specific disease categories.
3. Training: The model is compiled using the popular Adam optimizer and categorical cross-entropy as the loss function. It's then trained for 30 epochs in batches of 32 images.
4. Prediction: After training, the final model can take any new leaf image, preprocess it, and instantly output a predicted disease label along with a confidence score indicating how certain the model is about its prediction.

IV. Results and Discussio

The proposed EfficientNet-B0 model demonstrated superior performance across all key metrics. It achieved an impressive classification accuracy of 97.8%, significantly outperforming both ViT (94.2%) and ResNet-50 (92.6%). The performance metrics for the proposed model were recorded as follows:

- Precision: 98.1%
- Recall: 97.5%
- F1-Score: 97.8%

Critically, the EfficientNet-B0 model also recorded the fastest average inference time at 32 ms per image, confirming its suitability for real-time applications. The model's efficiency stems from its lightweight architecture, which delivers top-tier results with significantly fewer parameters (~5.3 million) compared to heavier models like ResNet-50 (~25 million). This results in a final model size of around 20 MB, making it easy to deploy on devices with limited memory.

V. Conclusion

Conclusion: A High-Performing AI Solution

The study developed an AI system using EfficientNet-B0 that achieved an impressive 97.8% accuracy in identifying plant leaf diseases, outperforming major models like Vision Transformer (ViT) and ResNet-50. Its key strengths are its lightweight design and rapid speed (32 ms inference time), which make it perfect for real-time use on mobile devices in the field. While successful, the system has limitations. Its accuracy can decrease in poor lighting or with blurry images, and it is currently trained on a specific set of crops and diseases.

- Future Work: The Path Forward Future efforts will focus on addressing these limitations and enhancing the system's practicality:
- Dataset Enhancement: We plan to expand the dataset with more diverse, real-world field images, including a wider variety of crops and rarer diseases.
- Improving Robustness: To make the model more reliable in various conditions, we will integrate multimodal data, such as soil and weather information.
- Practical Deployment: The primary next step is to develop a comprehensive, user-friendly mobile application complete with offline functionality to ensure it's accessible to farmers anywhere.

In summary, this system is a significant step forward for smart agriculture, with the potential to empower farmers, reduce crop losses, and promote sustainable farming practices.

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