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A Deep Learning-Driven IoT Systems for Real-Time Crop Health Evaluation and Disease Prediction

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Abstract - **Deep learning and remote sensing are used to monitor and manage crop health in this study. Food security and agriculture depend on this. Global food system issues include disease outbreaks, pest infestations, and climate change. This research paper describes how remote sensing technologies give high-resolution crop health data at many scales. These platforms include satellites, drones, and IoT sensors. CNN, RNN, and transformer-based architectures change dataset analysis. These include precision agriculture, soil health evaluation, disease detection, and yield prediction. The chapter covers CNNs, RNNs, and transformer topologies for precision agriculture, early disease detection, yield prediction, and soil health monitoring. Spectral indices and geographical data integration for crop stress, nutritional deficiencies, and growth pattern analysis are emphasized. We also study data augmentation and transfer learning advancements to address the lack of labelled agricultural datasets and improve model performance in various circumstances. Addressing computational demands, scalability, and agricultural uses of analytical findings. To properly utilize emerging technology, article promotes cross-disciplinary collaboration, policymaker support, and infrastructural investment and analyzes how deep learning and remote sensing might improve crop productivity, environmental resistance, and food security.**

Keywords -Deep learning, Machine Learning , Crop Health, Internet of Thing, Prediction

I. INTRODUCTION

Agriculture is vital to humans because it provides food, clothing, and shelter. Research shows that every 1% increase in agricultural yield reduces total destitution by 0.6-2.2% [1]. While scientists expect the world's population to reach 9.7 billion by 2050, food supply must increase by 70% to meet demand [2]. Rainfed agriculture is estimated to supply one-third or more of the global food production increase during the next few decades. Increasingly severe weather events are affecting agricultural productivity. Thus, climate, air pollution, and water availability affect agricultural [3]. There are a number of elements that offer a substantial risk to farms, which can result in a decrease in productivity if they are not properly monitored and controlled. There are three categories that can be used to classify these factors: scientific, biological, and ecological [4]. The goal of crop health monitoring is to systematically discover problems like pests, diseases, and nutrient deficiencies early on by following and assessing plant health and growth phases using technologies like remote sensing, drone photography, and IoT devices. By giving farmers access to data and insights in real-time, this approach improves crop output, reduces waste, and helps the agricultural sector remain sustainable. Protecting food security and increasing agricultural efficiency can be achieved by understanding this creative technique.

Figure 1: Process of managing crop health and other factors using Sensors and AI.

Why crop health is so important?

A vital part of the intricate web of relationships among humans, animals, and the natural world is a healthy plant life, which is necessary for the survival of all living things. About 80% of the food that humans eat comes from plants, and animals get most of their nutrition from plants as well. Nevertheless, the threat to our plants is greater than it has ever been, thus it is more important than ever to educate people on why plants need to be healthy and what they can do to protect themselves from pests and diseases. We can fortify the world's food supply system with a better grasp of how to curb the proliferation of exotic pests [5]. The preservation of botanical health significantly impacts the well-being of both humans and animals, serving as a crucial factor in food security and safety, providing jobs in herb-based cultivation and agriculture, supplying medications, and contributing to healthy ecosystems [6]. There are several features that provide the importance of crop health. Key points about crop health:

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- **Produced and Superior:** Increased food production per acreage, higher nutritional content, and other positive traits are all signs of healthy crops.
- **Management of Insects and Disease Agents**: Both the prevention of large crop losses and the reduction of dependency on chemical pesticides can be accomplished by early monitoring and treatment of diseases and pests.
- **Assurance of Food Supply:** It is essential to keep crops in good health in order to provide a consistent supply of food, particularly in areas that are susceptible to food insecurity.
- **Influence on the Environment:** Reduced reliance on potentially harmful inputs like pesticides and other fertilizers is associated with healthier crops.

Factors affecting crop health

Soil fertility, water availability (rainfall and irrigation), temperature, sunshine, pests and diseases, wind, soil structure, nutrient levels, crop variety, management practices (tillage, fertilization), and environmental conditions (climate change) are all things that can affect a crop's growth and development [7]. Key aspects to consider:

➢ **Climate factors:**

Temperature: The ideal temperature range for each crop differs; excessive heat or cold might impede growth.

Rainfall/Irrigation: The availability of sufficient water is essential for the growth of plants; nevertheless, fluctuations in rainfall or drought can have a substantial impact on production.

