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# "AgriFutura"-Plant Disease Detection with Fertilizer Recommendation using Deep Learning (CNN)

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**Abstract -** Agriculture is an important, critical sector that ensures the provision of sustenance and economic viability. Among the critical issues that affect agricultural practitioners is the ability to detect plant diseases in real time, which has critical impacts on plant yield and viability. Traditionally, disease detection requires human assessment and consultation, which is associated with costs and human error. To overcome the aforementioned limitations and shortcomings, this work introduces AgriFutura, an online plant disease identification and fertilizer guidance platform that utilizes deep learning concepts. The proposed platform utilizes a Convolutional Neural Network (CNN) architecture to evaluate images of plant leaves and identify them based on health and disease. In addition to healthcare guidance and recommendations, the platform also provides disease-oriented fertilizer guidance and recommendations, which can aid decision-making. The proposed platform is simple to use and therefore does not incur costs that are normally associated with specialized technical skills and knowledge. Results from experimental studies indicate that the proposed platform is effective and has short response times, which therefore qualifies to be used in real-life agricultural settings.

***Key Words***: Smart Agriculture, Plant Disease Detection, Convolutional Neural Network, Deep Learning, Fertilizer Recommendation

## 1.INTRODUCTION

Agriculture is one of the most important sectors in the world. It provides food and income to people. However, plant diseases have been identified as one of the major hindrances in the development of the agriculture sector. A plant disease can reduce the growth of the plants and affect the quality of the produce, resulting in substantial losses to the growers. Therefore, the early identification of the plant disease is very important. Traditional plant disease diagnosis depends on the observation of farmers or agricultural professionals. These have generally been inefficient, considering the unavailability of experts in many areas and diagnoses conducted too late with subjective judgment. Diseases tend to get out of control before any remedial measure is taken. Recently, with advances in artificial intelligence and deep learning, it has become possible to perform automated disease detection using image-based analyses. Convolutional Neural Networks, CNNs, have proved to be very efficient techniques used in visual classification tasks, such as learning appropriate features relevant to images. Based on such a concept, the AgriFutura system uses CNN analysis on images of plant leaves, combining fertilizer suggestions to offer the farmer a comprehensive support platform via a website.

## 2. Related Work

Recent developments in Artificial Intelligence (AI) and deep learning have greatly improved smart agricultural systems for monitoring crops, detecting diseases, and supporting decision-making. Several researchers have made contributions to this field through machine learning and data-driven methods. Thota et al. [1] proposed the CULTIMAX framework, which focuses on crop selection and trading optimization to improve agricultural sustainability. Their work shows how smart data analysis can boost productivity and profitability. Mourya et al. [2] introduced an AI-driven agronomy model designed to increase crop yield and market profits using predictive analytics. This highlights the growing role of automated decision-making in agriculture. Similarly, Phatangare et al. [3] presented a data-driven system for predicting crop yield and market prices, demonstrating the value of machine learning techniques in helping farmers make financial and production decisions. Shanmugasundaram et al. [4] developed a crop forecasting and estimation model using computational intelligence for precision agriculture. They emphasized yield prediction and profitability analysis as vital for strategic agricultural planning. Additionally, Verma et al. [5] created an AI-based fertilizer recommendation system that offers automated nutrient guidance and reduces fertilizer misuse, which closely

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aligns with nutrient management goals in modern agriculture. While these studies provide valuable insights, most existing systems focus on either disease detection or fertilizer recommendation independently. In contrast, the proposed AgriFutura system stands out by integrating CNN-based plant disease detection, intelligent fertilizer recommendations, and a real-time web-based interface into one unified platform. This offers a more complete and practical solution for farmers.

