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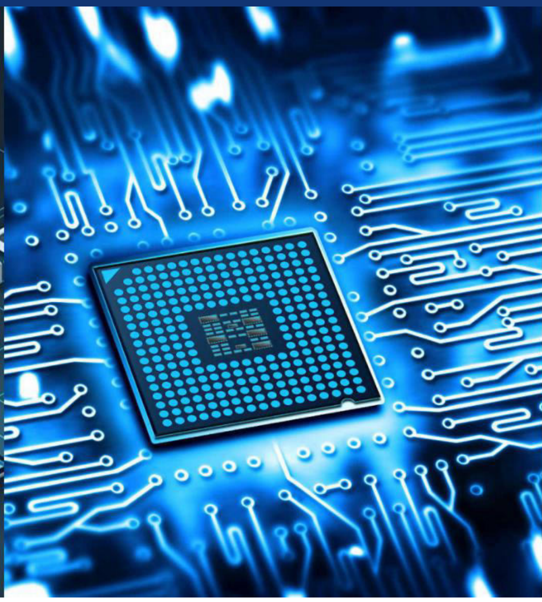


# International Journal of Innovative Research in Computer and Communication Engineering

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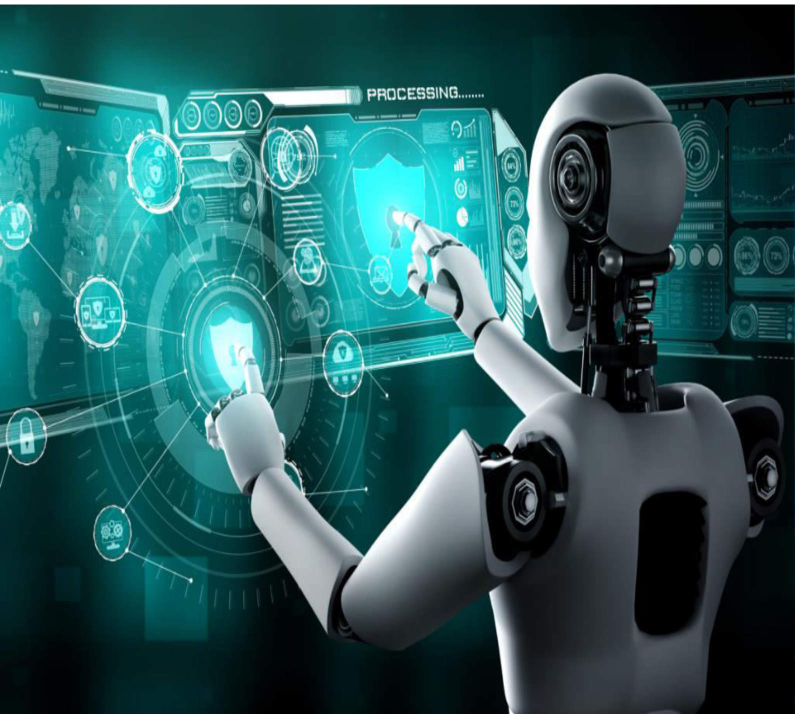

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# AI-Driven Crop Disease prediction and Management System

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**ABSTRACT:** In response to the issues of volatile climate patterns and infestations by pests, this proposal aims at creating a software application capable of assisting farmers in identifying plant diseases and detecting pests. The main aim is to equip farmers with a tool that allows for early identification, which will aid in making well-informed decisions in crop management. Through the use of machine learning algorithms and sophisticated image recognition methods, the suggested software is expected to deliver precise identification of pests and diseases. This technological solution has the potential to play an important role in minimizing crop losses and reducing the dependency on chemical inputs in agriculture. The proposed software is an invaluable tool for farmers around the world, providing a functional means to increase their capacity to effectively counteract new threats to crop health. With this innovation, the agricultural community can enjoy a more sustainable and more resilient approach to agricultural practices, ensuring long-term viability and productivity under threatening environmental conditions.