Sunlight: Photosynthesis, an essential mechanism for crop expansion, is influenced by both the strength and period of light.

Wind: Strong winds can hurt plants. Wind can break branches, uproot small plants, and blow off tree and bush leaves. Desertification can also result from high winds rapidly losing leaf moisture, making plants more susceptible to drought stress. Wind-blown debris can rip plant tissues, compromising health and growth.

➢ **Soil factors:**

Soil texture and structure: Plants need ventilation and aeration for optimal root development. Well-draining soil prevents root rot, fungal infections, and oxygen shortage. Aeration increases root respiration and nutrition absorption by introducing oxygen. Compact or damp soil can suffocate roots and destroy plants. Farmers and gardeners can strengthen plant roots by adding organic matter, mulching, or aerating soil.

Soil fertility: A plant's ability to grow, develop, and stay healthy is heavily dependent on the availability of certain minerals, particularly potassium (K), phosphorus (P), and nitrogen (N). These macronutrients have distinct physiological functions in plants. Green plants need nitrogen to make chlorophyll, the photosynthetic pigment, and cell structure amino acids and proteins. In addition to DNA and ATP synthesis, phosphorus helps root development, fruit and blossom production, and energy transfer. Potassium regulates water intake, enzyme activity, and disease resistance, strengthening stems and improving drought tolerance.

pH level: The ideal soil pH range varies each crop, but plant health, nutrient availability, and productivity depend on it. Plants get nutrients from soil pH and chemical form. Azaleas and blueberries prefer 4.5–5.5 soils, but most field crops and vegetables prefer 6.0–7.0. Legumes and asparagus prefer a slightly alkaline atmosphere. Too acidic or alkaline soil makes some crops toxic or malnourished. Extremely acidic soils limit phosphorus and other nutrients, whereas manganese and aluminum-rich soils may inhibit root growth.

Challenges for crop health

Crop science is the study of agricultural cultivation with an eye toward improving crop quality, output, and resistance to disease and insects. There are several challenges such as:

Global Population Growth: Modern cultivation practices are now the foundation of agricultural output in order to fulfil the ever-increasing need for food. The ecology is harmed by these practices, which cause soil and water erosion, water contamination, and species extinction [8].

Effects of Global Climate Change: Climate change's devastating consequences on crop productivity and food security require innovative solutions. Drought-induced water stress reduces plant growth and harvests. Floods and heavy rains harm crops, impede nitrogen uptake, and spread diseases.

Deterioration of Soil and Depletion of Resources: A significant issue in contemporary agriculture is the reduction of arable land. Soil erosion transpires due to unsustainable agricultural practices, deforestation, urbanization, and other harmful land use and land cover activities. Three The global capacity for food production has declined, resulting in increased concerns regarding food security due to this loss.

Insects and Sickness: Pests and illnesses reduce agricultural yields and cost money. Autumn armyworms, which damage maize, are a serious economic issue. Due to insect pest geographic expansion, greater overwintering survival, and altered host plant and natural enemy interactions, climate change may threaten food security and crop losses [9, 10].

There are many additional obstacles farmers confront daily based on government plans and how much they know about them. Deep learning and remote sensing can help farmers cultivate and predict issues early on, therefore this chapter

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focuses on them. There are remedies to all these crop health issues and farmer obstacles. Like

Yield assessment: The prior to harvesting is estimations of yield data that is useful for farmers in making key decisions, such as how much fertilizer to apply, based on yield estimation. Insect infestation and drought are two examples of possible dangers that can be foreseen and prepared for [11].

Observation and categorizing: Monitoring crops during the growing season helps match supply and demand for important crops. Classify crops globally during the growing season to avoid a shortfall in one main crop kind and an excess in another [12].

The landscape classification: Undeveloped land converted into farmland enhances food production, but abrupt shifts release greenhouse gasses that harm ecosystems. Land cover maps help estimate crop sustainability and compatibility for balanced expansion [13].

Assessing the Impact of Droughts and Inundations: Identifying varietals that can withstand stress during unfavourable climatic conditions, such as drought and flood, is necessary to minimize crop loss caused by bad climate [14,15].

This research paper addresses these limitations to promote advanced solutions and suggest further study [16].

