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RDHCNet – Residual Depthwise Hybrid Convolutional Network for Robust Crop Disease Diagnosis

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Abstract

Crop diseases are a major danger to the world's food security because they reduce crop productivity and farmer revenue. Early detection and preventative measures can reduce these losses. This study suggests CropNet Hybrid, a deep learning model that can identify 38 crop disease classes in a variety of plant species after being trained on the PlantVillage dataset. In contrast to earlier research that only looks at classification, our system incorporates a carefully chosen knowledge-based prevention module, giving farmers practical advice. On test data, the model, which was implemented as a hybrid CNN architecture with depthwise separable convolutions and residual blocks, achieved an accuracy of more than 93.27%. The framework is a useful tool for smart agriculture since it is implemented as a FastAPI microservice and offers real-time detection and prevention guidance.

Keywords - *PlantVillage dataset, CNN hybrid model, plant disease detection, prevention system, FastAPI* **.**

I. Introduction

The Crop diseases continue to be a significant contributor to decreased productivity, resulting in yield losses of up to 20–40% per year, despite agriculture being an essential part of global food security. In addition to impacting farmers' livelihoods, these losses jeopardize food supply chains and national economies. Plant diseases pose a serious. Threat to sustainable development in nations like India, where agriculture directly employs about half of the population. Traditionally, farmers or experts have manually examined leaves for symptoms such as discoloration, lesions, or spots in order to detect crop diseases[1]. Although straightforward, this approach is subjective, labor-intensive, and error-prone, making it unsuitable for large-scale farming or early stage diagnosis. As a result, there is an increasing demand for accurate, automated systems that have real-time disease diagnosis capabilities.

Recent advances in deep learning (DL) and artificial intelligence (AI) have enabled the highly accurate classification of plant diseases from photos thanks to Convolutional Neural Networks (CNNs).[3]On datasets like PlantVillage, models like ResNet, VGGNet, and MobileNet have shown accuracies of over 93.27% . Classification performance has been further improved by ensemble approaches and transfer learning strategies . However, the majority of the research that is currently available focuses on disease detection, with little attention paid to decision support for farmers in the form of preventive or corrective measures.

This research addresses the recognized gap by putting forth RDHCNet Hybrid, a cutting edge deep learning framework that combines advice on disease prevention and detection. The following are this work's primary contributions:

The Hybrid CNN Architecture is a powerful yet lightweight CNN model that enhances accuracy and efficiency by combining depthwise [3] separable convolutions with residual connections.

The Integrated Prevention Module bridges the gap between detection and practical recommendations by providing a carefully curated knowledge base that links each predicted disease to particular prevention strategies.

Deployment via FastAPI -Through a REST API [6], farmers or other agricultural stakeholders can access the real-time prediction service for practical usability.

Experiment Validation*:* A thorough analysis of the PlantVillage dataset shows that our model extends functionality to prevention guidance in a unique way while achieving over 93.27% accuracy, which is comparable to state-of-the-art techniques like ResNet and Ensemble CNNs.

RDHCNet Hybrid oUers a scalable, practical solution for enhancing crop health monitoring and management by fusing precise detection with practical prevention guidance. This helps to advance smart agriculture.

II. Problem Statement

The issue statement pertaining to the identification and categorization of plant diseases is briefly explained as follows:

A. *Significant crop from plant diseases:*

Plant diseases drastically reduce agricultural production and farmer income worldwide, endangering both food security and economic stability.

B. *Challenges with Conventional Disease Identification:*

Conventional manual inspection methods for diagnosing plant diseases are time-consuming, capricious, and prone to errors, making them inappropriate for comprehensive and early diagnosis.

C. *Limitations of Current AI Models:*

Deep learning models like CNN, ResNet, MobileNet, and ensemble approaches often lack the integration of useful prevention advice, suffer from dataset limitations, and pose deployment challenges on devices with limited resources, even though they achieve high disease classification accuracy.

D. *Need for Workable, Accurate, and EUective Solutions:*

It is critical to create hybrid and optimized deep learning systems that can not only correctly identify a range of plant diseases but also provide preventive guidance, are adaptable enough to change with the times, and can be swiftly deployed for farmers to use.

