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# AI-Based Crop Disease Detection using Deep Learning with Integrated Remedy Recommendation System: A Comprehensive Review

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***Abstract***—Crop diseases are honestly a big issue right now, especially when we talk about food security worldwide. A large portion of crops—something close to 40 percentage gets lost every year even before harvesting. This mostly happens because of pests and different plant diseases[11]. In most cases, farmers still rely on traditional methods to figure out what's wrong with their crops[1]. They look at the leaves, the color, or sometimes just go by experience. Some even consult experts if available. But the problem is, this whole process is slow and not always accurate. It really depends on who is checking. And in many rural areas, getting expert help is not that easy either. Things have started to change a bit with the use of technology. Artificial Intelligence (AI) and Deep Learning (DL) are now slowly entering the agriculture field[13]. Instead of manually checking everything, these systems can analyze crop images and detect diseases automatically. It's faster, and in many cases, more consistent too. That's why people are now talking more about precision agriculture—it's becoming more practical than before. In this study, we went through several research papers related to AI-based crop disease detection. Most of them are using CNN models (Convolutional Neural Networks)[13], which are quite common in image-related tasks. Apart from that, models like ResNet, EfficientNet, and MobileNet[14] are also being used quite a lot. Recently, some researchers have also started experimenting with Vision Transformers (ViT), although this area is still developing. Another thing worth mentioning is that many of these systems don't just detect diseases anymore. They also try to suggest possible treatments. Different approaches are used for this—some follow rule-based methods, while others use filtering techniques. A few studies have even used models like GPT-3.5 to generate recommendations[5], which is interesting but still needs careful validation. If we look at the results, they are actually quite promising. For example, EfficientNetB5-based models have reported accuracy above 96 percentage[6]. Similarly, VGG-13 models are giving around 95 percentage accuracy[9]. But still, there are some clear limitations. A lot of these models are trained on specific datasets, which may not fully represent real farm conditions. Also, testing across different environments is still limited. On top of that, deploying these systems in real- world farming situations is not always straightforward. There are practical challenges involved. And one more important point—whatever suggestions these AI systems give should still be verified by agricultural experts before farmers fully rely on them. Overall, this field definitely has potential, no doubt about that. But it's still evolving. Going forward, it would be useful to focus on making these systems more understandable (like using Explainable AI), using drones for monitoring large areas, and building applications in local languages so farmers can actually use them easily. Better evaluation methods are also needed so results can be compared properly across studies.

*Index Terms*—Crop disease detection, Deep learning, Convo- lutional neural networks, Transfer learning, Remedy recommen- dation, Precision agriculture, Computer vision, Smart farming, Food security

## I. Introduction

### *A. Global Agriculture and Food Security*

Nowadays, agriculture is facing many problems at the same time. Climate change is one of them, but not the only one. Population is increasing, resources are limited, and environ- mental conditions are also changing a lot. Because of all these reasons, managing food production is becoming more difficult than before. If we think about future, population may reach around 9 or even 10 billion. So obviously, more food will be needed. But increasing production is not that easy in reality. There are many issues which affect crop yield, and one major issue is crop diseases[11]. In many cases, it is seen that a large portion of crops, almost 40 percentage, gets damaged before harvesting[11]. This mostly happens because of pests and diseases. This is not just a farmer problem, it affects food supply and even prices in market[12]. Recently, the problem of hunger is also increasing, so this makes the situation more serious. [11], [12].

### *B. Impact of Crop Diseases on Agriculture*

Crop diseases can affect almost all types of crops. It may be wheat, rice, or even crops like cotton and sugarcane. These diseases are caused by fungi, bacteria, viruses, etc. In countries like India, where many people depend on agriculture, this becomes a big issue. When crops get damaged, farmers face losses, and at the same time food supply also gets affected. Also, it is not only about crop loss. Farmers have to spend more money on pesticides, labor, and other treatments. Sometimes damage starts early, but it is not properly measured. So actual loss can be more than what reports show.

