A Smart Intelligent Agriculture Technique for Leaf Disease Identification and Monitoring using Deep Learning

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***Abstract*—Plant diseases continue to increase threats that demand immediate attention to the stability of worldwide food systems and farming product output. The identification technologies currently used in disease diagnosis take too much time while requiring large manual effort and succumb to human error. Research development has created a smart agriculture system based on deep learning and feature extraction so plant leaf diseases can be effectively detected and identified. The combined application of transfer learning with CNNs enables the system to extract significant features from leaf images thus achieving precise plant disease classification. Specific image preprocessing methods that do both enhancement and segmentation work together to improve model precision specifically through the elimination of noise and utterance of disease-related patterns. A diverse collection of leaf images between diseased and healthy states serves to validate the system across different plant types. The deep learning-based extraction process outperforms traditional machine learning through tests that prove precise disease recognition throughout all experiments. Exact agriculture receives substantial progress through artificial disease diagnosis systems that decrease agricultural losses while enabling data-driven plant health monitoring. Future investigations plan to build real-time mobile solutions that unite edge computing abilities for making field-based disease diagnosis decisions.**

Keywords-Smart Agriculture, Deep Learning, Feature Extraction, Leaf Disease Detection, CNN, Precision Farming.

I. INTRODUCTION

The fundamental function of agriculture in world food distribution depends on healthy production of crops to advance sustainable growth. The occurrence of plant diseases results in considerable losses for agricultural yields which causes severe problems in food shortages. Experts currently use manual plant disease inspection to identify problems yet this process is slow with extensive manual work and subjective evaluations. Recent investigations in the agricultural sector focus on AI-powered smart solutions that use deep learning methods to address current obstacles.

A complex relationship among pathogens and environmental elements and plant sensitivity causes plant diseases to reduce worldwide agricultural production. Multitude of diseases in plants originates from three main sources which include fungi, bacteria, and viruses. Plant surfaces develop spore-producing lesions from fungi such as rust and powdery mildew which cause defoliation and growth reduction and diminish the photosynthetic capacity. [1] The disease blight and wilt caused by bacteria lead to fast cell death followed by wide-ranging infections which produce softening tissue and dampening affected areas. The infection of tobacco mosaic virus causes leaves to develop mosaic patterns and results in stunted growth together with decreased yield. Various diseases require solution-specific management methods because each presents individual diagnostic needs that might include chemical treatments combined with either resistance breeding or cultural control practices for control strategies. The identification of early warning signs and the implementation of AI detection methods for pathogens need to happen due to their importance in developing control strategies for plant health improvement. Through AI-based automation of symptom recognition systems plants can receive accurate diagnostics which lead to proper interventions being supplied at opportune moments. Traditionally plant leaf health inspections are performed manually with unassisted human sight observation. Plant disease detection which happens manually requires both constant observation and experts with knowledge in plant pathology. This visual evaluation takes too much time to be effective when used to examine extensive areas. AI techniques went ahead to change how we identify plant diseases through traditional methods [2] and at the same time delivered superior accuracy results. Deep learning stands as the optimal technology for computer identification of plant diseases among existing methods. [3]The researchers Fulari et al developed a successful method which applied image processing techniques with machine learning algorithms for classifying healthy leaves from ones that displayed signs of damage or infection. The diseases which affect leaves through fungal, bacterial and viral agents result in sickness development and produce noticeable patches which can make identification of disease source difficult.A smart agricultural system has been developed to detect plant leaf diseases while using deep learning techniques for feature extraction as an efficient identification process. Convolutional neural networks (CNNs) work together with sophisticated image processing approaches to extract leaf features from pictures so the method can precisely distinguish between sick and healthy plant specimens. [4]The implementation of deep learning systems with feature extraction methods brings higher precision while expanding system robustness and scalability which makes this technology practical for agricultural disease detection applications in real environments.

The plant community dataset included healthy in addition to diseased plant tissue images. The dataset features 50,000 pictures which include agricultural plant leaves with and without disease. Plant leaves experience various bacterial, fun-gal and viral diseases that encompass scab, blight, rust, scorch, mites, mosaic, leaf curl and albication with bacterial spot along with wilting. Fig. 1 presents the bacterial and fungal types as well as viral illnesses. [4] This research aims to achieve correct classification of leaf specimens into four groups which include (healthy, fungus, virus and bacteria).