## I. INTRODUCTION

Agriculture is a paramount importance in India, serving as the backbone of the economy and a major source of livelihood for millions. It ensures food security, generates employment, contributes to exports, and plays a vital role in cultural traditions and rural development. The sector's resilience is crucial for overall economic stability and societal well-being. The agricultural landscape is continuously threatened by various diseases and pests that adversely impact crop health and yield. Yield loss due to a particular disease not only depends on the severity of the disease but also on weather conditions, the aggressiveness of the pathogen, and the capacity of the crop to make up for diminished photosynthetic surface. Plant diseases pose a multifaceted threat to agricultural produce, adversely affecting shelf life, nutritional content, yield, and overall aesthetic appeal. The ramifications are extensive, rendering certain crops unsuitable for the market. The predominant culprit behind plant diseases is fungi, with well over 100,000 species identified. Notably, only a relatively small fraction of these fungi can induce plant diseases Globally, an estimated14.1diseases. In India, the impact is particularly pronounced, with losses rangingfrom 15output due to the combined effects of pests, weeds, and diseases. Accurately estimating yield losses becomes paramount in strategizing disease management, determining thresholds that warrant acute control measures. This approach not only addresses economic concerns but also aligns with environmentally sensible practices, fostering a balanced and sustainable approach to agricultural disease management. In response to these challenges, our initiative is focused on providing farmers with advanced tools for the early detection and identification of crop diseases and pests through the implementation of Deep Learning models. The unpredictable nature of temperature changes and weather fluctuations significantly contributes to the vulnerability of crops, making it imperative for farmers to adopt proactive measures. Our approach leverages the power of the Learning field of Agriculture. Deep Learning is an Artificial Intelligence method that trains computers to process data in a manner that imitates the human brain. Deep learning models can identify intricate patterns in images, text, audio, and other data to generate precise insights and forecasts. There exist three categories of commonly utilized deep neural networks, i.e., Multi-Layer Perceptron (MLP), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN). In Deep Learning, a Convolutional Neural Network or CNN refers to a deep learning network architecture that learns directly from data. CNNs are best suited to look for patterns in images to recognize classes, categories, and objects. They are also very useful in classifying signal, time-series, and audio data. By harnessing the capabilities of Deep Learning, we aim to empower farmers with a sophisticated tool that not only detects but also accurately identifies the nature of the threats to their crops. Farmers may not be able to accurately identify the disease of the crop or the pests attacking their crops, to take preventive measures, which may further lead to yield loss. In essence, our Deep Learning based Integrated Crop Protection Management system serves as a technological ally, offering farmers a reliable means to enhance their decision-making processes and implement targeted interventions. We aspire to contribute to the sustainability and productivity of agricultural practices, ultimately fostering a more resilient and secure future for farmers and productivity E. Detection of Tomato Leaf Diseases for Agro-Based Indus- tries Using of agricultural practices. Rest of the section is contributed as follows: Section2deals with the detailed analysis of literature survey. Section3contains the process of proposed CNN method. Section4provides the results of the CNN model for the plant diseasedetection and pests identification.

## II. LITERATURE REVIEW

A. Deep Learning Model for Plant Disease Identification and Classification with Pesticide Recommendation.
It employs PDDC-Net system employs deep learning models for detecting and classifying plant diseases along with pesticide suggestion. PDDC-Net is able to detect and classify plant diseases accurately, which can assist farmers in taking timely action so that crop loss can be prevented. The system is able to suggest pesticides for plant diseases, which can reduce time and resources for farmers. The data used in this research is limited to rice diseases, and the system might not work as efficiently on other crops.
PDDC-Net might not be available to farmers who lack access to technology or the internet.

B. Machine Learning and Deep Learning for Plant Disease Detection and Classification

It applies Machine Learning and Deep Learning approaches to plant disease detection and classification. Delineates the most promising Machine Learning and Deep Learning methods for plant disease detection and classification. Does not give an exhaustive overview of all ML and DL methods applied to precision agriculture, but only specifically for the detection and classification of plant diseases

C. Plant Disease Classifier: Detection of Dual-Crop Diseases Using Lightweight 2D CNN Architecture
It trains the 2D CNN model on the training set. Visualizes the detection obtained by the trained model using class activation maps and a heatmap produced using the Grad-CAM technique. The 2D CNN model is lightweight and needs less storage space and parameters compared to transfer learning models. The methodology obtains high accuracy in plant disease detection in tomato and cotton leaves. Plant Disease Classifier is effective for dual-crop diseases in tomato, however, its effectiveness with other crops or diseases may not be as good.

D. Wheat Disease Classification Using Continual Learning
Employing few-shot learning methods using state-of-the-art EfficientNet as the base architecture. Employs an attention- based mechanism for feature extraction to minimize false positives even from a small number of images from new classes. Evades the pitfalls of data-thirsty deep learning architectures. Has the capability to adapt to new classes with small data. Results are not strictly comparable to other work.Novel PCA DeepNetEmploys a PCA DeepNet architecture with 10 CNN layers for the identification of tomato leaf diseases. The architecture can be further optimized to minimize computational time and complexity while ensuring high accuracy. It is restricted to the identification of tomato leaf diseases and does not deal with other forms of plant diseases.

