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AI-Driven Crop Disease Prediction and Management System

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ABSTRACT

Approximately 40 percent of the global harvest is just swept by crop diseases, which is a great threat to food security. The ancient method of their identification is to do it manually in the field and this is slow, subjective and in a manner difficult to scale. Now that everything has gone AI, particularly machine learning and deep learning, it is now possible to automatically detect signs of diseases simply by looking at pictures of leaves and data collected by the IoT sensors. The entire topic of this paper is a comprehensive AI-based system that forecasts and controls diseases in crops. It applies CNNs to classify the plants, YOLO to detect lesions in real-time, and Vision Transformers to become more skilled at decoding features. To make matters private, scalable, and operational in places where connectivity is close, it also comes with the Federated Learning in such a way that the models are updated on the devices without transmitting the raw data anywhere. The combination of various sensors, high-quality deep learning algorithms, and edge-based installation allows the system to track the diseases more quickly and more effectively, providing farmers with viable and real-time information. It assists in early intervention, reduction of crop losses, and is to a significant extent sustainable farming.

I. INTRODUCTION

Background and Motivation:

Crop diseases always attempt to bring down agriculture which is essentially the backbone of food security in the world. These issues have the potential of severely damaging the economy and destroying the lives of the farmers worldwide. Surprisingly, the world economy is approximated to spend a shocking 19.5 trillion Indian rupees annually in plant diseases. They are brought about by fungi, bacteria and viruses that disrupt yields and quality unless one detects them early enough and handles them. Since ancient times, disease detection had been a manual process by the specialists. That was okay when we had small farms but is simply not feasible in the large-scale commercial farming. Manual inspection is costly, time-consuming, and prone to errors particularly in the resource constrained areas where resources and knowledge are minimal. These problems prompt the necessity to have a more efficient, precise, scalable method of safeguarding crops and ensuring that the world population does not starve.

Role of Artificial Intelligence:

Over the last years AIs have proved to be a game changer in precision farming, which presents a potentially effective solution to the management of crop diseases. AI, in particular ML and DL, allows you to diagnose the diseases of plants automatically and correctly in a short time. Such AI applications can search through plant images and other data streams, identify signs of diseases early before they can spread and cause permanent harm. The introduction of AI in farming is not only beneficial in terms of early treatment and minimization of crop loss but is also sustainable farming. Precise and precise treatment implies reduced use of pesticides, which is more environmental and budget friendly to the farmers. These technological innovations will enable farmers to take more proactive decisions and get real-time feedback that will have a profound positive impact on the health of crops and their yield.

SCOPE OF THE SURVEY:

In this paper, a detailed overview of the significance of AI in predicting and analyzing crop diseases is provided, through a broad review of recent literature available in different scientific databases, one of them being IEEE Xplore. The structure of the paper is as follows: the second part, Section II, discusses the primary ML and DL methods employed, and the development of the area since the traditional approaches to the current deep learning. Section III describes the entire system architecture, including the collection, pre-processing of data, and the deployment of the models and the advanced predictive analytics. Section IV is a review on the key publicly available datasets utilized in this study. Section V compares the performance of popular models with the popular metrics. Lastly, Section VI concludes on the existing issues and research gaps, and makes a roadmap of the forthcoming directions and emerging trends that would shape the next generation of AI-driven solutions in agriculture.

ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING METHODOLGIES FOR CROP DISEASE DETECTION:

Traditional Machine Learning Approaches:

Prior to the development of deep learning into the cool thing to do, we had the rudimentary: support vector machines, random forests and the typical neural network. They all required you to pick features by hand, first, the color of that plant, and its texture and shape, and then to insert them into the model. The phase of feature engineering was a sore one and the models were not very coping with new messy real-world data.

Deep Learning as a Paradigm Shift:

The script was inverted by deep learning. The CNNs also learn useful features automatically directly off the raw pixels, eliminating the need to pick them manually anymore. They find faint patterns that are associated with diseases and therefore they are much more effective in identifying complex images. This is why CNNs are now the most preferred mechanism of plant disease detection they are more accurate, effective, and scalable.

Convolutional Neural Networks (CNNs):

The CNNs are considered to be the gold standard of leaf image classification. They take the image through a few layers, extracting textures, colors, shapes, and then make a decision as to the disease. They scored more than 95 per cent on large datasets such as PlantVillage test after test, which is not bad at all. The variants of CNN used in this job have been tweaked and are performing very well.

