RES MILITARIS
Social Science Journal

AI-DRIVEN APPROACH FOR MULTICROP DISEASE CLASSIFICATION WITH PESTICIDE RECOMMENDATION SYSTEM

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ABSTRACT

A country's inventive growth is dependent on the agricultural sector. Agriculture, the foundation of all nations, offers food and raw resources. Agriculture is hugely important to humans as a food source. As a result, plant diseases detection has become a major concern. The history of using technology in agriculture dates back several decades, but the application of deep learning in crop disease detection gained prominence in the early 21st century with the advent of powerful computing systems and large datasets. In the traditional system, farmers heavily relied on manual observation and knowledge passed down through generations to identify crop diseases. Agricultural experts would physically inspect the crops, diagnose diseases based on visible symptoms, and suggest remedies. While this method had its merits, it was time-consuming, dependent on the expertise of the observer, and sometimes led to misdiagnosis. Therefore, the need for an advanced approach like deep learning in crop disease detection arises from the growing global population and the subsequent increase in food demand. Timely and accurate identification of crop diseases is crucial to prevent significant yield losses. By automating the detection process, farmers can take swift actions to mitigate the spread of diseases, thereby ensuring higher agricultural productivity. Moreover, providing precise pesticide suggestions reduces the environmental impact of farming by minimizing the unnecessary use of chemicals. Deep learning algorithms, particularly convolutional neural networks (CNNs), have proven to be highly effective in image recognition tasks, making them ideal for identifying patterns in images of diseased crops. The introduction of deep learning in agriculture, specifically in crop disease detection and classification, has revolutionized the way farmers manage their crops. By leveraging advanced technologies, farmers can now detect diseases in crops more accurately and efficiently. This has significant implications for food security, as it enables timely intervention and suggests appropriate measures, such as pesticide usage, to curb the spread of diseases.

1. INTRODUCTION

1.1 Overview

The history of multi-crop disease classification and pesticide recommendation systems can be traced to the intersection of agriculture and emerging technologies. In the late 20th century, early attempts to automate disease detection focused on basic rule-based systems. However, the true revolution came with the integration of machine learning in the early 21st century.

As computer vision and image recognition technologies advanced, researchers began applying these tools to agricultural images, enabling more accurate and efficient identification of crop diseases. This laid the foundation for multi-crop disease classification systems, which could analyze images from various crops and distinguish between healthy and infected plants.

Simultaneously, the development of pesticide recommendation systems gained momentum. Initially, these systems relied on expert knowledge and predefined rules. However, with the rise of machine learning algorithms and access to vast datasets, these systems evolved to incorporate dynamic factors such as weather conditions, soil health, and historical disease patterns.

Deep learning models, particularly convolutional neural networks (CNNs) in computer vision applications, enhance the precision of crop disease detection. By learning intricate patterns and features within images, these models can distinguish between healthy and infected plants across various crops.

Prior to the advent of computing technology, agricultural scientists relied on manual observation, experimentation, and domain knowledge to identify crop diseases and recommend treatments.The understanding of plant diseases dates back centuries, with early efforts focused on documenting symptoms, identifying pathogens, and developing rudimentary treatments.Agricultural extension services and research institutions played a crucial role in disseminating knowledge about crop diseases and management practices to farmers.The development of computing technology in the mid-20th century provided new tools for data analysis, modeling, and decision support in agriculture.Early computer-based agricultural systems focused on basic tasks such as data management, weather forecasting, and crop yield estimation.

The 1980s saw the emergence of expert systems in agriculture, including disease diagnosis and management.Expert systems were rule-based computer programs that encoded domain-specific knowledge provided by agricultural experts.These systems helped farmers and agricultural professionals make informed decisions about disease identification, treatment selection, and pest management.

1.2 Problem Statement

Design and implement a robust multi-crop disease classification and pesticide recommendation system using deep learning methodologies. The system should leverage convolutional neural networks (CNNs) or other advanced deep learning architectures to accurately identify and classify diseases across diverse crops based on input images. Additionally, integrate a recommendation mechanism that considers the identified diseases, crop characteristics, and environmental factors to suggest appropriate pesticides for effective and targeted crop protection. The goal is to develop an intelligent and scalable solution that enhances precision in disease detection and pesticide recommendations, ultimately optimizing agricultural practices and promoting sustainable crop management.

The problem at hand involves addressing the challenges in modern agriculture related to crop disease identification and management. The goal is to develop a sophisticated multi-crop disease classification and pesticide recommendation system employing deep learning techniques.Agricultural productivity is significantly hindered by the prevalence of diseases affecting various crops. Traditional methods of disease identification and pesticide application lack precision, often leading to inefficient resource use and environmental concerns. Therefore, a solution is needed that leverages the power of deep learning, specifically convolutional neural networks (CNNs) or similar architectures, to enhance the accuracy of disease classification.

The system must be capable of analyzing input images of crops and accurately identifying the presence of diseases across multiple crops. The deep learning model should be trained on diverse datasets encompassing various crop types and diseases to ensure robust performance in real-world scenarios.Furthermore, the system should go beyond disease identification by incorporating a pesticide recommendation mechanism. This involves considering the identified diseases, specific characteristics of the crops, and environmental factors. The recommendation system should provide targeted and effective suggestions for pesticide application, aiming to optimize crop protection while minimizing environmental impact and resource use.

By addressing these challenges through deep learning, the envisioned solution aims to revolutionize crop management practices, promoting sustainable agriculture, and ultimately contributing to global food security. The successful implementation of such a system could significantly improve the efficiency and effectiveness of pest control in agriculture, benefitting farmers and ecosystems alike.

1.3 Research Motivation

We have gone through this research because considering an example. Andhra Pradesh has 13 districts six agro-climatic zones, and five different soil types. The state has 10.1 million of cultivated area but the profit is only upto 55% only. The major cause of less profits in agriculture is lack of proper knowledge about soil types and its importance and the different types of crops which we can grow and also the major reason of less profit is identifying the crop disease late and to cure it usage of harmful chemicals which provide instant benefits and later it destroy everything like soil it makes the soil toxic as well weak and un nutrient so the automatically the next yield will be effect automatically.to overcome it we have gone through these project. The main motto of this research is to improve the accuracy and profit in the agriculture sector. And it is also about developing the phenomenal changes in agriculture sector with different technologies. We want to dedicate our knowledge that we have extracted in this stream to our nation so that is the main motto of choosing this project which brings the different changes in the agriculture that defines the profits and growth of nation as well farmers.

Food Security Concerns: With the world's population increasing, there is a growing need to ensure food security. Crop diseases can significantly affect agricultural productivity, leading to food shortages and economic losses. By accurately identifying and treating crop diseases, agricultural productivity can be enhanced, contributing to global food security.

Limited Expertise: In many regions, there is a shortage of agricultural experts who can accurately diagnose crop diseases. AI-driven systems can act as virtual experts, leveraging vast amounts of data to identify diseases with high accuracy, even in regions lacking specialized human expertise.