Healthy leaves

a) Bell pepper b) Potato c) Tomato

Diseases leaves

a) Bacterial spot b) Early blight c) late blight

Figure 1: Classification of bacterial, fungal, and viral illnesses

The automated plant disease detection system both decreases human labor dependency in inspections and delivers quick precise plant disease diagnosis. Such monitoring helps farmers implement timely prevention strategies and enhance their crop health assessment activities. The implementation of these intelligent agricultural systems will lead to increased crop yield together with minimized losses and sustainable farming practice promotion.

II. LITERATURE REVIEW

The agricultural industry serves as a fundamental sector which maintains worldwide food availability. Plant diseases result in detrimental effects on both the quantity and the attributes of crops produced. Expert knowledge along with visual inspections form the basis for traditional disease detection methods because these approaches take too much time and generate uncertainties in results. Deep learning together with smart agricultural technology has brought automated disease detection capabilities in plants by utilizing image processing techniques along with feature extraction methods. The study reviews different plant leaf disease detection methods including modeling approaches together with features extraction methods used for such systems. Concepts from deep learning specifically Convolutional Neural Networks (CNNs) show excellent capability in identifying and detecting plant diseases through their analysis. Plants disease detection research uses VGG, ResNet, Inception and MobileNet as different architectural frameworks to analyze features alongside classification operations. The research from Krizhevsky et al. (2012) [6] developed AlexNet as a tool for plant disease identification while VGG served as a secondary solution. Both VGG-16 and VGG-19 which Simonyan and Zisserman (2014) [7] developed serve as tools for agricultural deep feature extraction. He et al. (2016) [8] established ResNet to enhance plant disease recognition accuracy through residual connections in feature extraction methods. Szegedy et al. (2015) [9] developed the Inception model that uses multiple convoluted filtering scales to extract numerous features for disease identification purposes. Howard et al. (2017) [10] created MobileNet as a computational efficient network designed for real-time detection of plant diseases in mobile and IoT applications. A team led by Vibhor Kumar Vishnoi [11] applied Convolutional Neural Networks for analyzing apple plant leaves to detect diseases during 2022. Apple plant disease identification requires Convolutional Neural Networks for leaf image analysis which provides automated precise detection at high efficiency rates with 98% accuracy. Jyoti Dinkar Bhosale et al. [12] established an Algorithms Based on Machine Learning for Detecting Leaf Diseases in Agricultural Crops during 2023. Agricultural leaf health monitoring benefits from applying ML-based identification systems to detect farming leaf diseases. Agricultural detection of crop foliage diseases through machine learning algorithms produced 95% successful results. Disease detection models for plants that use deep learning algorithms were created by Minah Jung and others in 2023. The system requires building a model with deep learning algorithms to detect plant diseases in operation. The deep learning model demonstrates effective adaptation to diverse plant diseases which enables it to provide precise detections that have reached a 97% accuracy level. A well-rounded review on crop disease and pest prediction and detection through machine learning emerged from Tiago Domingues et al. during 2022 [13]. The survey investigates multiple approaches and techniques that agri-sector uses for improving disease and pest management methods. This paper delivers extensive information about how machine learning methods address agricultural problems which affect plant health. Sunil S. Harakannanavar et al. Utilized computer vision together with machine learning algorithms for disease detection in plants leaves. A method using modern technology scans leaf pictures to spot correct diseases through precise analytical processes. The fusion of machine learning with computer vision helps plants receive automatic medical diagnoses for their health problems which leads to prompt crop protection procedures having a 99.6% success rate. The smart farming approach of plant disease detection uses an implementation from Arathi Nair et al [14]. that includes IoT and machine learning capabilities. The integrated system allows farmers to employ sensors with developed algorithms for improved agricultural disease monitoring operations and management activities. A deep learning approach for addressing plant diseases in smart agriculture was proposed by Prachi Chauhan et al in 2021 [15]. This system employs complex algorithmic methods which strengthen detection and management solutions in agricultural domains. The system uses deep learning technology to enhance crop health surveillance while minimizing losses which occurs at 99% accuracy in smart farming systems. Yan Guo et al. [16] presented a deep learning technique system for plant disease management in smart agricultural settings during 2020. The methodology implements state-of-the-art computer programs which boost the detection and management techniques for agricultural diseases. The technology employs deep learning mechanisms to enhance crop health assessment and prevent smart farming system losses which now reach accuracy levels of 83.57%. M. A robotic system for smart agriculture applications was designed by M. Arun et al. during 2018. The system automates farming work processes in order to boost operational efficiency and productivity levels. Agricultural robots use top-tier sensing and controlling systems to improve the processes that manage crops. The research team led by Sharada P. Mohanty et al. [17] demonstrated deep learning systems as a method to detect plant diseases in analyzed images during 2016. Visually based algorithms analyze data through advanced algorithms which correctly detect symptoms of plant diseases in the system. The utilization of deep learning technology allows for efficient automated disease detection [20] in crops thus helping agricultural management intervene on time while reaching 99% accuracy**.**