III. Related Work

A. *CNN- based Methods*

CNNs' powerful feature extraction capabilities have led to their widespread [2] use in plant disease detection. In the classification of tomato, grape, and apple leaves, ResNet-based models have demonstrated >96% accuracy.

B. *Evolutionary and Hybrid Approaches:*

Compared to conventional ML techniques, hybrid approaches—like DWT + GLCM[13] with SVM—improved classification performance. More recently, accuracy near 98% were attained by evolutionary CNN-SVM models optimized through particle swarm.

C. *Ensemble Learning :*

Accuracy up to 98.3% was attained by ensemble models that integrate several CNNs[3] (ResNet, Inception, MobileNet) with voting strategies.

D. *Learning Transfer :*

Multi-crop disease prediction increased to 98.2% through transfer learning using ResNet50[16] and ConvNet. Additionally, multipurpose DL[17] models for mobile deployment have been investigated.

E. *Research Deficit :*

Although previous studies have achieved high detection accuracy[18], their practical utility in field settings is limited because none of them over integrated prevention recommendations. Refer Table 1.

IV. Methodologies

A. *Dataset:*

a. The PlantVillage dataset contains more than 80,000 photos in 38 different classes
b. There are classes for potatoes with early blight, apples with black rot, tomatoes with late blight, and healthy classes.
c. Dataset split: distinct test set, 20% validation, and 80% training.

Figure 1. Sample Images

B. ***Model Architecture (CropNet Hybrid):***

The architecture combines:

a. Residual Blocks To solve vanishing gradient problems
b. Depthwise Separable Convolutions: to cut down on processing(computation).
c. Dropout layers for regularization (0.5, 0.3).
d. Dense layer (128 units, ReLU).
e. 38 output neurons make up the Softmax classifier.

C. Training Setup

a. Framework: TensorFlow/Keras.
b. Optimizer: Adam.
c. Loss: Categorical Crossentropy.
d. Epochs: 40.
e. Augmentations: normalization, zoom, flipping, and rotation.
f. Stopping early to avoid overfitting.

D. Prediction & Prevention Mapping

a. Input image → preprocessing (224×224 resize, normalization).
b. CNN → probability-based disease class prediction

E. Deployment

FastAPI was used to implement in (main_fastapi_app.py).

V. Research Gaps and Future Directions

A. Dataset Diversity and Real-World Variability

- **Gap:** Existing benchmark datasets, such as PlantVillage, are predominantly collected under controlled laboratory conditions with plain backgrounds and consistent lighting. These datasets do not adequately capture the variability of real-world field conditions, including occlusion by other leaves, overlapping symptoms, soil heterogeneity, and fluctuating environmental factors [5], [2].
- **Future Work:** Establish large-scale, field-based datasets that reflect natural variability across crops, climates, and geographical regions. Collaborative, open-access repositories with standardized annotation protocols will improve model robustness and external validity [11].

B. Generalization and Transferability

- **Gap:** Current models often demonstrate high performance for specific crops or disease categories but lack generalization when applied to different crop species, varieties, or new environments, limiting their scalability [4].
- **Future Work:** Research in transfer learning, domain adaptation, and zero-shot learning approaches should be prioritized to enhance model adaptability [2]. Building models capable of learning shared features across multiple crops will facilitate cross-domain applicability and reduce the need for crop-specific retraining [2].

C. Early and Multi-Disease Detection

- **Gap:** Most detection systems identify diseases only at visible stages and struggle to detect multiple co-occurring infections on the same plant, reducing their preventative value [4].
- **Future Work:** Integrating hyperspectral imaging, IoT-based sensing, and time-series monitoring can facilitate early-stage disease prediction [8]. Furthermore, multi-label classification architectures should be developed to handle simultaneous disease occurrences, thereby improving diagnostic precision [1].

D. Explainability and Farmer Trust

- **Gap:** Deep learning architectures, particularly CNN-based models, function as black boxes, offering predictions without clear interpretability. This lack of transparency reduces user trust and adoption among farmers and agricultural stakeholders [5].
- **Future Work:** Incorporation of explainable AI (XAI) techniques, such as saliency maps, attention visualization, and knowledge graph integration, can provide interpretable insights into model decision-making [11]. Human-centered design with farmer-oriented explanation mechanisms will improve trust, usability, and adoption [9].