Environmental Sustainability: Traditional methods of pesticide application can lead to overuse, resulting in environmental degradation and health hazards. An AI-driven system can recommend precise pesticide treatments based on disease identification, reducing the overall use of pesticides and minimizing their negative environmental impact.

Economic Efficiency: Crop diseases can cause significant economic losses for farmers. By accurately diagnosing diseases and recommending targeted treatments, an AI-driven system can help farmers minimize losses and optimize their crop yields, leading to increased economic efficiency and sustainability.

Data Availability: The availability of large datasets containing information about crop diseases, including images, symptoms, and geographical data, has grown significantly in recent years. AI-driven algorithms can leverage these datasets to build robust disease classification models and pesticide recommendation systems.

Technology Accessibility: With the increasing availability and affordability of technologies such as smartphones and drones, farmers in remote areas can access AI-driven solutions for disease diagnosis and pesticide recommendations, democratizing access to agricultural expertise and improving outcomes for smallholder farmers.

Overall, the motivation for research in AI-driven approaches for multicrop disease classification with pesticide recommendation systems lies in addressing pressing agricultural challenges, enhancing food security, promoting environmental sustainability, and improving economic outcomes for farmers.

1.4 Application

Enhanced Precision: Deep learning techniques, such as convolutional neural networks (CNNs), provide superior accuracy in multi-crop disease classification, ensuring precise identification of diseases across various crops.

Adaptability to Diverse Crops: The system should be designed to handle a wide range of crops, considering variations in leaf structures, sizes, and textures to create a comprehensive and adaptable solution.

Large and Diverse Dataset: Training the deep learning model requires a large and diverse dataset encompassing different crops and their associated diseases, ensuring robust performance and generalization capabilities.

Pesticide Recommendation Customization: The system should take into account specific crop characteristics, environmental conditions, and disease severity to provide personalized and optimized pesticide recommendations tailored to each situation.

Integration of Environmental Factors: Incorporating weather conditions, soil quality, and other environmental factors into the recommendation system enhances its precision and relevance in different agricultural contexts.

User-Friendly Interface: Designing an intuitive and user-friendly interface for farmers or agricultural practitioners to interact with the system facilitates easy adoption and ensures practical usability in the field.

Scalability: The system should be scalable to accommodate the increasing variety of crops and evolving agricultural landscapes, allowing for widespread adoption and long-term applicability.

Resource Efficiency: By precisely targeting pesticide application, the system contributes to resource efficiency, minimizing the use of chemicals while maximizing the effectiveness of crop protection measures.

Real-Time Disease Detection: Implementing a real-time disease detection mechanism allows for timely identification, enabling prompt intervention and preventing the spread of diseases within crops.

2. LITERATURE SURVEY

G. K. Srikanth, et al. [1] proposed a method in the abstract involves an integrated and collaborative platform for automated disease diagnosis, tracking, and forecasting in the context of plant diseases. Here are the key components of the proposed approach In recent years, there has been a significant shift towards leveraging advanced technologies like deep learning for predictive modeling in agriculture. One such approach involves utilizing environmental data pertaining to crop growth to develop predictive models for disease and pest infestations.

Maheng, et al. [2] proposed a method for crop disease detection and pest prediction, based on AI and deep learning, involves the following key aspects:through the application of deep convolutional neural networks (CNNs), researchers have achieved an impressive accuracy rate of 99.35% in identified 14 crop species and 26 diseases from controlled leaf images. This breakthrough not only surpasses the capabilities of traditional methods but also addresses critical challenges such as labour costs, accuracy, and environmental impact. Despite these advancements, challenges persist, including data-intensive tasks, processing time, and storage limitations associated with deep learning approaches.

Venkatasaichandrakanth.p,et al. [3] proposed a method for pest detection and classification using deep learning involves the following key aspects:Looking ahead, the integration of artificial intelligence (AI) and deep learning holds tremendous promise for revolutionizing crop disease management and prevention, ushering in an era of more efficient, accurate, and sustainable agricultural practices."

Ramya N, et al. [4] proposed a method for plant disease detection using deep learning involves the following key aspects agricultural technology advancements, deep convolutional neural networks (CNNs) play a pivotal role. These sophisticated algorithms excel in swiftly recognizing disease indications and symptoms from plant leaves and stems, thereby facilitating the promotion of healthy crop growth. Additionally, employing pre-trained deep learning .

Tirkey,et al. [5] proposed a method utilizes deep learning, specifically YoloV5, InceptionV3, and CNN models, for real-time identification and detection of insects in Soybean crops. Achieving high accuracies of 98.75%, 97%, and 97% respectively, the YoloV5 algorithm stands out for its exceptional speed at 53fps, making it suitable for efficient real-time insect detection. The study aims to streamline agriculture practices by reducing the workload of producers through a simplified yet effective solution.

Ramanjot ,et al. [6] proposed a method for plant disease detection in India, focusing on data sources, pre-processing, feature extraction, data augmentation, and model selection. A comprehensive analysis of 182 papers from 2010 to 2022 identifies 75 relevant works, providing a valuable resource for researchers aiming to enhance system performance and accuracy in plant disease identification through data-driven approaches.

Ma L,et al. [7] introduced CTR_YOLOv5n,has been improved YOLOv5n model for detecting common maize diseases (leaf spot, gray spot, and rust) in mobile applications. The model incorporates a Coordinate Attention (CA) mechanism and a Swin Transformer (STR) detection head (TR2), enhancing accuracy by 2.8% compared to the original model while significantly reducing memory size to 5.1MB, meeting lightweight requirements for mobile use.

Shoaib M, et al. [8] explored the application of Machine Learning (ML) and Deep Learning (DL) techniques for early identification of plant diseases, addressing the limitations of manual detection methods. Focusing on advancements between 2015 and 2022, the study emphasizes improved accuracy and efficiency in plant disease detection through experimental validation.

Guerrero A , et al. [9] Tproposed a Convolutional Neural Network (CNN)-based model for identifying and classifying tomato leaf diseases in Mexico. Utilizing a public dataset and additional field photographs, the model incorporates generative adversarial networks to mitigate overfitting.

Ahmed I, et al. [10] presented an automated method for early detection of plant diseases on large crop farms using machine learning and deep learning techniques. Utilized the "Plant Village" dataset with 17 diseases across 12 crop species, the study employs support vector

3.PROPOSED SYSTEM

3.1 Overview

- **Importing Libraries:** Importing necessary libraries such as Tkinter for GUI, Matplotlib for plotting graphs, NumPy for numerical operations, OpenCV for image processing, Keras for building and training neural networks, and others.
- **Global Variables:** Several global variables are declared to be used across functions, such as filename, X (input data), Y (labels), model, and accuracy.
- **GUI Initialization:** The main Tkinter window is created with a specific title and geometry.
- **Functions:**

- **UploadDataset:** Allows the user to upload the dataset containing images of crops with associated labels.
- **ImageProcessing:** Processes the uploaded images, normalizes them, and prepares them for training.
- **cnnModel:** Builds and trains a convolutional neural network (CNN) model for crop disease classification. It either loads a pre-trained model or creates a new one using transfer learning.
- **predict:** Allows the user to upload a test image, performs prediction using the trained model, and displays the predicted disease along with the suggested pesticide.
- **graph:** Plots the accuracy and loss graph based on the training history.
- **close:** Closes the GUI window.
- **GUI Components:**
- **Labels:** Display the title and headings.
- **Buttons:** Perform specific actions such as uploading dataset, image processing, model building, prediction, plotting graph, and exiting the application.
- **Text Box:** Displays messages and information about the processing steps and results.
- **Configuration and Styling:** Various configurations such as font, size, color, and placement are set for GUI components to enhance readability and aesthetics.
- **Main Loop:** The mainloop() function of Tkinter is called to run the GUI application indefinitely until the user closes the window.