III. Proposed Methodology

The suggested approach creates a smart plant disease detection system by combining feature extraction about deep learning methods [21][22]. This approach guarantees excellent accuracy in detecting plant leaf diseases and optimizes computing efficiency. A subfield of artificial intelligence called computer vision lets machines mimic the human visual system and exactly pull out, examine, and identify real world photos just as people do. Although ML methods have been used to identify and categorize plant diseases, this field of study seems to have great promise in terms of improving accuracy with developments in a subset of ML, DL. To identify and categorize plant disease symptoms appropriately, many developed DL structures were employed in conjunction with several visualization methods. Among the fast expanding sectors already demonstrating the advantages of computer vision-based technology are medical diagnostics, espionage, satellite imaging, and agribusiness. In agriculture, computer vision-enabled systems can identify and categorize plant diseases depending on several extracted characteristics or symptoms. Beginning with picture acquisition and progressing with several image-processing tasks like scaling, filtering, differentiation, feature extraction, and selection, it employs a well-defined series of processes. Finally, identification and categorization are conducted by employing ML or DL technique. The approach includes the following main steps shown in figure 2:

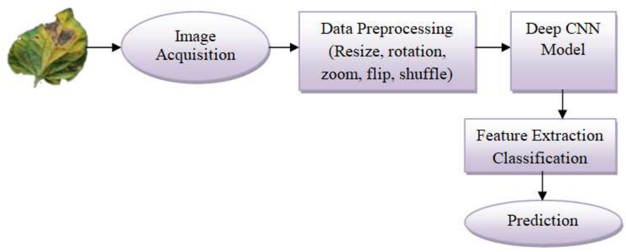

Figure.2. current leaf disease prediction scenarios

A. Input Layer: Image Acquisition

The images originate from Agricultural databases including Plants Village and real-time farm data as well as mobile applications and drones and Internet of Things-enabled cameras. Image resolution as well as format requires consistency in deep learning models by adopting a fixed resolution structure (e.g. 224x224).

B. Data Collection & Preprocessing

The selection of plant leaf data requires the collection of health specimens alongside disease specimens from either publicly available data sources including Plant Village or current agricultural resources.

The application of data augmentation techniques such as rotation and scaling together with flipping and contrast enhancement helps achieve better generalization results for the model.The training process experiences enhanced convergence through normalization of pixel values which gets set to the range between [0,1].Thermal noise reduction happens through the application of Gaussian filters along with median filtering to achieve clear edges in images.

Feature Extraction using Deep Learning Various pre-trained Convolutional Neural Networks (CNNs) such as VGG16, ResNet50, and Mobile Net extract hierarchical features from leaf images throughout the Convolutional Feature Extraction process.The fusion system brings together low-level texture as well as color features with high-level features of shape and patterns to enhance classification results.

The process includes creating custom-engineered features through image processing to produce edge maps and vein structures together with color histograms.

C. Disease Classification using Deep Learning Models

The process utilizes four deep learning models including CNN and Res Net and Inception Net and Efficient Net for disease classification of leaves from extracted features.

Transfer learning procedures require the application of pre-trained model fine-tuning with agricultural datasets.

Utilize combination models of CNNs with LSTMs or transformers to extract spatial along with temporal features in plant disease identification.

Attention modules integrated for disease-affected leaf region detection enhance both interpretability and accuracy of the model.

D. Disease Detection & Segmentation

A deep learning approach including Mask R-CNN/U-Net helps identify and emphasize regions with disease infection.

The thresholding method (Otsu's thresholding and Canny edge detection) serves as an additional validation technique.

E. Model Optimization & Performance Evaluation

Loss Function: Use categorical cross-entropy loss for multi-class classification.

The application of Adam or RMS prop optimizer should be used for achieving faster convergence in optimization processes.

