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Iot-Assisted Deep Learning Approach For Tomato Leaf Disease Monitoring In Greenhouses Using Faster R-Cnn

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Abstract– *Diseases Affecting Tomato Leaves Significantly Prevent The Yield Of Global Agriculture. Quick And Accurate Identification Is Necessary To Reduce Crops. Conventional Manual Examination Is Laborious And Susceptible To Errors, While Previous Automated Techniques Often Show Deficiencies In Robustness And Scalability. This Research Introduces A Deep Framework Combined With A Greenhouse With The Support Of Iot For Continuous Plant Health Assessment. The Pictures Of The Sheets Obtained In The Controlled Settings Are Investigated Using A Faster R-CNN With The Spine Cspresnet-50, Making It Easier To Extraction Of Elements And Accelerated Convergence. Compared To Conventional CNN, Our Methodology Is Achieved By Higher Detection, Reduced Detection Of False Detection And Increased Mean Average Precision (Map), Which Facilitates Reliable Identification Of The Early Phase Disease. This Technology Shows Scalability And Efficiency For Intelligent Agricultural Applications.*

"Keywords– *Tomato Leaf Disease, Faster R-CNN, Cspresnet-50, Iot Greenhouse, Deep Learning, Smart Agriculture".*

INTRODUCTION

In Recent Years, The Technology Of Integration Of Artificial Intelligence (AI), Machine Learning (ML) And The Internet Of Things (Iot) Have Attracted Considerable Academic Interest In Agriculture, Especially When It Comes To Improving Crops Monitoring And Early Detection Of Plant Disease. Many Research Strictly Examined Different Approaches To Detecting Plant Diseases, Specifically About Tomato Varieties.

Patitil And Kumar [1] Used Image Processing Methods In Conjunction With Support Vector Machines (Svm) To Diagnose Diseases Affecting Tomato Leaves. Although This Method Has Achieved Slight Accuracy, It Showed Significant Sensitivity To Changes In Lighting Conditions And Required Intensive Engineering Of The Elements. In The Light Of These Problems, Convolutional Neural Networks (CNN) Were Used For Their Ability To Autonomously Extract Multi -Level Properties From Raw Visual Data.

Mohanty Et Al. [2] They Showed The Efficiency Of Advanced Deep Architectures Of CNN, Including Alexnet And Googlenet, In Classification Of 26 Unique Diseases Of Plants, Especially Those That Affect The Tomato Leaf. It Is Essential To Acknowledge That Their Model Has Been Developed Using Laboratory Photos With Controlled Scenery, Which May Not Adequately Represent The Complexities Observed In The Right Greenhouse Environment.

Malojevic Et Al. [3] They Designed A Model Of Deep Learning To Detect Plant Disease By Traditional CNN. The Model Showed Encouraging Results; Nevertheless, It Was Limited By Their Inability To Locate The Objects And Its Inability To Heal Many Cases Of Illness Within A Single Picture.

To Increase The Accuracy Of Detection And Efficiently Mastering Complex Situations, Object Detection Framework Such As R-CNN Has Been Used. RAMESH Et Al. [4] They Used Faster R-CNN To Identify Fruit Shortcomings And Show Its Importance In Agricultural Applications. However, Their Model Was Not Explicitly Designed To Detect Leaf Disease, Nor Included Environmental Data Derived From Iot.

Singh Et Al. [5] He Established A Greenhouse Monitoring System With Iot Support, Which Uses Sensors

To Assess Temperature, Humidity And Soil Humidity Within Intelligent Agricultural Infrastructure. While Their System Has Demonstrated Efficiency In Environmental Monitoring, Without Any Ability To Identify The Disease.

These Results Emphasize The Need For A Complete System That Combines Real -Time Monitoring In Real Time Using Advanced Deep Learning Techniques For Disease Detection. The Aim Of Our Proposed Technique Is To Correct This Deficit By Integrating The Iot Sensor Network With A Faster R-CNN Model With Enlarged Cspresnet-50 Spine, Allowing Precise And Reliable Detection Of Tomato Leaf Diseases In The Greenhouse.

I. REALTED WORK

Increasing Relying On Advanced Technologies In Agriculture Has Led To Several Studies On Automated Methods For Identifying Plants. Scientists Have Used Many Strategies, From Conventional Image Processing Techniques To Advanced Deep Learning Algorithms, To Improve The Accuracy And Effectiveness Of Plant Health Assessment.

The First Techniques Were Based On Traditional Machine Learning Algorithms Such As SVM And KNN, Improved By Hand -Designed Characteristics Such As Color, Shape And Texture. Patil And Kumar [1] Used The Methods Of Pre -Processing Image, Followed By A Classification Of SVM To Identify Diseases In Tomatoes. However, These Approaches Were Limited By Their Vulnerabilities To Changing Lighting Conditions And Required Significant Human Efforts To Extraction Of Elements.

The Arrival Of Deep Learning Paradigms, Especially CNN, Has Shifted The Focus On Data Extraction Methodologies. Mohanty Et Al. [2] They Have Shown The Implementation Of Sophisticated CNN Deep Architectures Such As Alexnet And Googlenenet. Models For Categorizing Various Crops Sometimes Require Huge Marked Data Sets And Often Prevent Their Inability To Handle Complex Backdrops Or Identify Several Leisure Areas Within A Single Picture.