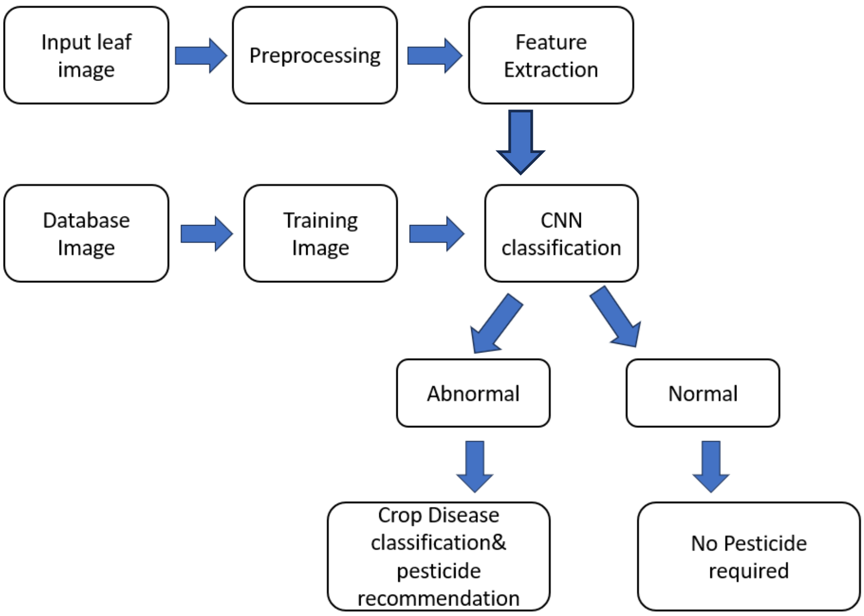


Fig 4.1.1 Flow Diagram of Proposed CNN Model

3.2 Image Preprocessing

Image preprocessing is a fundamental step in preparing raw image data for input into Convolutional Neural Networks (CNNs), ensuring that the data is standardized, enhanced, and augmented to improve the network's performance and robustness. Each preprocessing step serves a specific purpose in refining the data for optimal learning by the CNN.

Resizing involves adjusting the dimensions of images to a fixed size, ensuring uniformity across the dataset. This step is crucial as CNNs typically require inputs of consistent dimensions to process images efficiently. Resizing can be achieved through scaling, cropping, or padding techniques, depending on the desired output dimensions and aspect ratio.

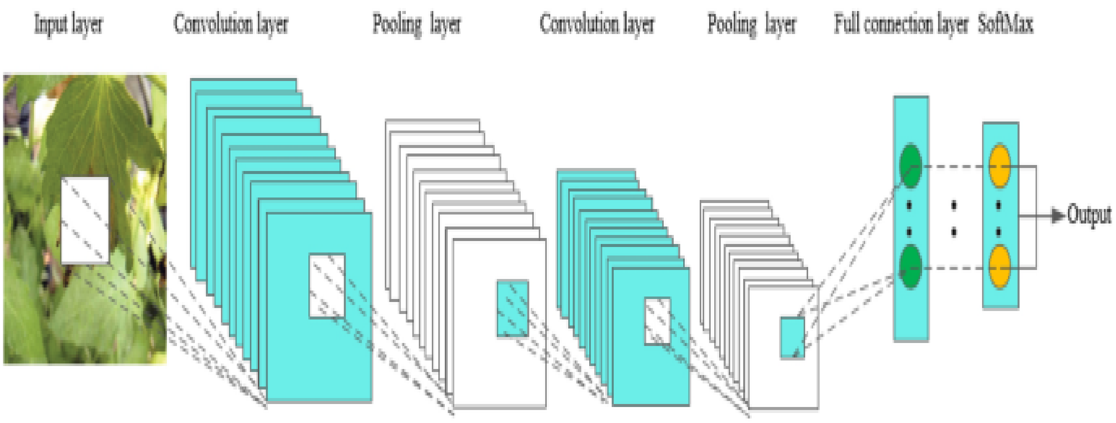


Fig 3.2.1 Different layers of image preprocesing

Normalization involves scaling the pixel values of images to a common range, typically [0, 1] or [-1, 1]. Normalizing the pixel values helps in standardizing the input data, making it easier for the network to learn and converge effectively. This step is often performed by dividing the pixel values by the maximum intensity value (e.g., 255 for 8-bit images) or by subtracting the mean and dividing by the standard deviation.

Data augmentation techniques are applied to generate additional training samples from existing data, thereby increasing the diversity and size of the training dataset. Common data augmentation techniques include rotation, flipping, translation, scaling, shearing, and zooming. These transformations introduce variations in the input data, helping the network generalize better to unseen variations during training and reducing the risk of overfitting.

Noise reduction techniques are employed to enhance the quality of images by reducing unwanted artifacts and distortions caused by factors such as sensor noise or compression artifacts. Filters such as Gaussian blur, median blur, or bilateral filter can be applied to smooth out noise and improve the clarity of the images, making them more suitable for analysis by the CNN.

Histogram equalization is a technique used to improve the contrast of images by redistributing pixel intensities to cover the entire dynamic range. This helps in enhancing the visibility of details in images with low contrast, making them more suitable for feature extraction and analysis by the CNN. Histogram equalization can be particularly useful for enhancing the visual appearance of images captured under challenging lighting conditions.

Preprocessing steps involve extracting relevant features from the images to enhance their discriminative power and informativeness for the CNN. Techniques such as edge detection, texture analysis, or blob detection can be employed to extract salient features from the images, which can then be used as input to the CNN or combined with the original images to provide additional contextual information.