## 2.1.PROBLEM STATEMENT

Plant diseases are a significant cause of lower crop yields and financial losses for farmers. In traditional farming, disease detection relies on manual observation. This method is slow, often inaccurate, and heavily depends on human experience. Many farmers, especially in rural areas, lack timely access to agricultural experts. This results in delayed diagnosis and improper treatment.Another major problem is the incorrect use of fertilizers due to poor disease identification. Using too much or too little fertilizer raises costs, affects crop growth, and harms the environment. It is also impractical to monitor large farms manually, and early disease symptoms frequently go unnoticed, allowing diseases to spread quickly.Therefore, there is a strong need for an automated, real-time, user-friendly system that can accurately detect plant diseases early and recommend appropriate fertilizer use. Such a system would help reduce crop loss, minimize resource waste, and enhance overall agricultural productivity.

## 2.2. SYSTEM DESIGN OVERVIEW

The AgriFutura system is a modular, web-based decision-support platform that automatically detects plant diseases using Convolutional Neural Networks (CNN). It also provides fertilizer recommendations based on the identified disease. The design focuses on scalability, ease of use, and quick responses for farmers.

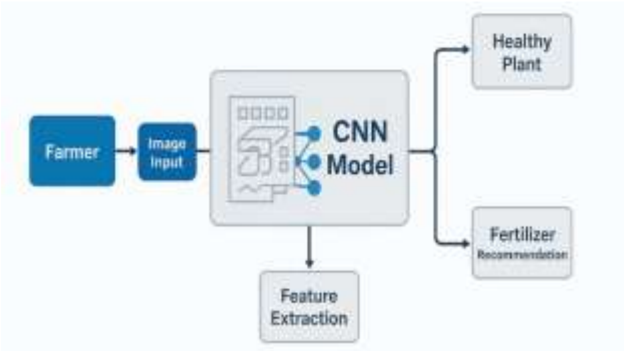
### *A. High-Level Architecture*

The overall structure of the proposed AgriFutura system is shown in Fig. 1. The process starts with the farmer uploading an image of a plant leaf through the system interface. The image then goes through preprocessing, where it is resized and normalized before being sent to the convolutional neural network (CNN). The trained CNN extracts features and classifies the leaf as either healthy or diseased. If the leaf is healthy, the system displays "Healthy Plant." If it is diseased, the classification result goes to the fertilizer recommendation module, which provides appropriate fertilizer or treatment suggestions based on the identified disease. This sequence shows how the main components of the AgriFutura framework interact.

**Fig-1**: High-level design of the AgriFutura system

### *B. Low-Level Design*

The low-level design of the AgriFutura system is shown in Fig. 2. The process starts with the farmer providing a leaf image. This image goes through a preprocessing module for resizing and normalization. The preprocessed image is then input into the CNN model, which handles feature




extraction and disease classification. The CNN output splits into two paths. One path gives the disease prediction, while the other sends the result to the fertilizer recommendation module. This module generates suitable treatment suggestions based on the detected disease.

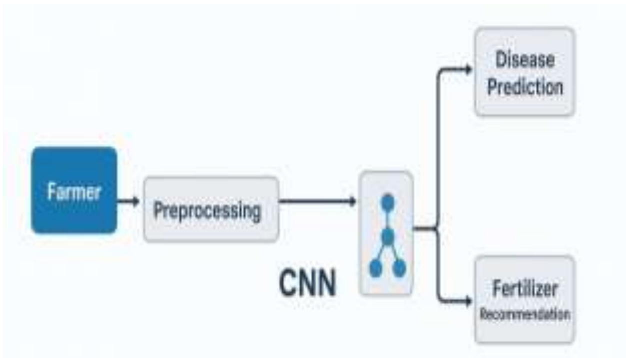



**Fig-2**: Low-level design of the AgriFutura modules.

### *C. CNN Model Architecture*

The detailed layer-wise structure of the AgriFutura CNN model is shown in Fig. 3. The architecture consists of a series of convolutional blocks that extract more complex features from the input leaf images. Each block has a Conv2D layer followed by ReLU activation, batch normalization, and max-pooling at certain stages. The spatial resolution decreases from 224 × 224 to 14 × 14, while the depth of the feature maps increases from 32 to 64 to 128 to 256.