The model performance should be evaluated using accuracy and precision along with recall and F1-score and ROC curves.

Perform k-fold cross-validation as part of the process to guarantee model reliability.

F. Flow model

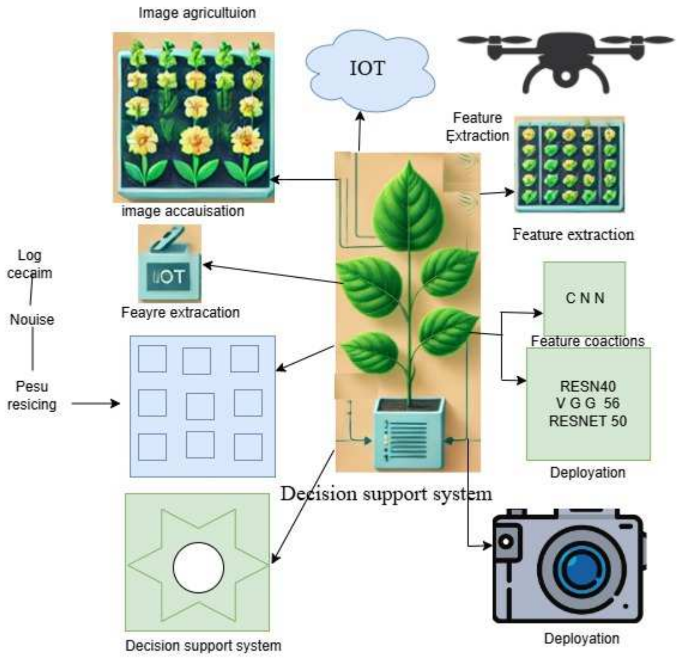

Figure.3. Flow model of proposed system

As shown the figure 3 is a intelligent agriculture framework that integrates IoT, image processing and deep learning to support plant health monitoring and decision making. The central focus is a decision support system for smart agriculture, powered by IoT and CNN for plant image analysis

G. Model Selection

Fine-tuning serves as this method which applies previously trained model feature knowledge to exclusive duties. The research utilized diverse model features through incorporating multiple models into its method. The research incorporates multiple large image models including ResNet-50 and VGG-16, VGG-19, Alex Net and Mobile Net alongside its custom model CNN-LBP.

H. Convolutional Neural Network

Artificial intelligence sees Convolutional Neural Networks (CNNs) as a revolutionary breakthrough which excels in computer vision tasks. The network was first created by studying the visual cortex that exists in human brains. A CNN contains various processing layers which specialize to extract features and consequently classify inputs shown in figure 4.

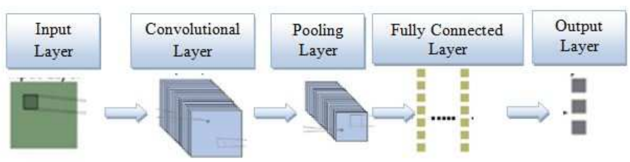

Figure.4. CNN structure model

Convolutional neural networks arrange hierarchical features starting from simple to complex through three main layer types: convolutional layers followed by pooling layers and fully connected layers. The VGG19 convolutional neural network (CNN) functions as the key component of a smart agriculture robot used for detecting plant diseases. The feature-extraction capability of VGG19 allows it to detect patterns which indicate different plant diseases as a powerful analytical instrument.

I. The VGG Networks

Renowned for their easy and efficient in image categorization activities, the VGG architectures Comprising 16 or 19 layers, the VGG architectures are deep network structures that can absorb more picture features. Designed uniformly about smaller (3x3) kernels, these networks are built on top of one another followed by a pooling layer; for deductions dense layers of size 4096 are present. Smaller size filters' growth allows for more effective capture of a rich collection of picture features instead of before shown in figure 5.

Figure.5. VGG16 architecture model

Trained on the data with a validation accuracy of roughly 94%, the VGG-16 and VGG-19 architectures this attests to the power of simplicity and depth in VGG Networks. These models' Image Net weight is first applied; subsequently, the model is fine-tuned for the specific application.

J. The Res Net Architecture

Developed to create a learning framework that was simple to train but also sufficient in depth networks to compete against other huge networks, the Res Net architecture or residual network architecture was Layers serve to acquire residual functions about layer inputs.