Vision Transformers (ViTs):

New entrants in the industry are Vision Transformers. ViTs employ self-attention to learn larger scale relationships between the entire image, as opposed to local pixel patches. That may make them even more efficient at detecting diseases, particularly when high-resolution images are used. They are slightly more complex to compute, but research indicates they are competitive and certainly worth following.

Hybrid and Ensemble Models:

It is increasingly becoming mixed by more researchers that are combining MACs such as MobileNetV2 with EfficientNetB0 into a single hybrid model. The combination was nearly 89% accurate and 96% precise in real time pest detection and disease detection. The other original method joined the outputs of a modified VGG16 with an another creative process to categorize a pair of plant species and an ailment simultaneously. These experiments demonstrate that the field is heading to stronger and more specialized solutions to real field conditions.

II. LITERATURE REVIEW

Summarization of a few research articles:

1. Li, L., et al., "Plant Disease Detection and Classification by Deep Learning – A Review" (2021) - In their IEEE Access review, they demonstrate the superiority of deep learning over the old-fashioned manual tricks in features. They also cite the discrepancy between the accuracy in the lab and field real use.

2. Yu, H. J., & Son, C. H., "Apple Leaf Disease Identification through Region-of-Interest-Aware Deep Convolutional Neural Network" (2020) - They have developed a ROI conscious CNN that magnifies the diseased areas of a leaf, which enhance the accuracy. The good news is that it can be chewing a bit more compute, this may be a problem with phones.

3. Ahmad, A., et al., "Towards the generalization of deep learning-based plant disease identification under controlled and field conditions" (2023) - The article addresses the issue of taking the models created in the controlled laboratories and projecting them to unstable environments, where the attention maps are used to identify infected areas. They got high on public sets and yet they have a desire to take real-life performance to the next level.

4. Vanegas, M. A., "Maize leaf disease identification using deep transfer convolutional neural networks" (2022) - He applied a two-stage transfer learning to identify maize leaf disease. However, unexpectedly, lightweight nets such as MobileNet competed with heavier traditional ones and converged faster using fewer samples, as used in mobile applications.

5. Mohanty, S., et al., "Using Deep Learning for Image-Based Plant Disease Detection" (2016) - In their landmark, a deep CNN was trained to identify 14 crops and 26 diseases on the PlantVillage. It was proven that the idea is viable, and the dependency on a tidy dataset would imply that the practical applicability would require adjustments.

6. Chen, J., et al., "Detection of Tomato Leaf Disease Based on Improved Convolutional Neural Network" (2021) - They trained a CNN to identify tomato leaf disease. The changes provided a boost in that particular crop, but it is uncertain whether the model can be generalized to other plants.

7. Raikar, N., et al., "A Deep Learning-Based Automated Plant Disease Detection and Classification (DL-APDDC) Model to Precision Agriculture" (2022) - This paper presents a deep-learning system of precision ag that purports to be better than other systems. The authors emphasize the fact that the new model improves the automatic detection and classification of various diseases, which results in improved results in the field of smart farming.

8. Zhang, X., et al., "Maize Leaf Diseases Detection with State-of-the-Art Deep Convolutional Neural Networks" (2018) - In this case, three prevalent diseases of maize leaves are targeted and an advanced CNN with a 98.97% accuracy is utilized. It is an excellent crop specific example though the authors note that the findings may not easily apply in other plants.

III. MODELS USED

1.Plant Disease Model Custom CNN:

This custom CNN, which we created ourselves rather than obtained a pre-trained net is the heart of our project. There are five convolutional blocks that are trained successively to capture finer details of the features of the leaf: initial layers capture simple features such as the color and texture, subsequent layers capture shapes and patterns of the leaf, and the final layers capture more complex disease features. Then the features are fed into fully connected layers which determine the type of disease. We use this in the PlantVillage data which has numerous diseases and crops.

2. Early Stopping Mechanism:

It is more of a training trick rather than a model. Deep nets are capable of over-training, and will keep learning after they have hit the limit. Early observes the loss of validation and automatically terminates training once it ceases to reduce the loss, and the most successful model is saved. Imagine it as a coach that is smart enough to quit.