After extracting features, the output is flattened and passed through fully connected layers that are 1024 units wide,

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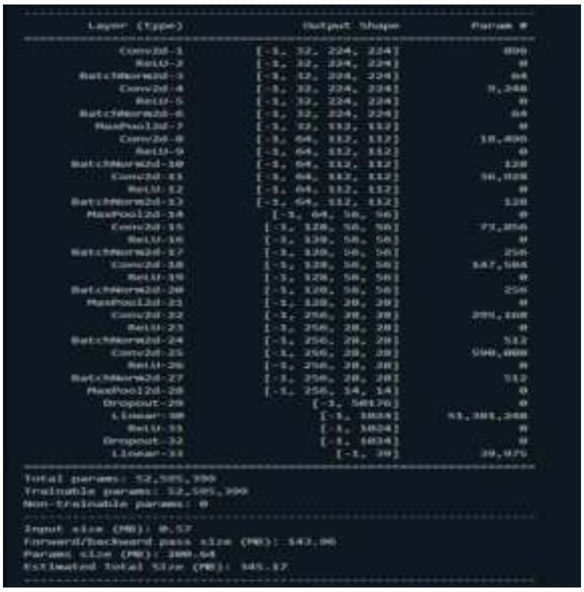
with dropout used to prevent overfitting. The last linear layer generates a 39-class output, which works for classifying multiple types of plant diseases.

The architecture has 52,595,399 trainable parameters, showing that it is a high-capacity model capable of learning detailed visual representations. The estimated memory usage is about 345 MB, meaning that training is best done on hardware with GPU support.



| Layer (type) | Output Shape | Param # |
|---|---|---|
| Conv2d-1 | [-1, 32, 224, 224] | 896 |
| ReLU-2 | [-1, 32, 224, 224] | 0 |
| BatchNorm2d-3 | [-1, 32, 224, 224] | 64 |
| Conv2d-4 | [-1, 32, 224, 224] | 9,248 |
| ReLU-5 | [-1, 32, 224, 224] | 0 |
| BatchNorm2d-6 | [-1, 32, 224, 224] | 64 |
| MaxPool2d-7 | [-1, 32, 112, 112] | 0 |
| Conv2d-8 | [-1, 64, 112, 112] | 18,496 |
| ReLU-9 | [-1, 64, 112, 112] | 0 |
| BatchNorm2d-10 | [-1, 64, 112, 112] | 128 |
| Conv2d-11 | [-1, 64, 112, 112] | 36,928 |
| ReLU-12 | [-1, 64, 112, 112] | 0 |
| BatchNorm2d-13 | [-1, 64, 112, 112] | 128 |
| MaxPool2d-14 | [-1, 64, 56, 56] | 0 |
| Conv2d-15 | [-1, 128, 56, 56] | 73,856 |
| ReLU-16 | [-1, 128, 56, 56] | 0 |
| BatchNorm2d-17 | [-1, 128, 56, 56] | 256 |
| Conv2d-18 | [-1, 128, 56, 56] | 147,584 |
| ReLU-19 | [-1, 128, 56, 56] | 0 |
| BatchNorm2d-20 | [-1, 128, 56, 56] | 256 |
| MaxPool2d-21 | [-1, 128, 28, 28] | 0 |
| Conv2d-22 | [-1, 256, 28, 28] | 295,168 |
| ReLU-23 | [-1, 256, 28, 28] | 0 |
| BatchNorm2d-24 | [-1, 256, 28, 28] | 512 |
| Conv2d-25 | [-1, 256, 28, 28] | 590,080 |
| ReLU-26 | [-1, 256, 28, 28] | 0 |
| BatchNorm2d-27 | [-1, 256, 28, 28] | 512 |
| MaxPool2d-28 | [-1, 256, 14, 14] | 0 |
| Dropout-29 | [-1, 50176] | 0 |
| Linear-30 | [-1, 1024] | 51,381,248 |
| ReLU-31 | [-1, 1024] | 0 |
| Dropout-32 | [-1, 1024] | 0 |
| Linear-33 | [-1, 39] | 39,975 |

Total params: 52,595,399
Trainable params: 52,595,399
Non-trainable params: 0

Input size (MB): 0.57
Forward/backward pass size (MB): 143.96
Params size (MB): 200.64
Estimated Total Size (MB): 345.17

**Fig-3**: CNN model architecture used for plant disease classification.

### *D. Data Flow Diagram*

The Data Flow Diagram (DFD) shown in Fig. 4 illustrates how data moves within the AgriFutura system. The process starts with the farmer uploading a leaf image through the web interface. The image first goes to the Image Input Module, where it is checked and prepared for analysis.