## III. PROPOSED METHOD

With the intent of addressing the prevailing research gap and enhancing the accessibility of crop protection solutions, our proposed methodology centers around the implementation of a Sequential Convolutional Neural Network (CNN) model. The Sequential model in the realm of neural networks, particularly in frameworks like TensorFlow and Keras, represents a linear stack of layers. This model type is characterized by a straightforward, feedforward architecture, making it well-suited for building simple neural networks where data flows sequentially from input to output. The sequential nature of the model implies that each layer in the stack has precisely one input tensor and one output tensor, creating a step-by- step of data processing. This approach is designed to significantly improve the accuracy and applicability of the model, while simultaneously addressing challenges related- quality and user-friendliness. Our methodology is tailored to assist farmers in the detection of plant diseases across a diverse range of crops. Specifically, it targets 2 key crops, namely Apple and Potato. The utilization of the model ensures that the model is capable of accurately identifying diseases affecting these crops, contributing to a more comprehensive and inclusive agricultural

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support system. In tandem with disease detection, our proposed methodology extends its capabilities to pest detection. The integration of the Sequential model and the meticulous consideration of a diverse dataset encompassing these 2 crops and 10 pests enhances the versatility and reliability of our proposed methodology. Coupled with an emphasis on user-friendly implementation, our approach strives to bridge existing gaps and offer farmers an efficient, accessible, and comprehensive solution for integrated crop protection management. Model Construction Process consists of a few steps, like data collection, pre-processing, deciding the model architecture, training the model with the datasets, testing the model, and evaluating the model's performance.

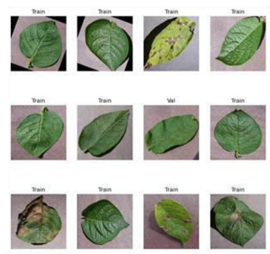

Fig 3.1. Images from the Dataset

A. Data Collection and Pre-processing

Assemble a diverse and representative dataset containing ages of various crops, diseases, and environmental conditions. Annotate the dataset with accurate labels for plant species, diseases, and other relevant attributes. Resize and standardize- ize images, perform data augmentation to enhance diversity, and split the dataset into training, validation, and testing sets.

B. Model Architecture

Experiment with different deep learning architectures, emphasizing those designed for small-scale object detection and robustness to environmental variations. Discuss transfer learning methods, taking into account pre-trained models and fine-tuning for the particular goals. Upon trying out various models, we determined the Sequential CNN model to be the best with both datasets. Figure 3.2 illustrates the architecture of the Sequential CNN model employed. The model is constructed using a data augmentation layer, several layers of convolutional layers, and max pooling layers. Flattening is performed at the end of such convolutional and max pooling layers. It serves to transform all the resulting 2-dimensional arrays from pooled feature maps into one long continuous linear vector. The flattened matrix is passed as input to the fully connected layer in order to classify the image.

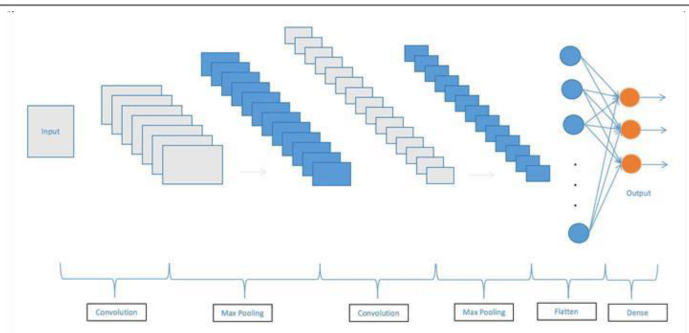


Fig. 3.2. Layers of the Sequential Model

used for this model training are previously separated into training and testing sets. We randomly divide the dataset into three sets named as the train, validation, and test set. The splits may be 50/25/25 or 60/20/20 or any other effective ratio. We train the model on the train set. We test the model on the validation set while training the model. Hyperparameter tuning enables to adjust model performance to achieve the best results. Tuning is an integral part of deep learning, and selecting suitable hyperparameter values is vital to success. Hyperparameters are kernel size, number of kernels, stride

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length, and pooling size, which directly influence the CNN's performance and training speed. Additionally, the effect of hyperparameters grows as the network becomes more complex. Table 2 provides the hyperparameters values for our combined model. If you only have a limited amount of records in your data or are seeing a lot of records fail validation, you might need to significantly boost the number of epochs to allow the neural network to learn the data structure. Plant dataset contains massive data and the Pest dataset contains much lesser data in comparison with the Plant Dataset. Hence the epochs for plant disease detection model are fewer than the pest detection model.