Remote Sensing

A "Remote Sensing and IoT-Based Crop Health Monitoring System" collects real-time crop data over large areas using ground-based IoT sensors and aerial or satellite photos. This technology helps farmers increase crop yields through targeted interventions and resource efficiency by recognizing pests, nutritional deficits, and water stress early [17,18]. Remote sensing data is sent at light speed in harmonic wave patterns of various wavelengths by electromagnetic radiation. Identify and classify items and locations using electromagnetic energy. Remote sensing uses VIS, NIR, SWIR, FIR, and microwave [19,20]. Remote sensing measures and interprets electrical and magnetic electromagnetic waves. The electromagnetic spectrum interacts with materials for material analysis. Researchers use it to evaluate food and agricultural goods' chemical and physical qualities [21]. The electromagnetic spectrum can be used in various spectroscopic approaches to investigate material properties depending on its interaction with an item. Reflectance, absorption, transmission, and emission are the main interaction types in agricultural applications. [22].

Deep Learning:

In order for agronomists to maximize crop management, it is essential to gather and analyze data as part of crop monitoring. In order to get useful and accurate results. For the purpose of detecting diseases in plant leaves, a Convolutional Neural Network (CNN) architecture is proposed, employing Deep Learning techniques. After experimenting with several CNN hyperparameters, the proposed architecture was determined to have a disease classification accuracy of up to 95.81% [23].

Figure 2: Showing the Biz4intellia Solution for crop health monitoring [23].

A data-driven strategy from Biz4intellia IoT may help your farming business enhance operations and eliminate weaknesses. Innovative sensor gadgets help Biz4intellia improve prospects and make strategic decisions. Meeting seed quality, soil moisture, and other needs boosts agricultural productivity. Detailed reports with good graphics simplify data interpretation. Analyzing possibilities and business growth over time helps make smart decisions [24].

II. LITERATURE REVIEWS

Various methods for continuously monitoring agricultural operations and guaranteeing food security have been put up by various researchers in the literature. This study used image processing and computer vision to identify insect pests and plant diseases. Using smartphone photos to study insect pests and vegetable diseases [25,26]. Computer vision and computational imaging have created a new way to detect pest insects and plant illnesses. Pest insects and plant diseases are studied using cell phone images. Many neural network models and methods for plant disease detection have been developed and investigated [27]. In this article, application of computer vision and computational imaging is used to detect of pest insects and plant diseases has been devised. A number of models and methods for detecting plant diseases using neural networks have been developed and studied by researchers [28]. This research paper indicates that recognized tomato diseases might adversely affect tomatoes cultivated in greenhouses or open fields. Deep learning was used to detect illnesses in tomato leaves and goal was to conduct real-time deep learning algorithms on the robot. While in the field or greenhouse, the robot may diagnose diseased plants autonomously or remotely. AlexNet and SqueezeNet were tested as deep learning network topologies. These deep learning networks were trained and validated on the Nvidia Jetson TX1 [29, 30,31]. For training, PlantVillage tomato leaf photographs were used. An upgraded Faster R-CNN approach

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finds two crucial coconut maturation periods in a complex background with similar coconuts and their environment, preventing automatic detection. Faster R-CNN and ResNet-50 increase real-time and Google photo detection. The study evaluates crop health with artificial neural networks. SVM and genetic algorithm minimize loss and forecast disease kind. A natural selection-like evolutionary algorithm-based loss function optimization strategy for resilient parameters is proposed in this paper [32]. This study presents a deep learning-based grey wolf optimization method that responds to chemical and environmental changes. Chemistry and climate like pH, nitrogen, potassium, and phosphorus determine this study's crop recommendations. Levels of the comprehensive approach: First, it classifies key features with a convolutional neural network then grey wolf optimization determines the best crop by examining many criteria [33].

III. DATA COLLECTION

For the Crop Recommendation System, Kaggle CSV data is private from agricultural land. The simple CSV file format stores numerical and textual data in tabular form. The dataset usually includes soil pH, temperature, humidity, nitrogen, phosphorus, potassium, and rainfall. Additionally, the suggested crop is independent. Kaggle provides the Diseases Detection System dataset. Data in 80/20 format is already here. Both training and testing data sets contain eight crops, one healthy and one diseased. Eight healthy and unhealthy cropped photos were used in our investigation [34].