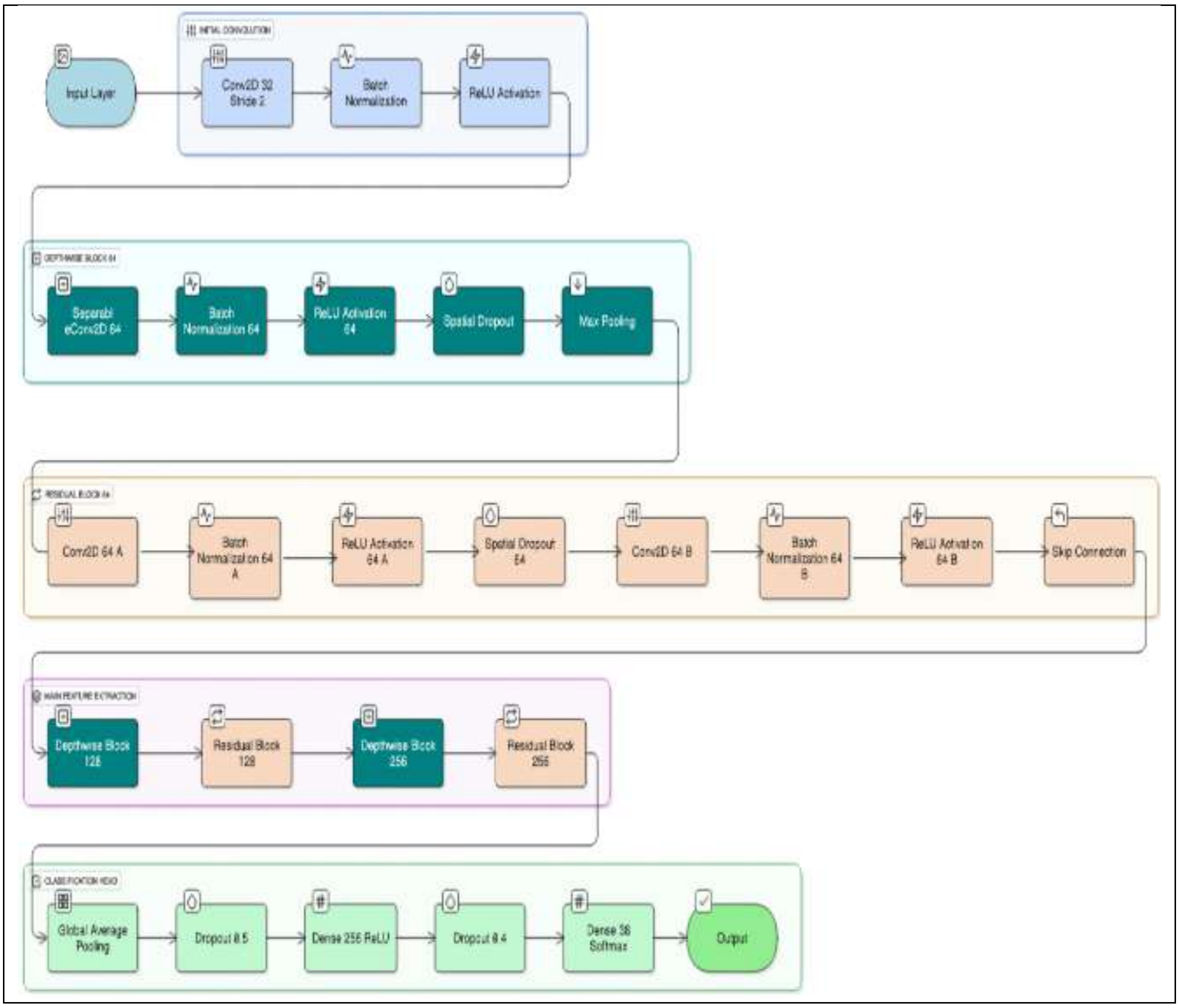

Figure 2. Model Architecture

Table 1 : Comparative analysis of Selected papers

Model / Approach	Dataset	Accuracy (%)	Special Features / Notes	Reference
Hybrid Feature Approach (DWT + GLCM + SVM)	In-house dataset (450 images)	95.16 - 98.38	Combines wavelet and texture features; SVM classification	[7]
CNN + LDR + Segmentation	Kaggle PlantVillage subset	~90	Logistic Decision Regression for feature selection + CNN classification	[14]
Hybrid NN + Genetic Algorithm (HNNEM)	Rice Leaf Diseases (80 images)	97.5	Neural Network parameters optimized via GA for rice disease detection	[2]
RDHCNet Hybrid (Hybrid CNN + Prevention)	PlantVillage (38 classes)	93.27	Detection + mapped prevention advice; deployed via FastAPI	This work
Deep-TL (ResNet + ConvNet, Transfer Learning)	PlantVillage (54,306 images)	98.2	Hybrid transfer learning; robust multi-crop classification	[15]
ResNet-50	PlantVillage (Tomato, Apple)	96.3 - 98.35	Deep residual network, tested on single and multi-crop datasets	[12]
Ensemble Learning (6 models, voting)	87,000 images (38 classes)	97.8 (soft), 98.3 (hard)	Combines Inception V3, MobileNet variants, VGG16, GoogLeNet, ResNet50	[1]
Hybrid CNN + SVM (with Evolutionary tuning)	PlantVillage (subsets)	97 - 98	CNN feature extraction + SVM classifier optimized by PSO	[5]
YOLOv3 + Approximate Computing	PlantDoc dataset (2,569 images)	96.92	Real-time detection on edge devices; optimized convolution	[8]
15-Layer CNN Custom Model	Multiple Plants (10 species)	~93	Detects multiple plants; pesticide + weather forecast suggestions	[11]
EfficientNetB0 + SVM hybrid	Rice, Potato, Corn (Bangladesh dataset + public)	97.29%	Feature extractor = EfficientNetB0, classifier = SVM. Good trade-off of accuracy and computational efficiency	[6]