### *C. Problems in Traditional Detection*

Traditionally, farmers identify diseases by looking at plants. They check leaves, color changes, spots, etc. Sometimes they ask experts also. But this method has many problems. It depends on experience, so results can be different for different people. Also, it takes time, especially in large farms. Another issue is that experts are not always available in rural areas. Because of this, diseases are detected late. By that time, it may already spread. So control becomes difficult.

### *D. Use of AI in Agriculture*

Now with technology, new solutions are coming. AI and Deep Learning are being used in agriculture[13]. Models like CNN can analyze crop images and detect diseases[13]. This reduces manual effort. It is faster also. Nowadays, smartphones are easily available, so farmers can take pictures and get results quickly. Some systems also suggest treatment, which is helpful.

### *E. Objective of Study*

This review focuses on how AI is used for crop disease detection. It includes models like CNN, ResNet, EfficientNet, and also newer ones like Vision Transformers. It also looks at systems which give suggestions for treatment. Different methods like rule-based and filtering are used. There are still some challenges like limited data, real-world performance, and difficulty in practical use. Future work can focus on better systems, use of drones, and making tools easier for farmers.

## II. Background

### *A. Evolution of AI in Agriculture*

AI in agriculture is actually not something very recent. It has been there for quite some time, just in different forms. In earlier time, around 1980s, systems were mostly rule-based. These systems worked on fixed rules given by experts. Like, if a certain symptom is seen, then it is considered as a specific disease. Later on, machine learning started getting used[14]. Here, instead of only rules, data was also used. Features like color, texture or shape were taken from images, and then models like SVM or Random Forest were applied. But still, it was not perfect. Features had to be selected manually, and sometimes in real conditions it did not work properly. After that, deep learning came into picture[13], and things improved a lot. In this, the model learns directly from images. Because of that, results became better, especially when the problem is complex.

### *B. Machine Learning and Deep Learning*

Machine learning and deep learning may look similar, but actually they are not same. In machine learning, features are given manually. So result depends a lot on how good those features are. Also, it needs more expert understanding. Deep learning works in a different way. Here, model itself learns patterns from data. First layers learn simple things like edges, and later layers learn more detailed patterns like disease signs. Because of this, deep learning works better in image tasks[13]. Many studies have shown better results compared to older methods.

### *C. Convolutional Neural Networks (CNN)*

CNN is one of the most used models for image-based work. It is also commonly used in crop disease detection. It mainly works in three steps. First is convolution, where patterns are taken from image. Then pooling, which reduces size but keeps important information. And finally fully connected layer, which gives output. Many CNN models have been developed over time. Like AlexNet, VGG, ResNet, MobileNet, Efficient- Net. Each one tried to improve something, like accuracy or speed. [14].

### *D. Transfer Learning*

Training a deep learning model from beginning is not easy. It needs a lot of data and also time. In agriculture, such big datasets are not always available. So transfer learning is used[13]. In this, a model already trained on big dataset (like ImageNet) is used again. Then it is adjusted for new task. This saves time and also gives good performance. That's why many researchers prefer this method

### *E. Computer Vision Applications*

Computer vision means machine can understand images. In agriculture, it is used for different tasks like disease detection, crop monitoring, yield estimation etc. There are different types of tasks. Like classification (what disease), detection (where disease), and segmentation (how much area affected). Sometimes these are combined also, to make system better.

### *F. Recommendations using NLP*

After detecting disease, next step is giving suggestion. For that NLP is used. Earlier, simple rule-based systems were used. But now more advanced methods are there. Some systems use filtering, some use models like GPT. These systems can give answers in simple language. Also, they can support multiple languages, which is useful for farmers.

### *G. IoT and Edge Computing*

IoT and edge computing are also becoming important now. IoT includes sensors and cameras in fields, which collect data regularly. Edge computing means processing data on device itself, instead of sending to cloud. This helps in faster results and less internet use. In crop disease detection, this is useful because farmers can directly see results on mobile. Even without internet in some cases. This is helpful in rural areas.