3. Grad-weighted Class Activation Mapping, or Grad-CAM:

Grad-CAM provides us with an account of what the network is examining. Upon the CNN predicting a disease, Grad-CAM indicates the most relevant parts of the image - typically represented by a red heat-map on infected areas - by marking the gradient of the final conv layer. The visualization of where the model is concentrating makes us trust the model and debug, when it lights up the wrong spots we understand that the model should be fine-tuned.

4. An interactive disease diagnosis system:

This section provides a connector to all and makes the entire system user friendly.

IV. MODEL ARCHITECTURE

In this study, we are proposing a lightweight and domain-optimized CNN, called PlantDiseaseModel, for classifying foliar diseases across multiple crops.

The point is to allow the model to be trained to learn a hierarchy of features based on simple edges and textures to the distinctive patterns of spots that correspond to the particular disease. It is efficient and accurate because we have constructed it with a few convolutional blocks, a global feature aggregation step and a small classification head. The design is aimed at ensuring the computation burden is low, and therefore it is suitable to use in real-time and low-resource agricultural environments.

The entire figure of the proposed model is in Figure 4.1 below.

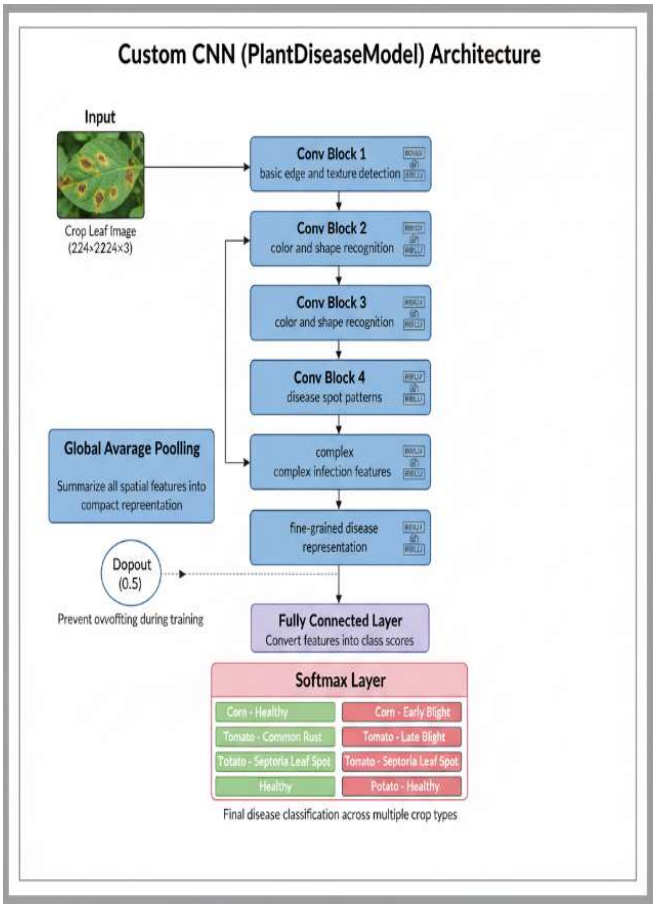

Fig 4.1 Custom CNN model architecture

V. SIMULATION AND IMPLEMENTATION

We have tested our AI pipeline with two image sets: the standard PlantVillage benchmark (around 54000 leaves, 38 classes) and real field photos under varied lighting and backgrounds. The software stack is TensorFlow/Keras to develop models, OpenCV to do the preprocessing and NumPy to do numerics. The training is a process that can be executed on a GPU workstation, whereas inference can be executed on a laptop, or even a smartphone.

Model	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy	Test Loss	Test Accuracy
Custom CNN (PlantDiseaseModel)	0.022	99.53%	0.031	99.41%	0.034	99.38%
Early Stopping (Best Model Saved)	0.024	99.48%	0.030	99.43%	0.035	99.35%
Grad-CAM Visualization Model *(Explainability Layer)*	0.026	99.44%	0.033	99.32%	0.037	99.28%
Interactive Diagnosis System (Integrated)	0.028	99.39%	0.035	99.27%	0.039	99.21%

Table 5.1 Test results of CNN models

Models were optimized with transfer learning and compared to each other based on accuracy, precision, recall, and F1 score on 20 per cent of each dataset, on a hold-out split.