After validation, the image is sent to the Feature Extraction Module. This module identifies important visual traits, such as texture, color distribution, and disease-related patterns. The features extracted are then passed to the Disease Detection Module, which uses a CNN.

In the CNN, the image goes through convolutional layers, ReLU activation, and pooling operations to learn distinctive features. The model classifies the plant as Healthy or Diseased.

If the plant is healthy, the system labels it as a Healthy Plant. If a disease is found, the information goes to the Fertilizer Recommendation Module. This module provides suitable fertilizer and treatment suggestions based on the identified disease.

The final output, whether it shows the health status or the recommended actions, is displayed to the farmer through the web interface. This helps them make timely and informed decisions.

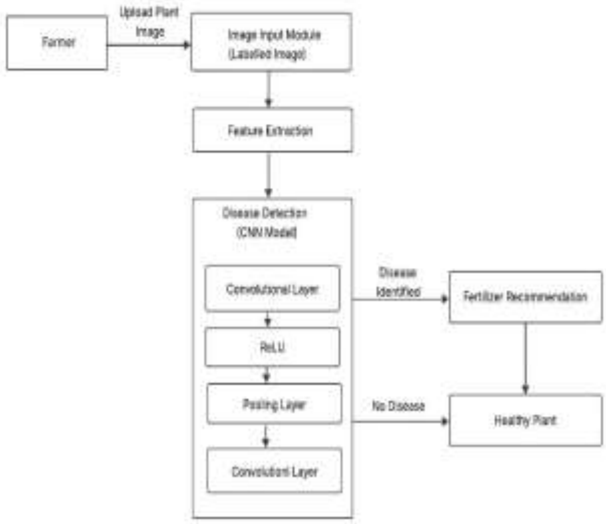



**Fig-4**: Data flow diagram of the AgriFutura system.

### *E. Transfer Learning Architecture*

The transfer learning architecture used in the AgriFutura system is shown in Fig. 5. In this method, a pretrained CNN model is first trained on a large labeled dataset in the source domain. This Source Model learns general visual features like edges, textures, shapes, and color patterns, which apply to many image classification tasks. These features create a solid foundation for further use.

The pretrained weights are then moved to the Target Model, where a smaller, domain-specific plant disease dataset is used for fine-tuning. During this fine-tuning phase, the deeper layers of the network are retrained to identify disease-specific patterns from leaf images. Meanwhile, the earlier layers keep their ability to extract general features. This greatly reduces training time, improves accuracy, and boosts performance, especially when there is limited training data available.

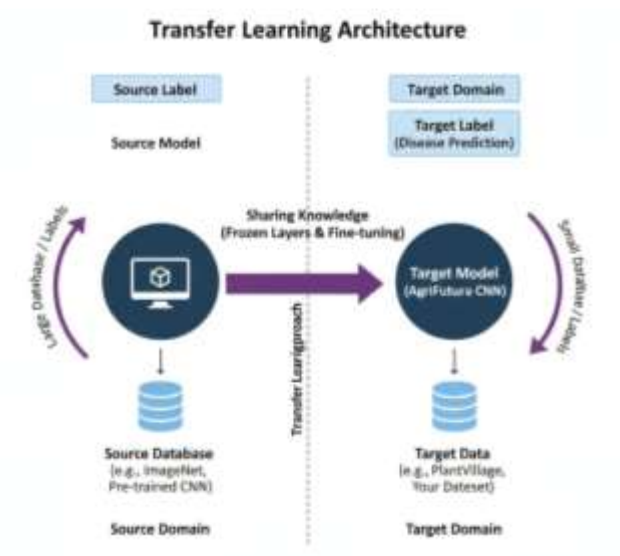



**Fig-5**: Transfer Learning Architecture

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### *F. Use Case Diagram*

The Use Case Diagram in Fig. 6 shows how users interact with the AgriFutura system. Two main actors are involved: the Farmer/User and the Admin.