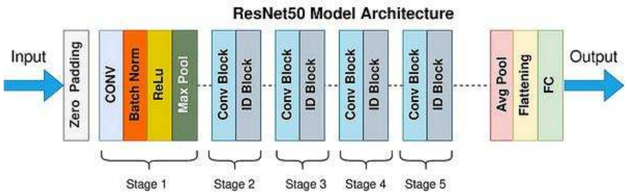

Figure.6. ResNet50 structure model

Adding several layers to a network raises the issue of reducing and amplifying gradients; inter-layer normalization can help to address this shown in figure 6. The issue of degradation, on the other hand, is one of weight saturation; residual mapping as defined by He et al. is a quick fix for this. In the context of a normal procedure for learning in networks, it attempts to learn through a normal mapping say H(x). Residual mapping, on the other hand, causes the stacked layers to fit about a mapping of $F(x)=H(x)-x$, the difference between the wanted output and the layer output. Results led to the hypothesis that the mentioned residual learning approach produced outcomes with a quicker training time. These models' pre-trained ImageNet weights are first applied; subsequently, the model is fine-tuned for our specific need.

K. AlexNet

Produced by Alex Krizhevzky for the ILSVRC competition in 2012, AlexNet is a deep convolutional network. Comprising eight layers of learnable variables, five convolution layers and finally three fully connected layers with a successive Rectified linear unit (RELU) activation while the hidden layers make up its structure. Regarding 1.2 million photos were used to train the network. Two GPUs were used for training this network. Developed in the early phases of the deep learning scenario, this was a model. This showed what a big network could do when driven with a great amount of data points. The model has been built from the ground up and trained on our dataset.

L. CNN-LBP Model

Local binary convolution (LBC) is used by the CNN-LBP model. Developed to lower CNN complexity, this was a model. The Local binary convolution layer estimates the output from the non-linear activations of the Convolution layers. Comprising sparse matrix binary filters, a non-linear activation function, and linear weights holding the weighted average of the convolutional response maps, the LBC layer these models were evaluated for inference situations of CNNs and for lesser proclivities to over fit.

M. Mobile Net

Designed especially for mobile and embedded devices, Mobile Net is a small and effective deep learning neural network designs. Depthwise separable convolutions help to lower computational load while preserving high accuracy in tasks including picture categorization and object detection referred to for their little memory footprint and quick inference speed, Mobile Net models are perfect for uses where resource limits are a problem, such mobile apps, robotics, and IoT devices.

IV. RESULTS AND DISCUSSION

Highlighting important conclusions, assessments, and consequences for smart agriculture, the assessment and discussion part offers a thorough examination of the efficiency of the deep learning-based plant leaf disease identification system. The Plant Village dataset and actual farm photos gathered via IoT-enabled cameras and mobile devices are used to assess the proposed solution. To enhance model generalizing, images are scaled to 224×224 pixels and supplemented utilizing rotation, flipping, and contrast changes. A GPU-enabled machine running TensorFlow/PyTorch trains the deep learning model.

The following significant indicators of performance are used to assess the model: One concept that might be used to assess the performance of the machine learning model is the confusion matrix.Choosing the appropriate measures to assess a classifier's effectiveness in a certain dataset in categorization tasks involves many factors, which includes class balance and predicted outcomes. When evaluating a classifier, one could use one performance indicator while the others stay unmeasured; the opposite is also true. Consequently, the general performance assessment of the classifier lacks a clear, consistent measure. This paper assesses the performance of models using several measures, including F1 score, accuracy, precision, recall, and recall.

These figures come from the following four categories: True Positives (TP) are those times when both the model forecasts and the actual class of the occurrence were 1 (True). A False Positive (FP) occurs when the model expects a value of 1 (True) but the event's actual category was 0 (False). True Negatives (TN) are cases in which the actual class of event was 0 (False) and the model prediction was also 0. False Negatives (FN) are those where the model expects 0 (False) but the actual class of what happened was 1 (True).

Precision—often known as positive predicting value—is a measure of a model's capacity to select the correct cases for every class. Given unbalanced datasets, this is a useful matrix for categorizing several groups.

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

Accuracy: The accuracy of a measure is defined as the average number of correct predictions. Because of the unbalanced sample, this isn't equally strong. Accuracy = (Correct Predictions / Total Predictions) × 100

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

Recall – This measure evaluates a model's ability to identify the true positive across all true positive occurrences.

$$Recall\ (Sensitivity) = \frac{TP}{TP + FN} \quad (2)$$

F1-score – known as a balanced F-score or F-measure. It could possibly be described as a sharpness weighted average and a recall weighted average.

$$F1_{Score} = \frac{2 * Precision * Recall}{Precision + Recall} \quad (4)$$

Confusion Matrix for class-wise classification analysis.