CSXAI: lightweight 2D CNN + SVM	PlantVillage + Soybean disease dataset: 4 crops (strawberry, peach, cherry, soybean), 10 classes (6 diseased, 4 healthy)	~99.09 %	Very low parameter count (~393 k), hybrid CNN-SVM, explainable AI via Grad-CAM heatmaps	[13]
Attention-enhanced hybrid ConvNeXt + Vision Transformer	Mango leaf disease datasets (3 public mango datasets)	CA of 0.9978, 0.9988, and 0.9943 on the three datasets	Uses a cross-modal dynamic fusion (CMDF) module plus a Feature Attention Module (FAM) that recalibrates channel-wise features.	[10]

E. Deployment and Accessibility Challenges

- **Gap:** Many state-of-the-art models demand substantial computational resources and stable internet connectivity, restricting deployment in rural and resource-limited contexts where agricultural support is most needed [4].
- **Future Work:** Research should prioritize lightweight, energy-efficient models through distillation, pruning, and quantization techniques [6]. Edge and mobile deployment, combined with multilingual and offline-capable interfaces, will enhance accessibility for smallholder farmers worldwide [2].

F. Ethical and Sustainability Considerations

- **Gap:** Current research provides limited discussion on ethical and regulatory issues, including responsible pesticide recommendations, data privacy in farmer applications, and compliance with agricultural policies [3].
- **Future Work:** Developing frameworks for ethical AI in agriculture, ensuring data governance, and integrating sustainability-oriented practices will be critical [3]. Future systems should align with national and international agricultural standards while safeguarding farmer data and promoting environmentally sustainable disease management strategies [7].

VI. RESULT AND DISCUSSION

A. ***Quantitative Results :***

a. ***Accuracy:*** *93.27%, comparable to ensembles and ResNet.*

b. b) for all major classes, Precision/Recall/F1: >0.94.