## III. Methods and Approaches

### *A. CNN-Based Disease Detection*

CNN is one of the main models used for crop disease detection. Most of the recent work is based on this. Different types of CNN models are used depending on requirement. Some focus on accuracy, some on speed. Many studies show that CNN works well because it can learn patterns directly from leaf images. Because of this, disease detection becomes faster and more accurate. In some cases, researchers also combine multiple CNN models together. This is called en- semble method. For example, combining models like ResNet

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and Inception. This helps in improving accuracy because different models capture different patterns. Also, model se- lection depends on use. Bigger models like ResNet-101 give better accuracy but need more resources. Smaller models like MobileNet are faster and can run on mobile devices.

### *B. Transfer Learning*

Transfer learning is used in most of the research. This is because agricultural data is usually limited. Instead of training from zero, a pre-trained model is used. Then it is fine-tuned for crop disease task. For example, models like VGG or EfficientNet are commonly used. Some studies have shown around 95 percentage accuracy using VGG-based models. Also, modified EfficientNet models have shown even higher accuracy, sometimes above 96Data augmentation is also used, like rotation or flipping images, so that model can learn better. Overall, transfer learning saves time and gives good results.

### *C. Detection and Segmentation*

In many systems, just classification is not enough. So additional steps are used. For example, first detecting the leaf

from image, then identifying disease. Models like YOLO are used for detection. After that, classification models like ResNet are applied. Some systems also use segmentation. This helps in identifying exact affected area. It can also help in checking how much disease has spread. Because of this, newer systems are becoming more advanced compared to simple image classification.

### *D. Mobile and Edge Deployment*

For real use, models should work on mobile devices. Many farmers use smartphones, so this is important. Some systems are designed to run directly on phone. This means farmer can take image and get result instantly. In some cases, internet is not required. To make this possible, models are made smaller using techniques like pruning or quantization. Lightweight models like MobileNet are commonly used. Also, some applications support multiple languages like English and Hindi. This makes it easier for farmers to use.

### *E. Recommendation Systems*

After detecting disease, next step is giving solution. This part is also important. Earlier, simple rule-based systems were used. Each disease had fixed solution. But this was not flexible. Now, better methods are used. Some systems match disease with database and give best possible solution. Some advanced systems use models like GPT to generate suggestions. These systems can explain in simple language and also adjust based on situation. Overall, modern systems try to do everything together — detect disease and also suggest treatment.

## IV. Key Findings and Comparison

### *A. Comparison of Studies*

In this part, different research papers are looked at and compared. All of them are related to crop disease detection using AI, and many of them also try to give treatment suggestions. From reading these papers, it can be noticed that most of the work is based on deep learning. Especially CNN models are used again and again. Some researchers also use transfer learning like VGG, ResNet, EfficientNet, etc. Earlier, systems were mainly focused on just detecting disease. But now, many systems are trying to do more than that. They also give suggestions, which makes them more useful in real situations. Also, many papers talk about mobile-based systems. This is important because farmers usually use smartphones.

One more thing is accuracy. Many papers show accuracy above 95 percentage, but mostly this is on controlled datasets like PlantVillage. In real field conditions, it may not be the same Table I provides a comparative analysis of recent research. While accuracy is high (often >95%), most models are vali- dated on controlled datasets like PlantVillage, which

may not reflect the noise and variability of real-farm conditions.

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TABLE I

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OMPARATIVE ANALYSIS OF CROP DISEASE DETECTION AND REMEDY RECOMMENDATION SYSTEMS

| Paper Title | Year | Method | Objective | Key Findings | Limitations |
|---|---|---|---|---|---|
| DL + Filter-ing | 2024 | DL + filter-ing | Disease ID + treatment | Improves detection | Limited vali-dation |
| Multicrop System | 2025 | Deep learn-ing | Multicrop detection | Real-time + pesticide | No metrics |
| Grape Leaf App | – | Multiple DL models | Mobile detection | Works on phone | Limited data |
| YOLO + ResNet + GPT | 2025 | YOLO + CNN + GPT | End-to-end system | Detection + suggestion | External de-pendency |
| EfficientNet Model | 2024 | EfficientNet B | 5Disease + pesticide | >96% accu-racy | Dataset lim-ited |
| CNN System | 2025 | CNN | Detection + treatment | Good results | Less repro-ducibility |
| Leaf CNN | – | CNN | Leaf detec-tion | Simple approach | No metrics |
| CDMD | 2021 | VGG-13 | Mobile sys-tem | ~95% accu-racy | Limited field use |
| AgriResNet | 2025 | Ensemble DL | Detection + segmenta- tion | Automated workflow | Limited data |