Preprocessing: To increase model quality and accuracy, eliminate noise before transmitting raw dataset pictures to the learning module. Noise like distortions, blurriness, and background features might hinder learning and recognition. Shearing corrects perspective distortions, rotation corrects photo orientation, and scaling scales image proportions to model input. Training and evaluation feature extraction, model performance, and anticipated accuracy improve with preprocessing [35].

The model's training and construction: Two steps make up this approach. Train transfer learning (TL) models on annotated training photos from a good dataset. These images teach the model essential features, patterns, and correlations for accurate detection or categorization. Augmentation and preprocessing may strengthen and generalize models. Second, test photos validate the learned model. Missed photos during training objectively evaluate model accuracy, precision, recall, and efficacy.

Based on specific agricultural precision activities, public image datasets are divided into three categories: controlling weeds, fruit detection, and others [36]. These categories are presented in Tables 1.

Table 1. Public image datasets.

S. No.	Dataset	Modality	Platform	Images	Annotations	URL
Weed control-related public image datasets.						
1	CWFI dataset [37]	Multispectral	Ground vehicle	60	Pixel Level	https://github.com/cwfid/dataset
2	Carrot-Weed [38]	RGB	Hand-holding	39	Pixel Level	https://github.com/lameski/rgbweeddetection
3	Plant seedlings [39]	RGB	Ground fixed platform	407	Image Level	https://vision.eng.au.dk/plant-seedlings-dataset
4	Grass-Broadleaf [40]	RGB	UAV	>10,000	Patch level	https://www.kaggle.com/fpeccia/weed-detection-in-soybean-crops
5	Sugar Beets 2016 [41]	Multimodal	Ground vehicle	>10,000	Image level	https://www.ipb.uni-bonn.de/datasets_IJRR2017/annotations
6	Open Plant Phenotype [42] Database (OPPD)	RGB	Ground fixed platform	7590	Image level, bounding box	https://gitlab.au.dk/AUENG-Vision/OPPD/-/tree/master/
Fruit detection-specific public picture datasets.						
1	MinneApple [43]	RGB	Hand-holding	>10,000	Pixel level	https://conservancy.umn.edu/handle/11299/206575
2	LFuji-air dataset [44]	LiDAR	Ground vehicle	Unspecified	Bounding box	http://www.grap.udl.cat/en/publications/LFuji_air_dataset.html
3	Mango YOLO [45]	RGB	Ground vehicle	1730	Bounding box	https://nextcloud.qriscloud.org.au/index.php/s/wvYJBt2rBX2dFJj
4	Fuji-SfM [46]	RGB	Ground based	288	Bounding box	http://www.grap.udl.cat/en/publications/Fuji-SfM_dataset.html
5	Orchard Fruit [47]	RGB	Ground vehicle	3704	Bounding box, circle	http://data.acfr.usyd.edu.au/ag/treecrops/2016-multifruit/
Public image datasets dedicated to other precision agriculture applications						
1	Oil radish growth [48]	RGB	Ground vehicle	129	Pixel level	https://vision.eng.au.dk/oil-radish/
2	GrassClover [49]	RGB	Ground based	>10,000	Pixel level	https://vision.eng.au.dk/grass-clover-dataset
3	Maize disease [50]	RGB	Multiple platforms	>10,000	Line level	https://osf.io/p67rz/
4	Sugarcane billets [51]	RGB	Ground based	156	Image Level	https://github.com/The77Lab/SugarcaneBilletsDataset
5	Fruit flower dataset [52]	RGB	Ground vehicle + hand-holding	190	Pixel level	https://data.nal.usda.gov/dataset/data-multi-species-fruit-flower-detection-using-refined-semantic-segmentation-network
6	Capsicum Annuum [53]	RGB	No imaging platform	>10,000	Pixel level	https://data.4tu.nl/repository/uuid:884958f5-b868-46e1-b3d8-a0b5d91b02c0

IV. METHODOLOGY

IoT Technology for crop health monitoring

Crop Health Monitoring using Popular IoT Technology: The use of remote sensing for crop categorization involves assessing crop properties by watching them from various locations, which may vary from a few meters to hundreds of miles from the chosen target. This technology has been demonstrated to be among the best options to track plants and