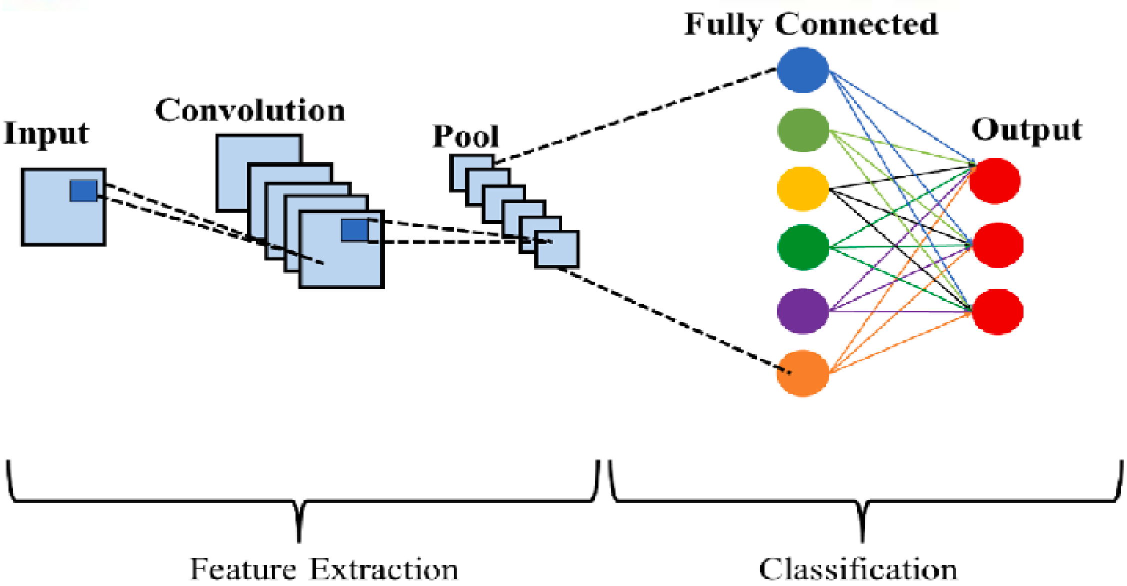


Fig 3.2.2 Image classification

In summary, image preprocessing serves as a critical preprocessing step in preparing raw image data for input into CNNs, ensuring that the data is standardized, enhanced, and augmented to facilitate optimal learning and performance by the network. Each preprocessing step plays a crucial role in refining the quality and suitability of the input data for training CNNs, ultimately leading to improved accuracy and generalization on various computer vision tasks..

3.4 Proposed Methodology

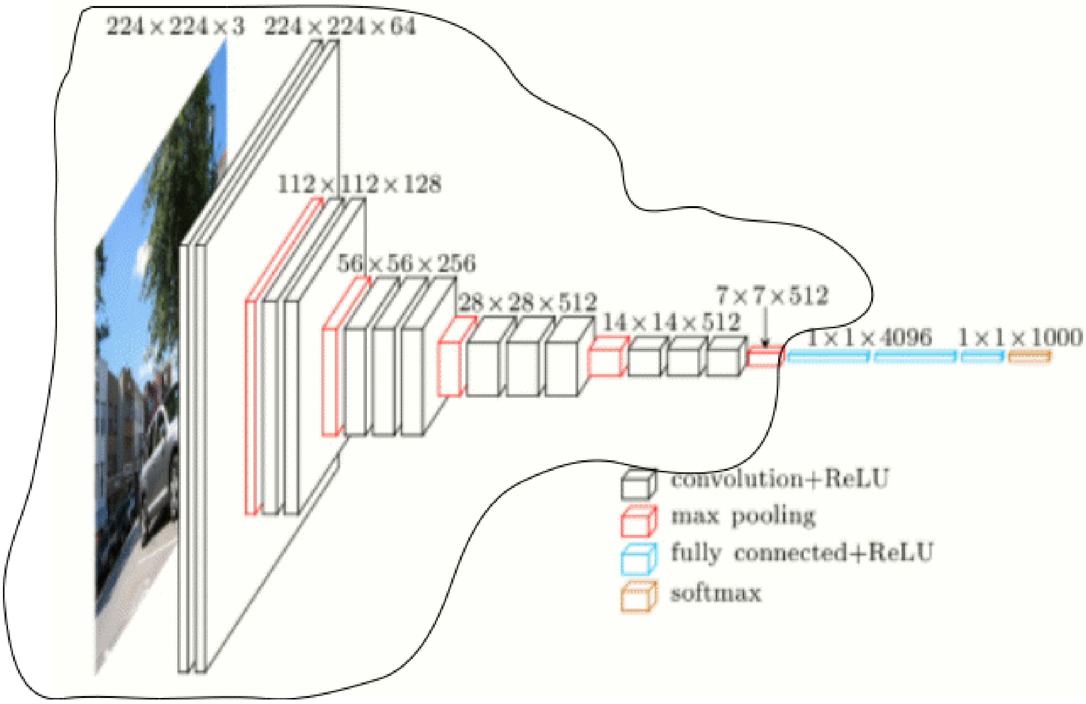
Convolutional neural networks have a methodology similar to that of traditional supervised learning methods: they receive input images, detect the features of each of them, and then drag a grader on it.However, features are learned automatically.The CNN themselves carry out all the tedious work of extracting and describing features: during the training phase, the classification error is minimized to optimize the parameters of the classifier AND the features.

What is a CNN ?

Convolutional neural networks refer to a sub-category of neural networks: they, therefore, have all the characteristics of neural networks. However, CNN is specifically designed to process input images. Their architecture is then more specific: it is composed of two main blocks.

The first block makes the particularity of this type of neural network since it functions as a feature extractor. To do this, it performs template matching by applying convolution filtering operations. The first layer filters the image with several convolution kernels and returns “feature maps”, which are then normalized (with an activation function) and/or resized.

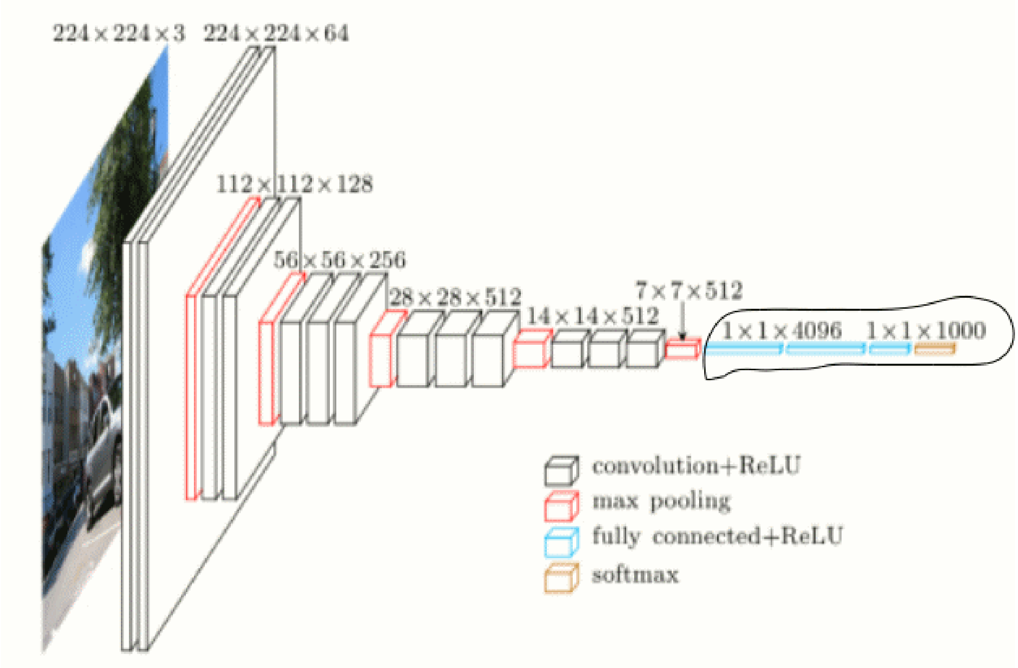
This process can be repeated several times: we filter the features maps obtained with new kernels, which gives us new features maps to normalize and resize, and we can filter again, and so on. Finally, the values of the last feature maps are concatenated into a vector. This vector defines the output of the first block and the input of the second.