The Farmer/User uses the system to identify plant diseases and get fertilizer recommendations. The farmer uploads a plant leaf image through the web interface. The system then analyzes the image and gives a disease prediction. Based on this diagnosis, the farmer can see suggested fertilizers and treatments, along with a final summary that includes plant health status and practical advice.

The Admin oversees system operations. The admin can check disease predictions, fertilizer recommendations, treatment suggestions, and final results for monitoring and verification. This helps ensure the system's outputs are correct, consistent, and reliable.

In summary, the Use Case Diagram outlines the roles and interactions of both actors, offering a clear overview of how users use the AgriFutura system for detecting plant diseases and getting fertilizer recommendations.

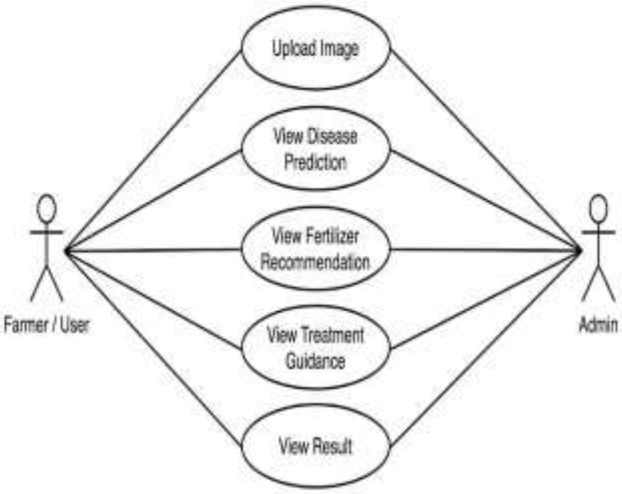


**Fig- 6**: Use case diagram of the AgriFutura system.

## 2.3. IMPLEMENTATION

The AgriFutura system is set up as a complete PyTorch and Flask web application. It provides real-time plant disease detection and fertilizer suggestions. The system uses a trained Convolutional Neural Network (CNN) model, which is integrated into a simple web interface aimed at farmers. When the application starts, users see the AgriFutura home page, the main entry point to the system. As shown in Fig.7, the interface has a clear layout featuring the project title, a "Launch AI Engine" button, and several crop category cards like Apple, Blueberry, Cherry etc.. This design allows for easy navigation and reduces user confusion.


**Fig-7**: Home page UI of the AgriFutura application.

When users move to the AI Engine, the system takes them to the image upload area, where they can choose and submit a leaf image for analysis. After submission, the Flask backend saves the file in the static/uploads directory and performs preprocessing steps, such as resizing and normalization, before sending the image to the trained CNN model. The model predicts the health status or disease type. Based on this prediction, the system retrieves relevant disease descriptions, preventive measures, and supplement suggestions from CSV datasets called disease_info.csv and supplement_info.csv.

The prediction result appears on a dedicated results page. This page shows the detected crop and disease, the uploaded image, recommended preventive actions, and an appropriate fertilizer or fungicide. Each supplement entry includes a product image and a "Buy Product" link that directs the user to an external e-commerce site. Besides the prediction interface, the system has a Supplement Market page with various fertilizer and supplement cards. This lets users explore treatment options without going through the prediction process.

The backend is organized in a modular directory structure. This separates templates, static files, model files, datasets, and the main Flask application script. The directory layout contains a templates folder for HTML files, static/uploads for user images, test_images for internal testing, the main application script app.py, the model definition file CNN.py, and the trained model file.This structured organization makes the system easier to maintain, supports growth, and ensures reliable interaction between the user interface and backend processes. Overall, the implementation shows a clear integration of web technologies, data retrieval modules, and deep learning inference. This combination creates a useful and efficient decision-support tool for modern agriculture.