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agricultural fields. Satellites, manned aviation, unmanned ground vehicles (UGVs), and unmanned aerial vehicles (UAVs) are the most dependable remote sensing equipment, offering superior performance compared to traditional methods for agricultural scouting, which typically need a substantial workforce. Despite ongoing advancements in satellite and aircraft-based remote sensing technology, constraints persist regarding geographical and temporal resolution, cost, and the efficacy of agricultural classification for agricultural landowners [54]. Satellite, airborne, and UAV sensors collected RS data for mapping crops and yield prediction. In Figure 5, 81% of crop-mapping and yield-prediction studies used satellite sensors, followed by UAVs (12%). Four crop-mapping experiments used aerial and aerial photos to verify model resilience. Satellite imaging is possible because satellites regularly record data. Data providers pre-process satellite pictures. Thus, the user may focus on app development rather than pre-processing. UAVs were utilized more in yield-prediction research than crop-mapping, yet they can accurately map crop boundaries [55]. Optic instruments are passive and rely on sunlight, limiting satellite views. Cloud effects also make optical imaging difficult because optical radiation cannot penetrate clouds, resulting in temporal data loss [55]. Multiple images can be taken from the same radiation. It transmits H or V-polarized signals. Also receives H and V polarized reflected signals. Thus, HH, VV, HV, and VH polarizations can record reflected signal intensities (Anon, 0000b). SAR imaging has downsides. Soil roughness and vegetation growth can generate SAR signal saturation bias, making crop growth and development harder to detect. Deep learning and polarimetric SAR data fix this [56]. Crop height, LAI, biomass, and chlorophyll content can be analyzed using optical imaging. Radar imagery shows agricultural structure, water availability, crop moisture, etc. Thus, these two crop monitoring sources complement each other [57]. Thus, merging optical and radar images for crop-type classification is becoming more common [58]. Some of the popular satellites offering optical and radar images with a brief description are listed in Table 2.

Table 2: Smart sensors and their utility in agriculture.

S. No.	sensors	Efficacy	Working criteria
1	Electromagnetic sensors [59]	Assess soil organic matter, residual nitrate, electromagnetic interactions in real time.	Recording soil electrical impulses with electrical circuits
2	Electrochemical sensors [60]	Helps monitor soil pH and nutrients.	Individual agricultural soil electrochemical gradient sensors.
3	Airflow sensors [61]	Evaluate soil-air accessibility,humidity, and mobility while stationary or moving.	It detects numerous soil parameters utilizing distinct traits.
4	Ultrasonic ranging sensors [62]	Aids pest, crop canopy, and weed detection.	To detect item proximity, uses ultrasonic sensor that sends and receives pulses.
5	Flexible and wearable sensors [63]	Senses plant shape, size, growth, and temperature.	Flexible sensors for plant mounting.
6	Battery-free and self-powered sensors [64]	Help sense temperature, humidity, etc. They check food quality.	Sensors use solar panels instead of batteries.

Indian agriculture relies on monsoon crops such as maize, finger millet, sorghum, and rice [65-66]. To ensure national and global food security, it must be monitored. This season's greater cloud probability makes optical satellite imagery inefficient. In Qadir and Mondal (2020), Google Earth Engine (GEE) was used to calculate backscatter coefficients and NDVI from S1 (SAR imaging) and S2 (optical imaging) [67]. Radar Optical cross Masking (ROM) method masks woodlands, plantations, and other non-dynamic features to find crop-suitable areas. To map tropical Vietnamese croplands without clouds, optical and SAR data from S2 and S1 were merged into a more relevant agricultural field database [68]. One or more sensors, a microcontroller, an ADC, a communication channel, memory, and a power source make up a smart sensor.The processor, usually a microcontroller, relays sensory data to the network. Traditional sensor systems process data with one resource. After local processing, the signal node transfers data to the network [69].

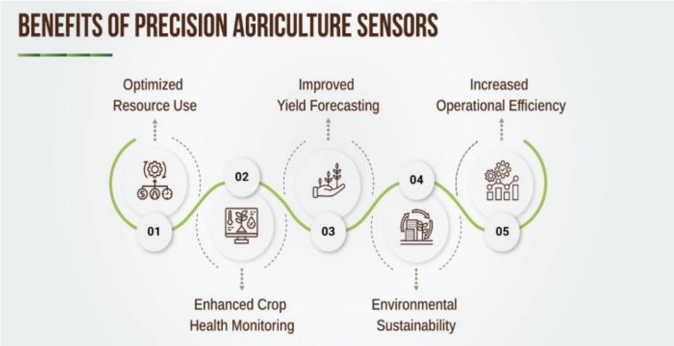

Figure 3: Steps to increase efficiency in crop monitoring using sensors.