The first block is encircled in black

Fig 3.3.1 First block of CNN

The second block is not characteristic of a CNN: it is in fact at the end of all the neural networks used for classification. The input vector values are transformed (with several linear combinations and activation functions) to return a new vector to the output. This last vector contains as many elements as there are classes: element i represents the probability that the image belongs to class i. Each element is therefore between 0 and 1, and the sum of all is worth 1. These probabilities are calculated by the last layer of this block (and therefore of the network), which uses a logistic function (binary classification) or a softmax function (multi-class classification) as an activation function.As with ordinary neural networks, the parameters of the layers are determined by gradient backpropagation: the cross-entropy is minimized during the training phase. But in the case of CNN, these parameters refer in particular to the image features.



The second block is encircled in black

Fig 3.4.2 Second block of CNN

The Different Layers of A CNN

There are four types of layers for a convolutional neural network: the convolutional layer, the pooling layer, the ReLU correction layer and the fully-connected layer.

The convolutional layer

The convolutional layer is the key component of convolutional neural networks, and is always at least their first layer.

Its purpose is to detect the presence of a set of features in the images received as input. This is done by convolution filtering: the principle is to “drag” a window representing the feature on the image, and to calculate the convolution product between the feature and each portion of the scanned image. A feature is then seen as a filter: the two terms are equivalent in this context.

The convolutional layer thus receives several images as input, and calculates the convolution of each of them with each filter. The filters correspond exactly to the features we want to find in the images.

We get for each pair (image, filter) a feature map, which tells us where the features are in the image: the higher the value, the more the corresponding place in the image resembles the feature.

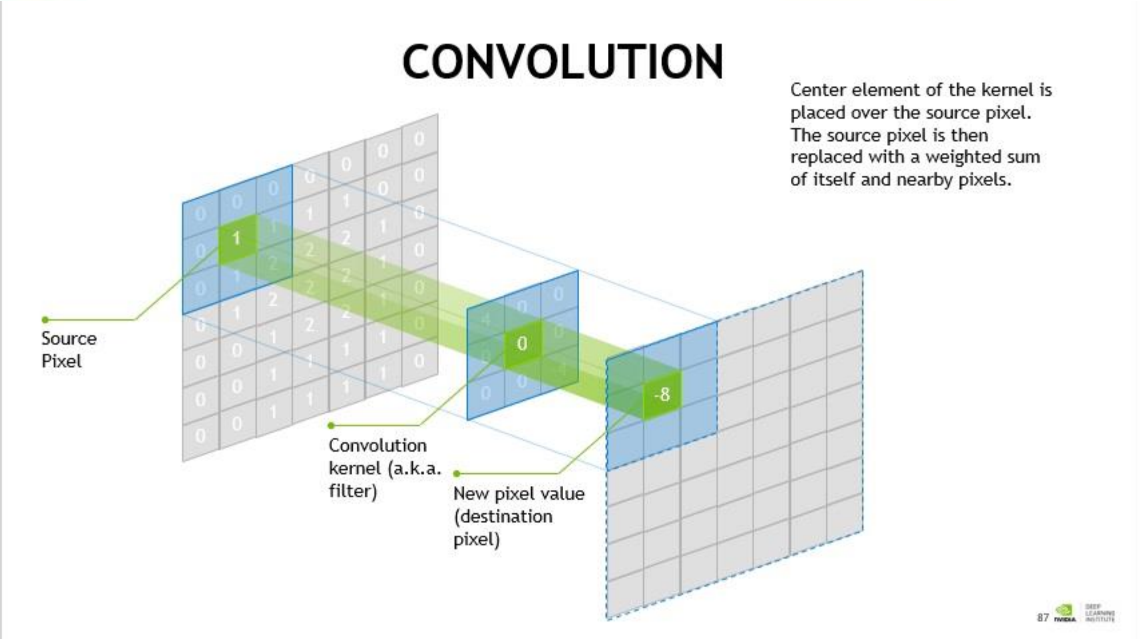


Fig 3.5.3 Convolutional layer

Unlike traditional methods, features are not pre-defined according to a particular formalism (for example SIFT), but learned by the network during the training phase! Filter kernels refer to the convolution layer weights. They are initialized and then updated by backpropagation using gradient descent.

The pooling layer

This type of layer is often placed between two layers of convolution: it receives several feature maps and applies the pooling operation to each of them.The pooling operation consists in reducing the size of the images while preserving their important characteristics. To do this, we cut the image into regular cells, then we keep the maximum value within each cell. In practice, small square cells are often used to avoid losing too much information. The most common choices are 2x2 adjacent cells that don’t overlap, or 3x3 cells, separated from each other by a step of 2 pixels (thus overlapping).

We get in output the same number of feature maps as input, but these are much smaller.The pooling layer reduces the number of parameters and calculations in the network. This improves the efficiency of the network and avoids over-learning.

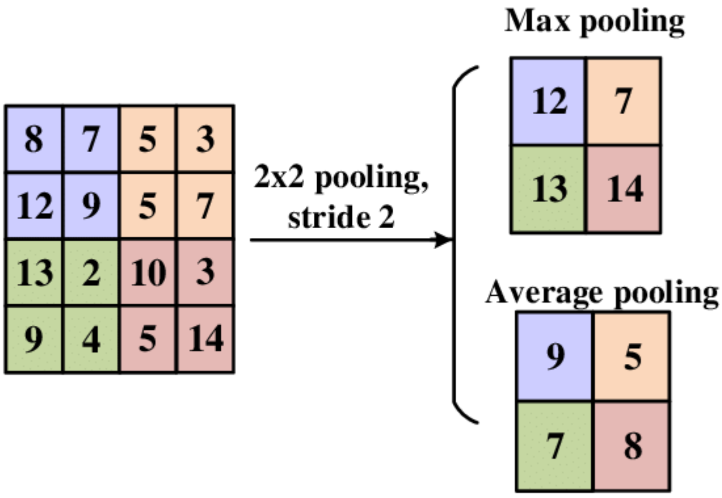


Fig 3.6.4 Pooloing Layer

The maximum values are spotted less accurately in the feature maps obtained after pooling than in those received in input — this is a big advantage! For example, when you want to recognize a dog, its ears do not need to be located as precisely as possible: knowing that they are located almost next to the head is enough.