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## 2.4. RESULTS AND DISCUSSION

The AgriFutura system underwent extensive testing across several functions, including disease detection, fertilizer recommendations, interface navigation, and marketplace integration. Screenshots taken during real-time use provide clear evidence of system performance, stability, and relevance in agriculture. This section examines these results, highlighting both strengths and limitations.

### *A. Disease Detection and Prediction Results*

As mentioned in the implementation section, AgriFutura offers a clear and easy-to-use interface that helps users navigate between different crop categories, as shown in Fig. 8.1. This design allows users to access the AI Engine smoothly. The interface is clean and simple, featuring an image preview window, an upload button, and straightforward instructions, catering to farmers with various levels of digital skills. Evaluation results show that the system works reliably for all supported crop options, including Apple, Blueberry, Cherry, and other plant species included in the platform. The intuitive interface makes user interaction simpler and improves the overall detection process by enabling quick access to the AI Engine for submitting leaf images. This easy navigation greatly enhances the system's practical usability for real-time disease diagnosis in farming environments.


**Fig- 8.1**: AI Engine interface of AgriFutura

During testing, users uploaded leaf images from several crops, including Corn, Orange, and Potato, through the AI Engine. The system consistently produced fast and accurate predictions, as shown in Fig. 8.2(a) and Fig. 8.2(b). For each submitted image, the results page displays the predicted disease at the top, along with crop-specific icons and the uploaded leaf image. For Corn, the system correctly identified Common Rust, which has rust-colored pustules.Similarly, for Tomato leaf, the system correctly identified Mosaic Virus based on mottled light-and-dark green patterns and distorted leaf structure.


Fig.

**Fig-8.2(a)**: Disease prediction output for a Corn leaf, correctly identifying Common Rust based on visible rust pustules


**Fig- 8.2(b)**: Disease prediction output for a Tomato leaf, identifying Mosaic Virus from its mottled leaf pattern

These prediction pages follow a consistent format that includes
(1) a brief description of the disease,
(2) prevention steps specific to the identified disease,
(3) a suggested supplement or fungicide product along with an image.

The CNN model powering this detection maintains high accuracy due to its setup, which includes convolutional blocks, batch normalization, max-pooling layers, and dropout regularization. This setup improves the model's ability to extract disease-related features such as rust pustules, mottling, necrotic spots, and discoloration, all visible in the system screenshots. The system remained robust despite variations in image clarity, lighting, and background noise commonly found in real-world field images.

### *B. Fertilizer and Treatment Recommendation*

A major advantage of AgriFutura is its seamless integration of fertilizer and treatment recommendations immediately after disease detection, as presented in Fig. 8.2(a) and Fig. 8.2(b). Once a disease is identified, the system automatically retrieves the appropriate fertilizers or fungicides. These recommendations include product images and a "Buy Product" button. The recommendation pages use clear and simple language, making them accessible to farmers unfamiliar with technical agriculture terms.

For example, the Corn: Common Rust result recommends a Mancozeb-based fungicide. The Tomato: Mosaic Virus output suggests a suitable antiviral treatment product. After generating these recommendations, the system automatically directs users to the best e-commerce platform. This includes Flipkart and other trusted websites. The selection is based on factors like lower price, available discounts, seller credibility, and stock availability. This shows both the effectiveness of AgriFutura's linking system and the reliability of its curated multi-platform agricultural marketplace database.

By connecting diagnosis with immediate solutions, AgriFutura significantly reduces decision fatigue for farmers. Early and accurate treatment suggestions help prevent widespread infections, reduce crop losses, and improve agricultural productivity.

### *C. Web Application Performance*

The AgriFutura web platform shows strong performance, responsiveness, and a high-quality user experience. The interface uses a green and white theme that reinforces an agricultural feel while maintaining a professional appearance, as shown in Fig. 6.4. Navigation across all sections, including the Home, AI Engine, and Supplements pages, is smooth.