Deep Learning for crop health monitoring:

Crop pests and diseases create massive production losses that threaten global food security. The urgent need for better crop pest and agricultural hazard identification methods. Deep learning is an effective photo recognition and categorization tool. Deep learning may computerize agricultural image analysis for recognizing crops that are healthy, insect species, and crop illnesses. Here are some deep learning-based crop and pest identification. This could boost crop production and food safety [70]. There are several commonly used deep learning models used for crop health monitoring algorithms such as VGG16, Convolution Neural Network (CNN), Xception, ResNet, DenseNet and EfficientNet etc.

- **VGG16 & VGG19:**

VGG16 is a convolutional neural network that uses 16 stacked convolutional layers to attain high accuracy. It is notable for its clarity and picture categorization abilities. Though initial

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training is statistically costly, transfer learning is made easier with its pre-trained weights in many applications that utilize computer vision [71].

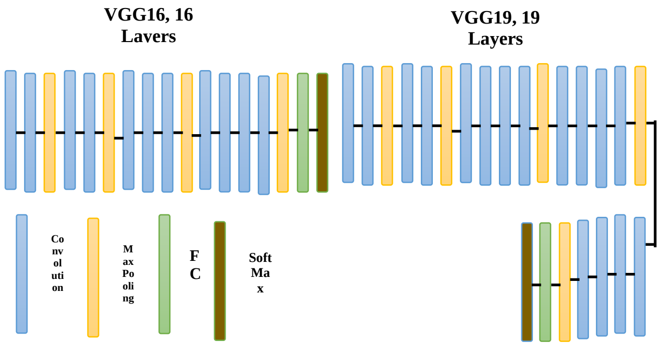

Figure 9. Figure (a)and (b) Showing the basic architecture of VGG16 and VGG19.

➢ **Convolutional Neural Network (CNN):**

Convolutional Neural Networks (CNNs) excel in processing visual input, including pictures. Optimally suited for tasks such as identifying things and image classification, they utilize specialized "convolutional" layers to identify patterns and features. Convolutional Neural Networks (CNNs) serve as a fundamental element of deep learning, instigating a transformation in computer vision [72].

Figure 10: Basic procedure to detect disease of crop using CNN model.

➢ **Transfer Learning (DenseNet201) & Inception:**

Densely Connected Convolutional Networks, also referred to as DenseNets, are recognized for their unique architecture. Direct connections among all layers facilitate robust feature propagation and promote feature reuse. Compared to traditional CNNs, DenseNet attains superior accuracy with fewer parameters owing to its dense connectivity. The efficient "inception components" employed by Inception models' deep learning architecture arrange convolutional layers in parallel pathways. The precision of visual recognition obligations, including image recognition and classification, is enhanced by extracting varied features at multiple resolutions [73].

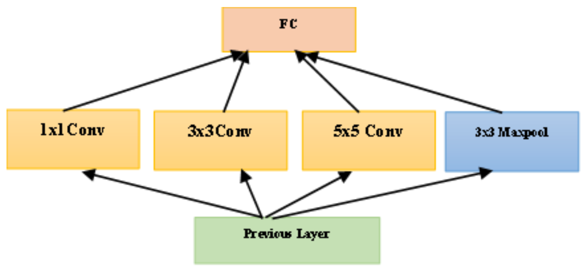

Figure 11: Basic architecture of Inception Module

➢ **ResNET Model:**

In 2015, Microsoft Research created a deep neural network architecture known as ResNet, an abbreviation for Residual Network. ResNet utilizes skip connections to train deep neural networks with multiple layers, thereby alleviating the vanishing gradient issue. The primary advantages of ResNet are the enhancement of network depth and the mitigation of negative impacts. The detecting technique necessitates accuracy and a margin for error to reveal multiple concealed layers. Identification mappings are beneficial in this procedure. Persist with residual learning until outcomes are evident. Deep learning researchers employ multiple layers to extract substantial insights from intricate images. This enables edge detection in the initial layers and tire discrimination in the later levels [74].