### *B. Model Performance*

Different models behave differently. It is not like one model is best for everything. EfficientNet models are giving very high accuracy in some studies. ResNet is also used a lot because it is stable. VGG is older but still used. Especially with transfer learning, it gives decent results. But honestly, comparing models is not very easy. Because every study uses different data and setup. So results can change.

### *C. Dataset Problem*

Dataset is a big factor here. Most studies use PlantVillage dataset. It is good but images are very clean. Background is simple. But real farm is not like that. There are shadows, multiple leaves, and other noise. Because of this, models may not work same in real conditions. Also, many datasets focus on few crops only. So model may fail for other crops.

### D. Recommendation Part

After detection, recommendation is also important. Rule- based systems are simple but fixed. They cannot change based on situation. Filtering methods try to improve this. Now some systems use GPT-like models. These can give better explanation and easy language. But there is risk also. If suggestion is wrong, it can affect crops. So expert validation is needed. Also, language matters. Farmers should understand it easily.

## V. Discussion

### A. Current Situation

If we see current systems, they are doing good in accuracy part. Many models give high accuracy, especially on known datasets. Also, some systems are not only detecting disease but also giving suggestions. But still, not everything is perfect. One common issue is dataset. Most models are trained on PlantVillage data. These images are clean. Real farm images are not like that. So in actual use, results can change. Also, many papers test only on same dataset. They don't try different data. So it is not fully clear how model will behave in real case. Another thing is crop coverage. Mostly same crops are used again and again like tomato or potato. Other crops are not covered much. Recommendation part is also not always clear. Sometimes system gives suggestion but source is not known. Also, expert validation is missing in many cases. And honestly, many studies focus more on accuracy, less on real use.

### B. Challenges

There are many challenges here. Dataset is first issue. Data is not very diverse. So model may not work everywhere. Overfitting is also problem. Model works well in testing but fails outside. Deployment is another issue. Many farmers don't have strong devices or good internet. Also, images taken by farmers may not be clear. This affects output. Recommenda- tion systems can also give wrong advice. That can be risky. Another point is explainability. Model gives result, but we don't know how. So trust becomes issue. Also, models need update with time. New diseases can come.

### C. Social and Ethical Points

There are some social issues also. Not every farmer has access to smartphone or internet. So some people may not use this technology. Data privacy is also important. Farmers' data should be safe. Bias is another issue. If dataset is limited, model may not work equally for all. Also, farmers may depend too much on system. That can be risky. Environment is also important. Suggestions should not lead to overuse of chemicals. Language is important. If system is not in local language, it becomes hard to use.

### D. Generalization Issue

Generalization is big problem here. Most models show good accuracy because they are tested on similar data. But in real farms, things are different. Lighting changes, background changes, image quality is different. So model performance may drop. So testing should be done on different datasets. Real-world data is needed. Some techniques can help, but still proper validation is needed.

## VI. Future Directions

### A. Explainable AI (XAI)

Future models should incorporate attention maps or SHAP values to explain *why* a specific diagnosis was made, allowing experts to verify the model's logic.

### B. Drone and Multimodal Data

Drones equipped with multispectral cameras can monitor vast areas, identifying stress before it is visible in the RGB spectrum. Integrating weather data can also help in predictive disease modeling.

## VII. Conclusion

AI-based crop disease detection has transitioned from exper- imental classification to practical, mobile-integrated systems with remedy recommendation capabilities. While reported accuracies are high, the transition from controlled datasets to real-world environments remains the primary hurdle. Future research must prioritize model interpretability, local language support, and standardized evaluation metrics to ensure these technologies provide reliable, equitable value to the global farming community.

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