**TABLE II. HYPERPARAMETERS**

| **Hyperparameters** | **Values** |
|---|---|
| Kernel size | (3,3) |
| Pooling size | (2,2) |
| Batch size | 32 |
| Number of Epochs (Plant Disease Detection Model) | 10 |
| Number of Epochs (Pests Detection Model) | 70 |

TABLE II HYPERPARAMETER SETTINGS

A. Training TABLE I NEURAL NETWORK LAYER SUMMARY

| Layer | Output Shape | Parameters # |
|---|---|---|
| sequential 1 | (32, 256, 256, 3) | 0 |
| sequential | (32, 256, 256, 3) | 0 |
| Conv2d 12 | (32, 254, 254, 32) | 896 |
| Max pooling2d 11 | (32, 127, 127, 32) | 0 |
| Conv2d 13 | (32, 125, 125, 64) | 18496 |
| Max pooling2d 12 | (32, 62, 62, 64) | 0 |
| Conv2d 14 | (32, 60, 60, 64) | 0 |
| Max pooling2d 13 | (32, 30, 30, 64) | 0 |
| Conv2d 15 | (32, 28, 28, 64) | 36928 |
| Flatten 1 | (32, 256) | 0 |
| Dense 1 | (32, 64) | 16448 |
| Dense 2 | (32, 3) | 195 |

B. Testing and Evaluation

Evaluate the trained models on the dedicated testing set to assess their generalization performance. Employ validation

Dividing the dataset into training and testing is a very important step in the model's performance. Both the datasetstechniques, such as cross-validation or holdout claim, to ensure goodness in assessing model effectiveness. Analyze

key metrics, such as accuracy, to gauge the model's perfor- mance on both the training and testing datasets. Iteratively refine the model based on validation results, adjusting hyperpa- rameters as needed to achieve optimal results in terms of both accuracy and generalization.

## IV. RESULTS

An integrated model solution encompassing both crop dis- ease detection and pest detection models. The model features a crop disease detection model capable of identifying diseases based on input leaf images. The model is trained to recognize diseases in 2 different crops: Apple and Potato. The model includes a pesticide detection model trained to identify pests in agricultural settings. The model is trained to recognize nine specific pests: Aphids, Armyworm, Beetle, Bollworm, Grasshopper, Mites, Mosquito, Sawfly, and Stem Borer.

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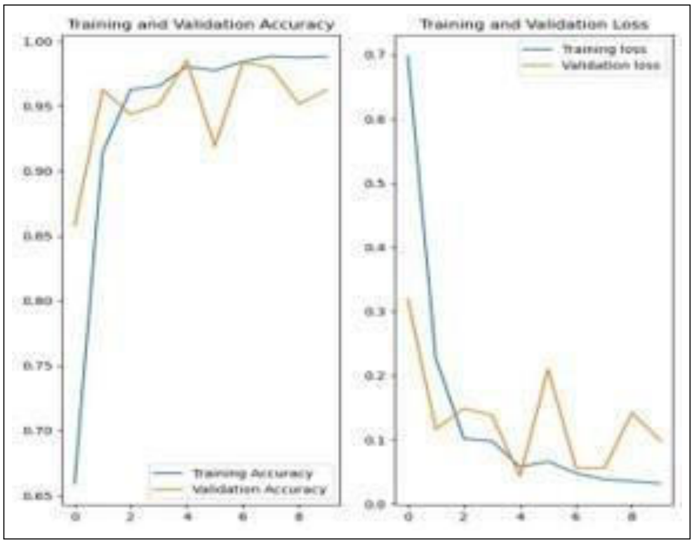


The integrated system aids farmers in easily identifying crop diseases, enabling them to take timely preventive measures. By pinpointing the specific crop disease, farmers can implement targeted interventions, safeguarding the overall health of the crop and enhancing yield.

The pest detection module assists farmers in identifying the type of pest affecting their crops. This information empowers farmers to take effective preventive measures against the iden- tified pests, contributing to better pest management practices. The integrated model serves as a valuable tool for farmers, providing actionable insights for disease and pest management. By facilitating early detection and appropriate intervention, the model contributes to crop health and, consequently, improved agricultural yields.

The model successfully detects the plant disease for both Apple and Potato with a accuracy of 99% and also detects the Pests for 10 different pests with a accuracy of 95%. These models are connected to the backend API using the FastAPI.It is a lightweight, quick (high-performance), web framework to create APIs with Python 3.7+ using standard Python type hints. It should be easy to use and quick to create high- performance APIs.

## V. CONCLUSION

In summary, the Integrated Crop Protection Management model is a transformative solution merging crop disease detection and pest identification for diverse crops. Future plans involve deploying this comprehensive tool as a mobile application, ensuring widespread accessibility for farmers. The model's deep learning capabilities empower farmers to swiftly identify and address crop diseases and pests, promoting targeted interventions. The impending mobile app launch reflects our commitment to user-friendly access, enhancing the practicality of this advanced agricultural tool. By leveraging technology, we strive to democratize crucial information for farmers, fostering sustainability and maximizing yields. The integrated model stands as a bridge between innovation and practical solutions, aiming to revolutionize global agriculture and contribute to food security.

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