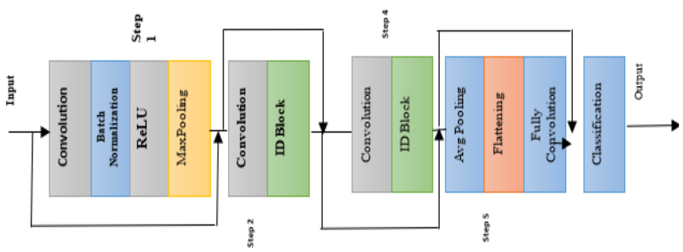

Figure 12: Basic Architecture of ResNet.

V EVALUATION METRICS:

The Parkinson disease dataset used to evaluate classification algorithms' accuracy, precision, recall, and F1 scores. These metrics evaluate classification models best. Equations show statistical measurements for the successful classification of cases and the wrong classification of instances (FP and FN). Where terms TP-True Positive, TN-True Negative, FP-False Positive, FN-False Negative are used showing in table 3.

Table 3: Different evaluation parameters to check the model's performance [75].

Metrics	Formula
Accuracy	$\text{Accuracy} = \frac{TP+TN}{(TP+TN+FP+FN)}$ (1)
Precision	$\text{Precision} = \frac{TP}{(TP+FP)}$ (2)

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Recall	$TPR/Sensitivity/Recall = \frac{TP}{(TP+FN)}$	(3)
F1-Score	$\text{F1 Score} = 2 \times \frac{\text{Precision} * \text{Recall}}{\text{Precision}+\text{Recall}}$	(4)

VI IMPLEMENTATION

Common deep learning models are used to evaluate the recognition accuracy. The following algorithms are included: CNN, ResNet, DensNet, Xception, VGG16-19 and so on.

A. Environment Setting

For implementation, we used mostly used deep learning models with batch normalization, maximum pooling, etc., and 10–20 epochs. The suggested technique is trained and tested on this hardware: CPU: Intel i9-9900k@3.60, 15.9 GB for Kaggle; GPU: NVIDIA-SMI, 12.0 CUDA. The network frameworks are written in Windows using Pytorch framework-2.0.0 and GPU: Tesla T4(Colab). For this purpose, we have used PlantVillage dataset to recognise plant health by predicting plant disease [76]. Where 43456 images belonging to 38 classes. Training 70%, Testing 20% and validation dataset distribution is 10%.

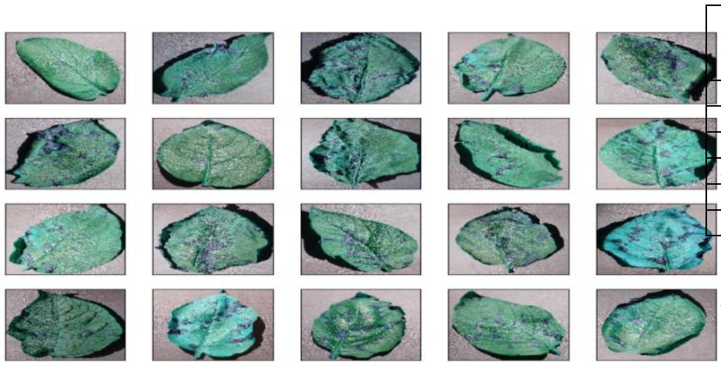

Figure 13: PlantVillage Dataset for recognition of crop health.

B. Purposed Algorithm:

Algorithm: Input ⟵ Dataset

Step 1: Analysis of Dataset:

- Determine distributions, patterns, and relationships to reveal data trends, events, and relationships.
- Investigate the target's bivariate relationships in great detail.

Step 2: Preprocessing Steps:

- Eliminate extraneous elements and remove any unnecessary components
- Find and handle outliers and missing values.
- Data with categories should be encoded.

Step 3: Apply Models:

- Use CNN, ResNet, Xception, DensNet, VGG16-19, EfficientNet models.
- Make sure that disease are identified thoroughly and comprehensively by prioritizing achieving a high recall for class 1.
- Apply network architectures

Step4: Analyse and Contrast the Models' Efficiency

- Use Accuracy, precision, recall and F1-score, to evaluate the performance of the models.