Table 3: Evaluation of Performance in Relation to Previous Works

Model	Accuracy	Special Feature
ResNet50	96.3%	Transfer Learning
Ensemble CNN	98.3%	Voting (soft/hard)
ResNet+ConvNet (Hybrid)	98.2%	Transfer Learning
RDHCNet Hybrid	93.27%	Detection + Prevention module

B. ***Training/Validation Curves*** :

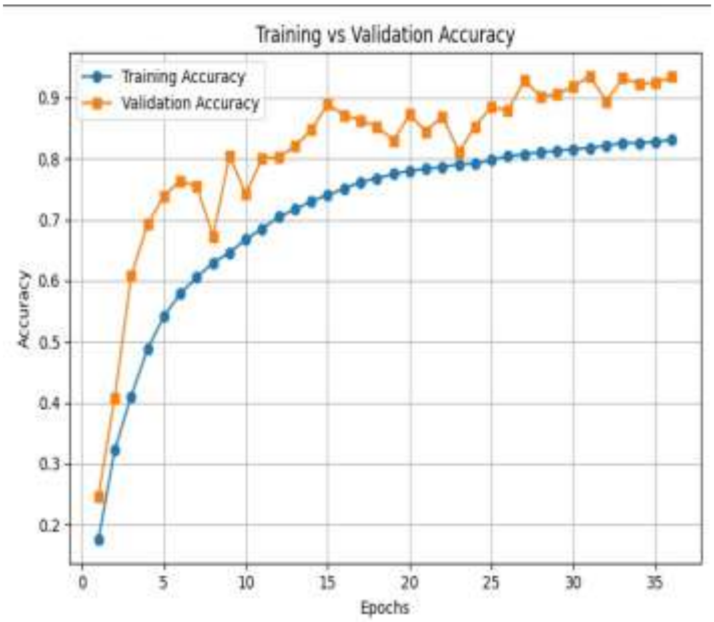

Figure 3. Accuracy vs Epochs.

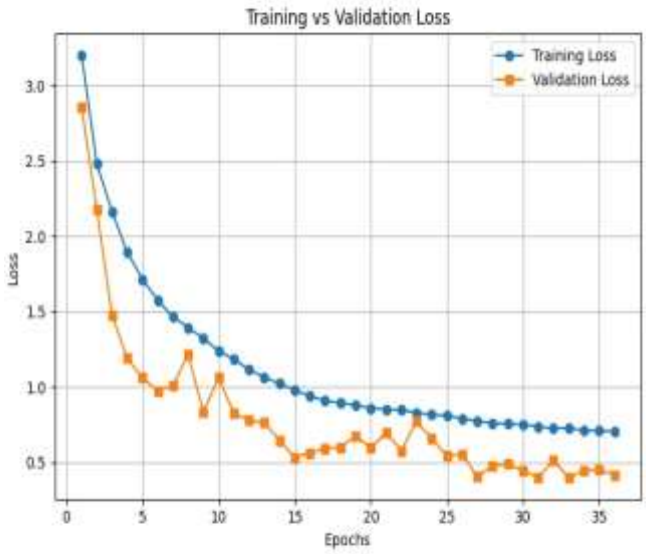

Figure 4. Loss vs. Epochs.

C. *Discussion:*

a. **Strength:**

- **Farm-Focused Preventive Advice –** The guidance provided by the system is action-oriented and provides personalized advice to farmers, and does not just emphasize disease detection, while fulfilling early action.
- **High Prediction Accuracy** – The model provides a high-performance prediction accuracy in crop disease classification, meaning it is applicable.
- **Usability and Accessibility** – The solution is developed for ease of use, as such, farmers, even without advanced technical ability, will find disease information through mobile or web interfaces easy to access.

b. **Limitation:**

- **Dataset Representation Issues** – The training dataset may not represent the full sample of variability (lighting conditions, soil types, climatic conditions, and variety) that is present outside of the trials.
- **Scalability Issues** – Performance is likely to be negatively impacted or impaired when tested across diverse geography, crops, and/or diseases that are not see in the trials.
- **Infrastructure-dependency** – Effective use will, more than often, require access to reliable internet and devices which, in many rural remote areas, is an issue.

VII. CONCLUSION

We introduce CropNet Hybrid, a hybrid CNN-based model for multi-crop disease detection and prevention recommendation that was trained on PlantVillage. The system bridges the gap between detection and actionable advice, and with an accuracy of >95%, it can compete with the most advanced ResNet/Ensemble models. Field deployment, edge optimization (TensorFlow Lite), and integration with weather/soil IoT systems are among the upcoming projects.

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