The ReLU correction layer

ReLU (Rectified Linear Units) refers to the real non-linear function defined by ReLU(x)=max(0,x). Visually, it looks like the following:

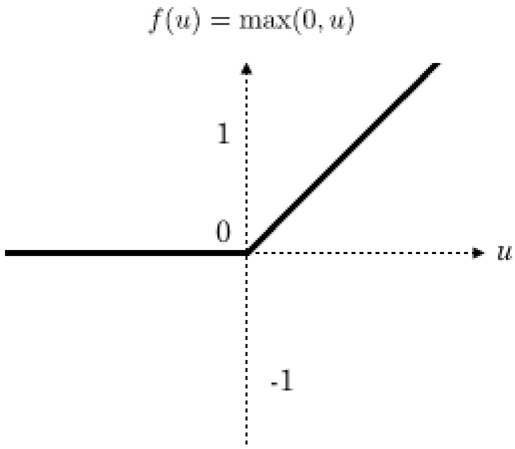


Fig 3.7.5 ReLU function Graph

The ReLU correction layer replaces all negative values received as inputs by zeros. It acts as an activation function.

The fully-connected layer

The fully-connected layer is always the last layer of a neural network, convolutional or not — so it is not characteristic of a CNN.This type of layer receives an input vector and produces a new output vector. To do this, it applies a linear combination and then possibly an activation function to the input values received.The last fully-connected layer classifies the image as an input to the network: it returns a vector of size N, where N is the number of classes in our image classification problem. Each element of the vector indicates the probability for the input image to belong to a class. To calculate the probabilities, the fully-connected layer, therefore, multiplies each input element by weight, makes the sum, and then applies an activation function (logistic if N=2, softmax if N>2). This is equivalent to multiplying the input vector by the matrix containing the weights. The fact that each input value is connected with all output values explains the term fully-connected.

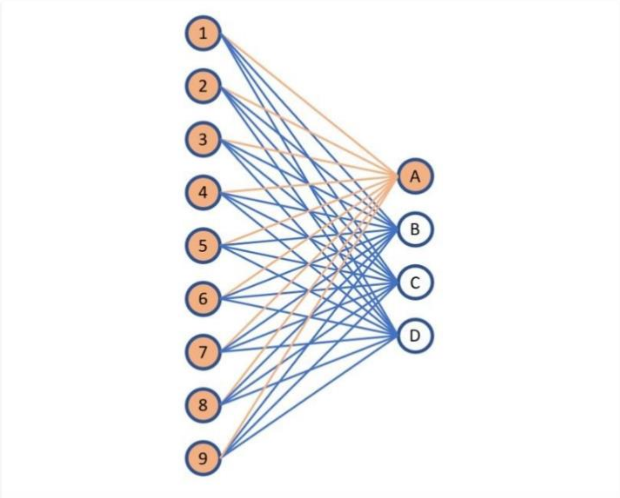


Fig 3.8.6 Fully Connected Layer

The fully connected layer determines the relationship between the position of features in the image and a class. Indeed, the input table being the result of the previous layer, it corresponds to a feature map for a given feature: the high values indicate the location (more or less precise depending on the pooling) of this feature in the image. If the location of a feature at a certain point in the image is characteristic of a certain class, then the corresponding value in the table is given significant weight.

The parmetrization of the layers

A convolutional neural network differs from another by the way the layers are stacked, but also parameterized. The layers of convolution and pooling have indeed hyperparameters, that is to say parameters whose you must first define the value. The size of the output feature maps of the convolution and pooling layers depends on the hyperparameters. Each image (or feature map) is W×H×D, where W is its width in pixels, H is its height in pixels and D the number of channels (1 for a black and white image, 3 for a colour image).

Benefits of using CNNs for deep learning

Deep learning, a subcategory of machine learning, uses multilayered neural networks that offer several benefits over simpler single-layer networks. Both RNNs and CNNs are forms of deep learning algorithms. CNNs are especially useful for computer vision tasks such as image recognition and classification because they are designed to learn the spatial hierarchies of features by capturing essential features in early layers and complex patterns in deeper layers. One of the most significant advantages of CNNs is their ability to perform automatic feature extraction or feature learning. This eliminates the need to extract features manually, historically a labor-intensive and complex process.

CNNs are also well suited for transfer learning, in which a pretrained model is fine-tuned for new tasks. This reusability makes CNNs versatile and efficient, particularly for tasks with limited training data. Building on preexisting networks enables machine learning developers to deploy CNNs in various real-world scenarios while minimizing computational costs.

As described above, CNNs are more computationally efficient than traditional fully connected neural networks thanks to their use of parameter sharing. Due to their streamlined architecture, CNNs can be deployed on a wide range of devices, including mobile devices such as smartphones, and in edge computing scenarios.

4. RESULTS

Fig 4.1 sample UI Application

Header: The webpage has a blue header with the text "AI driven Approach for multicrop disease classification with pesticide recommendation system" written twice.

Buttons: Below the header, there are six buttons with the following text:

- Upload Crop Disease Dataset
- Image Processing & Normalization
- Build Transfer Learning Model
- Upload Test Image & Predict Disease
- Accuracy & Loss Graph
- Exit

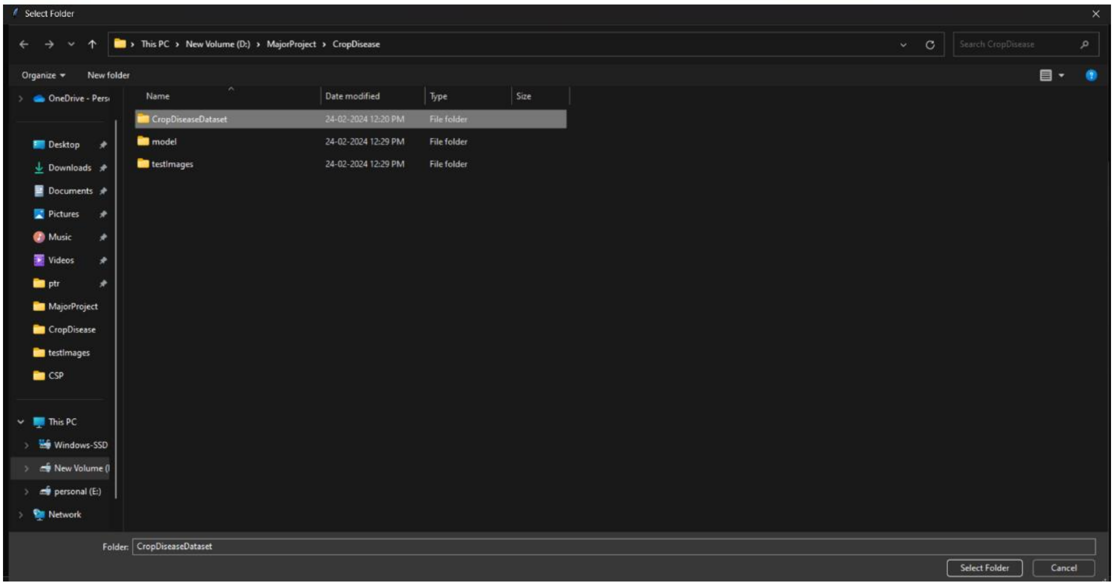


Fig 4.2 Selecting Dataset from File Manager

The process of implementing an AI-powered approach for crop disease detection and management begins with selecting the dataset from the local system file manager, as depicted in Fig 10.3.2. This crucial step involves the user interacting with the file manager interface to locate and choose the dataset containing images of crop diseases for training the model. Once the dataset is selected, as shown in Fig 4.2 the system acknowledges its successful loading, indicating readiness for training.