Stop

VII RESULTS

The PlantVillage dataset predicted plant ailments using a categorical cross-entropy loss function during detection network training, testing, and validation. Each iteration of deep learning model detection enhances accuracy and loss results by updating and adjusting network parameters during network training.We have run the model for around 10-50 number of epochs with "adam" optimizer and batch normalisation with learning rate 10^{-5}. It provided various accuracy values for different deep learning models.

Table 4: Models performance to detect diseases in PlantVillage dataset.

S. No.	Models	Accuracy (%)	Training Loss	Validation Loss	Test Accuracy (%)
1	CNN	98.98	0.0725	0.085	98.7
2	ResNet50	97.90	0.0612	0.079	97.0
3	Xception	98.25	0.0781	0.066	98.2
4	DenseNet	97.34	0.0952	0.105	97.5
5	VGG19	96.53	0.9642	0.095	98.2
6	EfficientNet	99.76	0.0063	0.008	99.5

Where CNN model achieved 98.98% accuracy and EfficientNet with 99.76% accuracy on around 25- 50 epochs. In this experiment EfficientNet model achieved the highest accuracy.

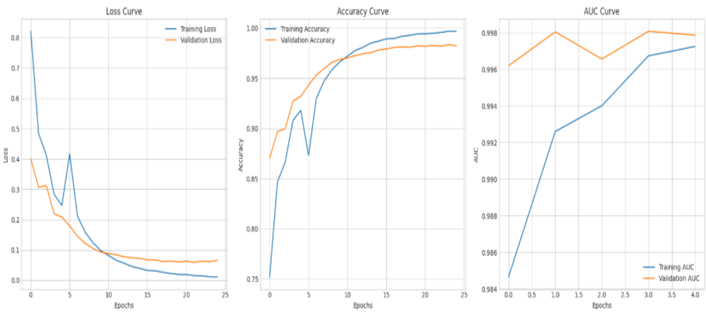

Figure 14: Performance of Xception Network on around 25 epochs where it took 13ms/step.

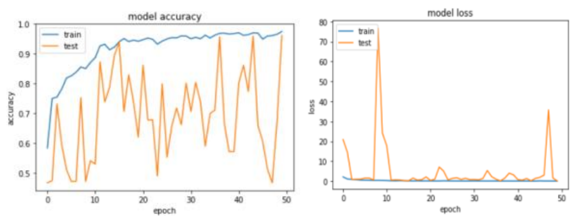

Figure 15: Performance of DensNet model with model accuracy and loss on over50 epochs.

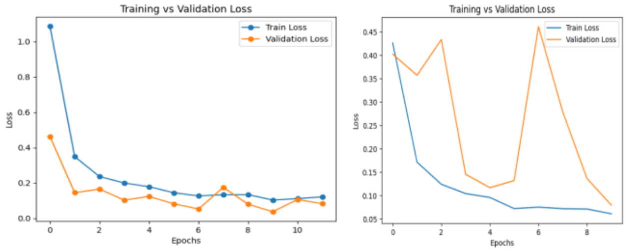

Figure 16: Performance of VGG19 and ResNet50 models with training and validation loss degradation over 12 epochs.

VIII CONCLUSION AND FUTURE WORK

IoT-enabled smart farming seems promising. Use advanced instruments to monitor rainfall, moisture, and temperature for maximum agricultural results. IoT devices measure soil nitrogen and water. Monitoring evapotranspiration based on the government enacted measures to support farmers EfficientNet deep learning architectures to reliably classify crop illnesses using data gathered from images. These models capture various features and patterns in crop images, improving disease detection and diagnosis accuracy. CO2 levels in farm areas enhances crop health surveillance. Use IoT traps with high-resolution cameras and accessories to deter pests. Advanced hardware and software are expensive, making IoT-based smart sensors in agriculture difficult to deploy. Rural farmers also grasp IoT devices poorly. Smart farming may be more easily implemented on a wide scale if This chapter suggests EfficientNet as the optimal model for financially, increase digital literacy, and provide smart sensor detection and prediction environment for farmers at low cost. In terms of deep learning architecture to maintain the crop health in terms of disease detection at early stage. This chapter utilizes most popular deep learning algorithms for the same CNN, ResNet, DensNet, Xception, VGG19 and classification and disease identification. It has enhanced crop productivity, decreased losses, and promoted sustainable agricultural practices through new disease management methods to maintain health of crops in healthy. Detecting infections early enables farmers to adopt preventive actions like targeted treatments or crop management practices, improving health and productivity.

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