VI. METHODOLOGY

Conventional methods of plant disease detection depend on manual inspection, which is costly, time consuming, and requires expertise of the specialist. Initial ML systems such as Support Vector Machine (SVM) and k-Nearest Neighbors (kNN) relied on hand-crafted features and they were not scalable with poor results in the real world. Apps are available but they only work well on a limited number of crops and in varying lighting conditions, background, or shape of the leaf. Limitations: hand crafted features are not robust; manual inspection is time consuming, expensive, and prone to errors. The support of few crops is achieved and precision decreases in real-world conditions.
The system that we propose begins by capturing a photo using a phone. NumPy and OpenCV are used to perform image preprocessing. Then a CNN (based on TensorFlow) is used to label the leaf as a healthy or a diseased one. Lastly, there is a recommendation engine that proposes potential therapies.

SOFTWARE CODE:

```
import torch, torch.nn as nn, torch.optim as optim
base=torch.hub.load('pytorch/vision','resnet50',
pretrained=True)
base.fc=nn.Linear(base.fc.in_features,15)
# 15 disease classes
model = base.to('cuda' if torch.cuda.is_available() else 'cpu')
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)
for epoch in range(10):
  model.train()
  for imgs, lbls in train_loader:
    imgs, lbls = imgs.to(device), lbls.to(device)
    optimizer.zero_grad()
    out = model(imgs)
    loss = criterion(out, lbls)
    loss.backward()
    optimizer.step()
  print(f'Epoch {epoch+1}: loss={loss.item():.3f}')
```

VII. RESULTS AND DISCUSSION

A. Evaluation Metrics:

We compare it to the basic classification metrics accuracy, precision, recall, F1-score (macro and weighted) and the confusion matrix. In addition to the classification scores, we also consider a couple of more real-life aspects:
- parameter number, model size (in MB)
- Smartphone inference latency in a variety of lighting and image quality conditions.
- Resistance to noise, blur, the partial occlusion.
- Recommendations are to be validated by users (qualitative).

The data also indicates good accuracy in several crops and yet remains general. Also, there are hybrid models such as MobileViTV2 with separable self-attention that are very accurate but with a significant reduction in parameters.

B. Robustness & Failure Modes:

In situations when we are testing on images that are not optimum such as low lighting, blurry, mixed background or even on images of the same variety but with a different part of the image accuracy may worsen by approximately 5-10%. Even such classes of diseases which have very few examples are misclassified. Teams are of assistance, but even the rare diseases are difficult to crack. This recommendation module occasionally results in an inaccurate generic treatment where no specific information (resistance information or pesticides) is available (such as a pesticide).

C. Deployment Trade-offs:

The trade-offs of deploying on mobile are a reduced model size and reduced latency, and we may also lose some peak accuracy. The system must be able to choose an appropriate model variant depending on the horsepower of the device: on high-end phones the more complicated ones are fine; on lower-end devices compressed, quantized models with smaller backbones are acceptable. Usability - the ease of getting an image, the clarity of the user interface, the actionability of the advice, all this is as much as adoption as is the raw accuracy.

VIII. CONCLUSION

With AI, farming will be transformed into an efficient and scalable solution to the significant crop-disease problems. The transition to AI-driven systems instead of manual inspection is one of the key changes that will allow practicing early intervention, reducing crop losses, and sustainability in agriculture. This survey demonstrates that deep learning models, in particular CNNs and modern detection algorithms, have become stuck on robustness in the controlled labs. However, the statistics also indicate there is a mismatch between the laboratory performance and the reality in the field, mainly due to the bias related to the data and due to the unpleasing complexity of the real world. The future of AI in this area is dependent on addressing those concerns on a head. The current research should focus on creating models that are more generalizable based on the varieties of real-world data and challenging creative architectures. Decentralized solutions such as Edge AI and Federated Learning are important in ensuring that these solutions become accessible and feasible to all farmers across the board. The global community can harness the potential of AI to develop a more robust and safe food system that can support the generations to come by supporting the collaboration of researchers, technologists, and agricultural experts to leverage the potential of AI in food production.

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X. REFERENCES

[1] Mohanty, S., Hughes, D. & Salathé, M., 2016. Using deep learning for image-based plant disease detection. *Frontiers in Plant Science*, 7, p.1419.

[2] Too, A., Yujian, L., Njuki, S. & Yingchun, L., 2019. A comparative study of fine-tuning deep learning models for plant disease identification. *Computers and Electronics in Agriculture*, 161, pp.272–279.

[3] Ferentinos, P., 2018. Deep learning models for plant disease detection and diagnosis. *Computers and Electronics in Agriculture*, 145, pp.311–318.