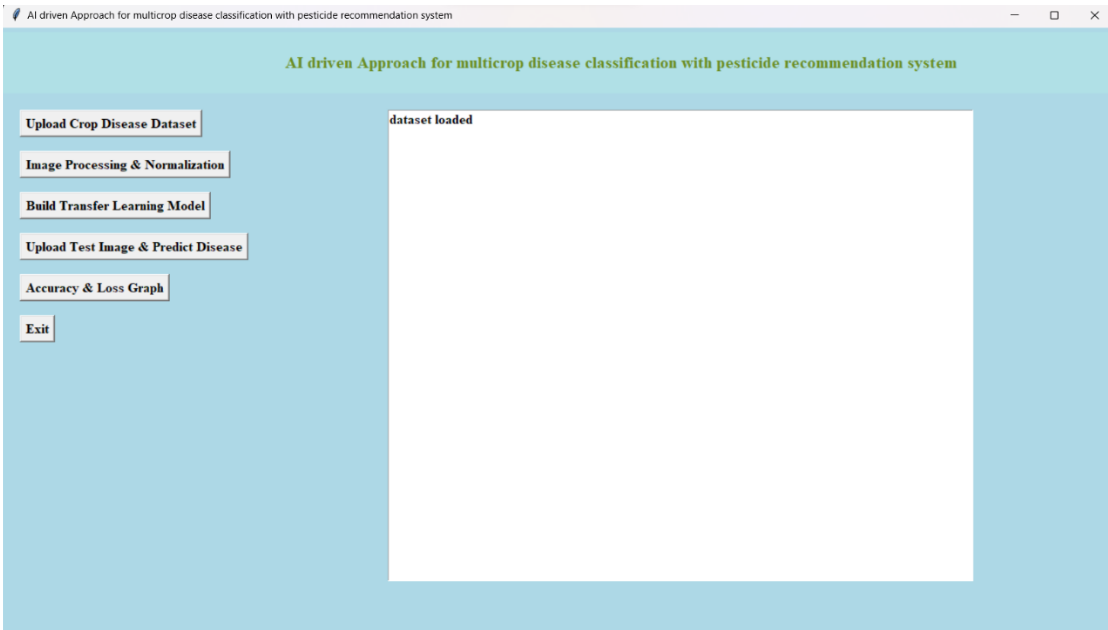


Fig 4.3 Dataset loaded Acknowledgement

Here the dataset is loaded successfully into model in order to train the model

Fig 4.4 Processed Images

After the dataset is loaded, the images undergo preprocessing, as illustrated in Fig 10.3.4 and Fig 10.3.5. Preprocessing techniques such as normalization, resizing, and augmentation are applied to prepare the images effectively for training the model. Following this preprocessing stage, the model is built, incorporating transfer learning, as depicted in Fig 10.3.6. The high prediction accuracy of 98.27% underscores the effectiveness of the transfer learning approach in training the model on the dataset.

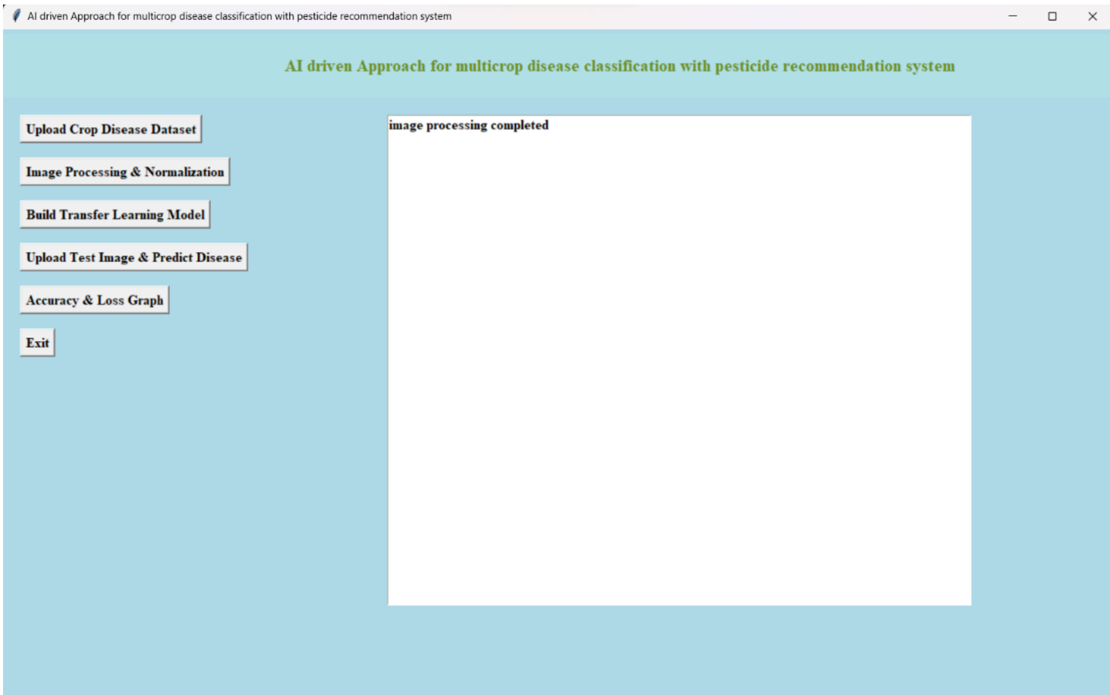


Fig 4.5 Image processing completion

Here the image represents the acknowledgement of completion of image preprocessing

Fig 4.6 Building transfer learning model

In the subsequent steps, as shown in Fig 10.3.7, Fig 10.3.8, and Fig 10.3.9, the model is tested by uploading a test image from the local system files. The model classifies the crop disease based on the uploaded image and suggests an appropriate pesticide for management. This real-world application demonstrates the practical utility of the model in diagnosing crop diseases and recommending tailored solutions. Additionally, Fig 10.3.10 provides a graphical representation of the training process, showcasing the iteration-wise accuracy and loss metrics. This visualization aids in monitoring and understanding the training progress and performance of the model over successive iterations.