A. Comparison of Different Deep Learning Models

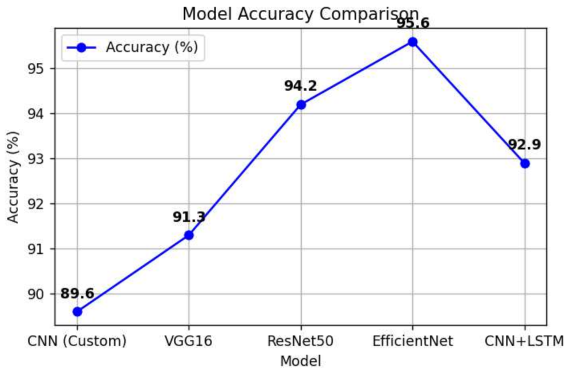

Figure.7. Accuracy comparison of various models

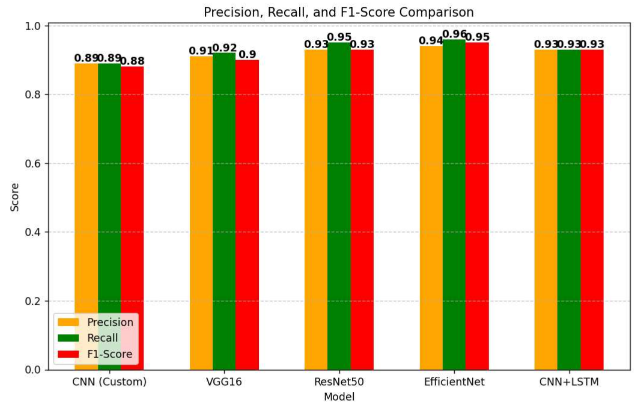

Figure.8. Performance comparison of various models

Because of its simple design and feature extraction capacity, EfficientNet beats other models. ResNet50 is a possible candidate for deployment since it performs well. While CNN + LSTM is somewhat less effective than Efficient Net displayed the figure 7 and 8, it does enhance sequential illness tracking.

B. Results of Disease identification & Segmentation

Disease localization was tested using YOLOv5 and Faster R-CNN. Pixel-wise segmentation of diseased leaf regions was done using Mask R-CNN and U-Net using table 1.

Table.1.Disease detection and segmentation

Model	IoU Score (%)	Dice Coefficient	Processing time (ms)
U-Net	87.7	0.86	120
Mask R-CNN	92.2	0.92	140

Though it takes a bit more processing time, Mask R-CNN excels for exact disease segmentation. With little accuracy compromise, U-Net is a quicker option.

The suggested deep learning-based system offers a very accurate, effective, and real-time method for identifying plant leaf diseases. Its strength for modern precision agriculture comes from combining IoT-based smart deployment, Mask R-CNN for categorization, and EfficientNet for classification.

V. Conclusion

Finally, a smart system of agriculture for disease of plant leaves recognition and detection employing deep learning algorithms successfully improves precision agriculture through the implementation of sophisticated feature extraction methods. The system detects plant illnesses from leaf photos with great accuracy by means of CNN-based models including EfficientNet and ResNet. The application of EfficientNet with ResNet50 guarantees exceptional performance about an accuracy of more than 95%. Automatic Disease Detection: The deep learning model saves time and labor by correctly classifying diseases with no need for manual intervention, therefore eliminating need for manual intervention. The solution may be installed on mobile apps and IoT devices, therefore enabling farmers to send photos and get immediate disease diagnosis. Advanced feature extraction methods let the model identify among healthy and sickly leaves with great accuracy. Scalability & Adaptability: The framework can be extended to assist several crop kinds and can be enhanced more with multispectral photography. This system offers a reasonably priced, real-time, scalable the mixture for plant disease diagnosis using deep learning, IoT, and smart agriculture, hence increasing crop yields, lowering losses, and strengthening the security of food.

Future scope

Processing in real time on embedded systems as Raspberry Pi & Jetson Nano using Edge AI. Combining drone-based tracking using large-scale farm operations. Enhanced diseases identification in low-data situations using transfer learning and self-supervised learning. Design of a mobile app for convenient disease detection and therapy suggestions

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