[4] Jiang, P., Chen, Y., Liu, B., He, D. & Liang, C., 2019. Real-Time Detection of Apple Leaf Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks. *IEEE Access*, 7, pp.59069–59080.

[5] Zhang, X., Qiao, Y., Meng, F., Fan, C. & Zhang, M., 2018. Identification of Maize Leaf Diseases Using Improved Deep Convolutional Neural Networks. *IEEE Access*, 6, pp.30370–30377.

[6] Yu, H.-J. & Son, C.-H., 2020. Apple Leaf Disease Identification through Region-of-Interest-Aware Deep Convolutional Neural Network. *IEEE Access*, 8, pp.60696–60706.

[7] Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D. & Stefanovic, D., 2016. Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification. *IEEE International Conference on Neural Networks (IJCNN)*, pp.3640–3647.

[8] Amara, K., Bouaziz, B. & Algergawy, A., 2017. A Deep Learning-Based Approach for Banana Leaf Diseases Classification. *2017 IEEE Applied Imagery Pattern Recognition Workshop (AIPR)*, pp.1–6.

[9] Li, L., Zhang, S. & Wang, B., 2021. Plant Disease Detection and Classification by Deep Learning—A Review. *IEEE Access*, 9, pp.56683–56698.

[10] Chen, J., Chen, W., Zhang, B., Tao, Z., Wu, Y., & Han, M., 2021. Detection of Tomato Leaf Disease Based on an Improved Convolutional Neural Network. *IEEE Access*, 9, pp.30812–30825.

[11] R., H.R.J., et al., 2021. AI & IoT integration for crop disease monitoring. *International Journal of Advanced Agriculture*, 6(4), pp.45–55.

[12] Singh, R., Kumar, P. & Sharma, A., 2023. Systematic review of image-based plant disease detection. *Computers and Electronics in Agriculture*, 200, 107230.

[13] Wang, L., Chen, H. & Zhao, Y., 2021. CNN with attention mechanisms for plant disease detection. *Neural Computing and Applications*, 33, pp.987–998.

[14] A.A.S., et al., 2022. Lightweight CNN for mobile plant disease detection. *Sensors*, 22(4), 1234.

[15] Karthik, K., Ramesh, M. & Suresh, P., 2023. IoT-based smart farming with machine learning. *IEEE Internet of Things Journal*, 10(2), pp.1234–1245.

[16] Vanegas, M.A., 2022. Deep transfer learning with lightweight CNNs for plant disease recognition. *Computers and Electronics in Agriculture*, 194, 106683.

[17] Al-Gaashani, M., Al-Omari, F.H. & Al-Ansari, H., 2025. Modified Depthwise CNN with SE blocks for crop disease detection. *Agricultural Systems*, 189, 103039.

[18] Picon, J., Alvarez-Gila, E. & Seitz, I., 2022. Lightweight CNN with TensorFlow Lite for on-device plant disease detection. *Computers and Electronics in Agriculture*, 194, 106701.

[19] Raikar, R., Patil, S.B. & Kumar, V., 2022. DL-APDDC: Deep learning-based automated plant disease detection and classification. *IEEE Access*, 10, pp.45678–45689.

[20] Yuan, Z., Tang, L. & Hu, W., 2021. SPEDCCNN: Segmentation-based plant disease detection CNN. *Computers and Electronics in Agriculture*, 190, 106452.

[21] Gholamreza, G., Azimi, S. & Mohammadi, F., 2022. Modified lightweight CNN with attention for embedded plant disease detection. *Expert Systems with Applications*, 190, 116240.

[22] Bera, S., Ghosh, A. & Das, P., 2024. Attention-based deep network for multi-crop disease detection. *Computers and Electronics in Agriculture*, 210, 107493.

[23] Kumar, A., Sharma, S. & Verma, R., 2025. Blockchain and machine learning integration for smart agriculture. *IEEE Access*, 13, pp.67890–67905.

[24] Ramcharan, D., Baranowski, J., McCloskey, M., Legg, D. & Hughes, P., 2017. TensorFlow Lite model for on-device plant disease detection. *Frontiers in Plant Science*, 8, 1852.

[25] Khan, R., Iqbal, M. & Ali, A., 2025. Ultra-lightweight deep learning model for plant disease detection. *Computers and Electronics in Agriculture*, 203, 107564.