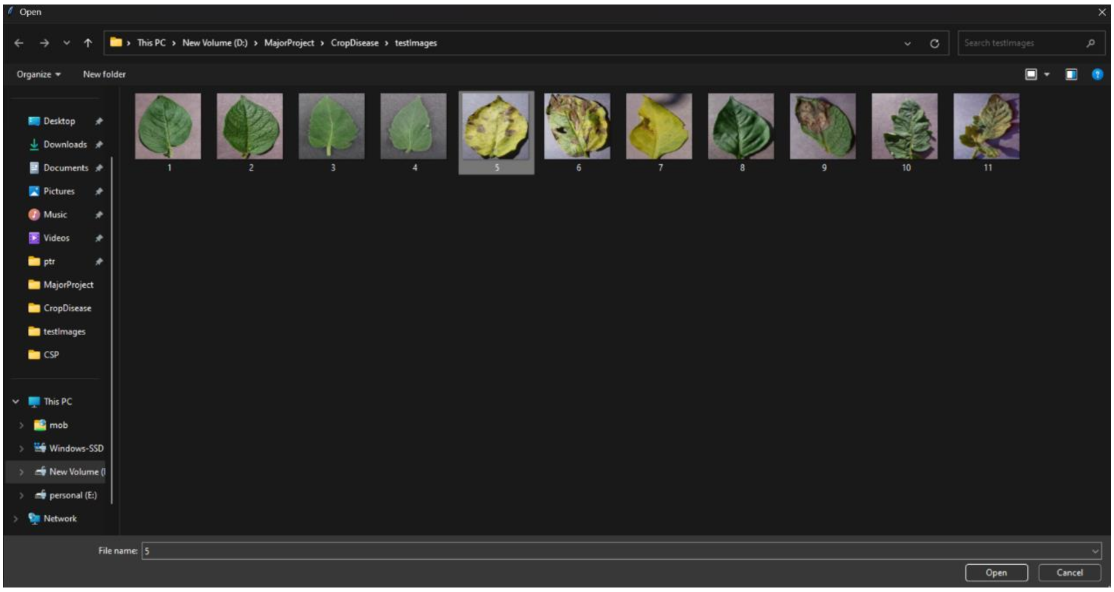


Fig 4.7 Selecting and Uploading Test Image from File Manager.

On clicking the upload dataset and predict disease button the model asks to upoad a test image from local system files, After uploading test image it gives output as below image

Fig 4.8 Crop disease classification and suggested pesticide

Fig 4.9 Crop disease classification and suggested pesticide

Here the image shows the output of model which classifies the crop disease and recommends the pesticide for that disease

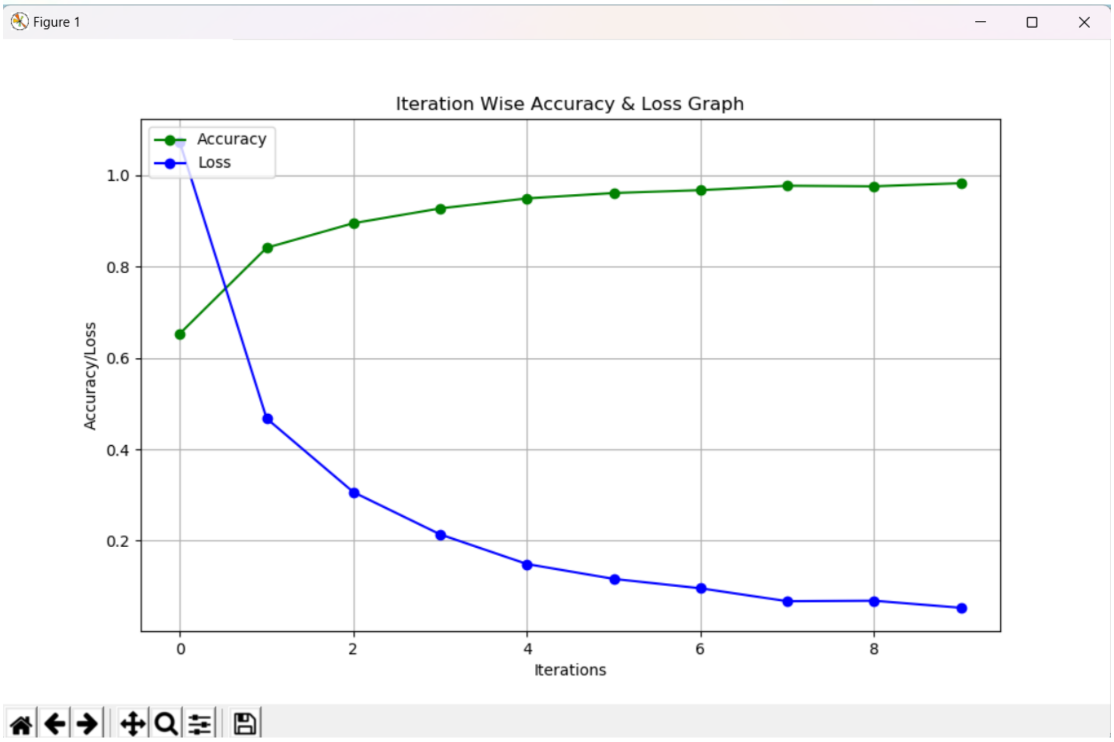


Fig 4.10 Iteration wise Accuracy and Loss Graph

Here the image represents the iteration wise accuracy and loss graph in which x-axis represents iterations and y-axis represents accuracy/loss

5.CONCLUSION

Conclusion

The project on AI-driven approach for multicrop disease classification with pesticide recommendation system has reached a significant milestone by successfully demonstrating its ability to accurately identify and classify diseases affecting multiple crops. Through the utilization of sophisticated machine learning and deep learning techniques, the system has proven its effectiveness in analyzing various symptoms and patterns associated with different diseases, thereby providing farmers with timely and precise recommendations for pesticide application.

Future Scope

Refinement of AI algorithms: Continuous refinement of the AI algorithms is imperative to enhance the accuracy and efficiency of disease classification and pesticide recommendation. This entails incorporating new data, fine-tuning existing models, and exploring advanced AI methodologies such as reinforcement learning and neural architecture search to further optimize performance.

Expansion to new crops and regions: There is immense potential in expanding the system to encompass a broader spectrum of crops and geographical regions. By gathering additional data specific to different crops and regions, and adapting the AI models accordingly, the system can effectively address the diverse agricultural practices and disease dynamics prevalent worldwide.

Integration with precision agriculture technologies: Integrating the AI-driven approach with other precision agriculture technologies, such as remote sensing, IoT sensors, and drones, can augment its capabilities. This integration enables real-time monitoring of crop health and facilitates proactive disease management strategies, thereby optimizing resource allocation and enhancing overall agricultural productivity.

Collaboration with agricultural experts and stakeholders: Collaborating with agronomists, plant pathologists, agricultural extension services, and farmers' organizations is crucial for validating the system's efficacy in real-world agricultural scenarios. Leveraging their domain expertise and soliciting feedback can facilitate the refinement of the system, ensuring its practical relevance and usability for farmers.

User-friendly interface and accessibility: Developing a user-friendly interface for the AI-driven platform, accessible through mobile applications or web portals, is essential to foster widespread adoption among farmers. By presenting recommendations in an easily understandable format and providing actionable insights, the system empowers farmers to make informed decisions and optimize their crop management practices effectively.

In summary, the AI-driven approach for multicrop disease classification with pesticide recommendation system represents a groundbreaking innovation in agriculture, offering tremendous potential to revolutionize crop protection practices. Through continued research, development, and collaboration, the system can address the evolving challenges in agricultural pest management, thereby contributing to the advancement of sustainable and efficient agricultural systems.

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