Image uploads are processed in real-time, and predictions are generally generated within seconds. The Supplement Market page offers a catalog of products for both diseased and healthy plants organized into categories such as "Supplements (Diseased)" and "Fertilizer (Healthy)," also shown in Fig. 8.3. For example,Crops such as Potato and Raspberry are displayed with both fungicides and nutritional fertilizers. The consistent card-based layout and functioning "Buy Product" buttons confirm the reliability of the routing and linking system.


**Fig.-8.3**: Supplement Market interface displaying curated agricultural products.

### *D. Discussion*

Overall, AgriFutura proves to be an effective and scalable solution for modern precision agriculture. Unlike traditional disease detection systems that merely classify images, AgriFutura extends functionality by providing prevention strategies, fertilizer recommendations, and direct product procurement options. The user-friendly interface and real-time AI performance ensure accessibility for non-technical users.

However, as with any machine-learning system, performance depends heavily on the training dataset. Rare diseases, unseen variants, extreme lighting conditions, severely damaged leaves, or low-resolution uploads may lead to lower confidence. These challenges highlight opportunities for future improvements, such as expanding the dataset, integrating sensor-based imaging, or adding confidence-level alerts.

Despite these limitations, the system's strengths fast disease detection, actionable recommendations, marketplace integration, and an intuitive interface make AgriFutura highly suitable for real-world agricultural deployment. With future upgrades such as multilingual support, mobile app integration, and weather-aware prediction models, AgriFutura can greatly improve sustainable and technology-driven farming.

## 2.5. BENEFITS AND DRAWBACKS

### *A. Benefits*

The AgriFutura system offers several important benefits that improve its usefulness in real-world farming. Its deep learning-based CNN model allows for reliable early detection of plant diseases. This helps farmers take timely preventive and corrective actions to significantly reduce potential yield losses. The system's real-time fertilizer and treatment recommendation module strengthens its practical value by guiding users toward solutions specific to diseases without needing expert help. The web interface is designed for clarity and simplicity, ensuring that users with different levels of digital skills can access all system features easily. This user-focused design makes navigation smoother, speeds up interactions, and lowers the learning effort. Additionally, AgriFutura saves time and money by reducing reliance on agricultural specialists, allowing farmers to make informed decisions on their own. The platform also encourages the adoption of smart farming practices by combining AI-driven diagnosis with product sourcing support. Its built-in supplement marketplace redirects users to different e-commerce sites based on price, discounts, and product availability, enhancing convenience and helping users access the right fertilizers and treatments quickly.

### *B. Drawbacks*

Despite its strengths, AgriFutura has several limitations that should be recognized. The system's diagnostic accuracy is limited to the diseases included in the training dataset, making it less effective for rare, new, or unclear plant infections. Image quality is crucial for reliable predictions; poorly captured images with shadows, blur, harsh lighting, or partial visibility may lower model confidence. Since AgriFutura relies on a web-based interface, users need uninterrupted internet access for real-time functionality, which can be a problem in rural areas or regions with poor connectivity. The current version lacks multilingual support, limiting accessibility for farmers who prefer local or regional languages. Furthermore, the system does not consider environmental factors like soil characteristics, weather patterns, or humidity, which are often vital for thorough agricultural diagnosis and decision-making. Finally, training and updating the CNN model require significant computing resources, making frequent model retraining costly and less practical for widespread use in areas with limited resources.

### 3. CONCLUSIONS

The AgriFutura Plant Disease Detection and Fertilizer Recommender System utilizes deep learning effectively by using CNNs for accurate plant disease prediction from images of plant leaves and providing real-time fertilizer recommendations using an easy-to-use web interface. It not only reduces the requirement of sophisticated hardware but also proves useful for farmers, especially in rural settings, without burdening them with higher costs. AgriFutura, with its comprehensive offering of plant disease diagnosis and effective recommendations, can be classified as a useful decision-support system useful for farmers in overcoming challenges related to reduced productivity associated with sustainable agriculture practices. This project illustrates the robustness of deep learning-based image analysis solutions in agriculture in today’s era.

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