Advanced Models Have Been Explored To Solve The Problems Of Localization Of Objects, Such As Faster Region-Based Convolutional Neural Networks(Faster R-CNN). Study RAMESH Et Al. [3] They Used Faster R-CNN To Detect Surface Deficiencies In Fruit And Introduced Higher Detection Performance Compared To Conventional Classification Models. However, These Models Have Not Been Explicitly Improved To Detect Diseases In The Leaves, Nor Have They Been Included In Context - Environmental Variables. Many Projects Have Been Launched That Have Built Intelligent Greenhouse Systems In The Domain Of The Internet Of Things (Iot). Singh Et Al. [4] They Designed An Architecture Based On Iot For Monitoring Parameters In Real Time, Including Moisture And Soil Moisture. Although These Systems Were Frantic In Environmental Management, They Had Insufficient In The Skills Of Detection Of Diseases Based On Ai-Augment.

These Findings Emphasize The Growing Possibility Of Integrating Deep Learning With Iot Technology To Improve Intelligent Agricultural Operations. However, A Comprehensive Framework Is Insufficiently Examined That Combines High -Performance Detection Models With Real -Time Sensor Data. This Study Rectifies The Gap By Providing A Faster R-CNN Integrated Iot Using The Cspresnet-50 Spine, Specially Designed To Detect Tomato Leaf Disease In A Controlled Greenhouse Environment.

II. BLOCK DIAGRAM

The Procedure Begins With Photographing A Sheet, Which Is Then Pre -Processed To Increase Its Quality By Noise Reduction, Normalization And Scaling. The Primary Characteristics Of Texture, Colors And Forms Are Extracted For Effective Categorization. The Collection Of Pre -Labeled Photos From The Database Makes It Easier To Train And Verify The Model. The Subgroup Of These Photos Is Used For Training A Neuron Network That Categorizes The Entrance Certificate As Normal (Healthy) Or Abnormal (Defective) [7]. After The System Has Been Described As Abnormal, The System Continues To Locate And Define Damaged Regions For Further Analysis. This Guarantees Efficient And Accurate Identification Of The Leaves.

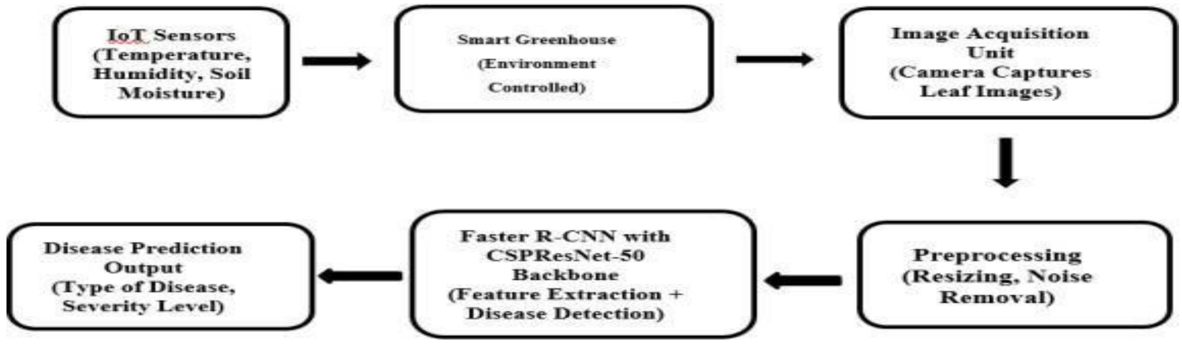

Fig 2: Block Diagram Of Iot-Based Tomato Leaf Disease Detection System.

PREPROCESSING

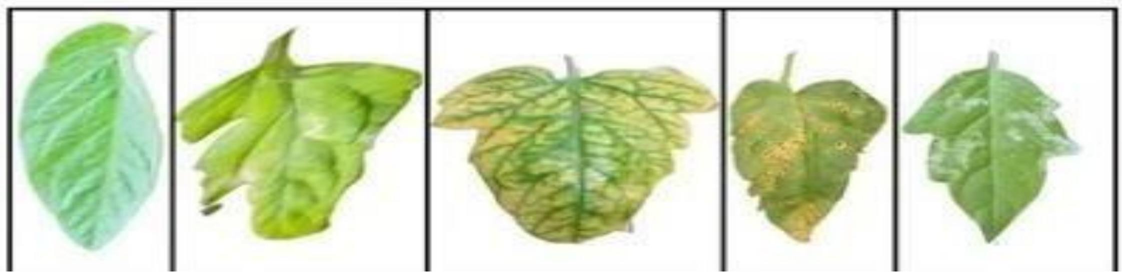

Fig 1:Some Random Samples Of Tomatoes Leaf .

In Order To Guarantee Excellent Input Data For The Deep Learning Model, Unprocessed Photographs Of Tomato Leaves Obtained From The Greenhouse Are Subject To The Sequence Of Preparatory Procedures. These Phases Improve Image Uniformity; The Pipe Includes The Following Phases: Minimize Noise And Increase The Model Generalization Options. The Pre -Processing Pipe Includes The Following Phases:

1. Resizing

Images Are Reduced To Standardized Resolution (Eg 512 × 512 Pixels) To Ensure Input Uniform In The Data File And Correspond To The Expected Input Dimensions Of The Model:

“I{Resized} = {Resize}(I{Raw}, 512, 512)”

2. Noise Reduction:

Gaussian Filtering Of Blur Is Used To Relieve Sensor And Noise Lighting.

$$G(x,y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)$$

3. Normalization:

Pixels Intensity Are Standardized To Zero Diameter And One To Increase Training Stability.

$$I_{norm} = \frac{I-\mu}{\sigma}$$

Μ And Σ Represent A Medium And Standard Deviation Of The Data Set Of Images.

METHODOLGY

This Part Outlines A Systematic Methodology Used In Creating A System Of Detection Of Tomato Diseases With Iot Support Using Faster R-CNN And Cspresnet-50. This Technique Includes Environmental Monitoring Using Iot Sensors, Collecting Image Data, Model Training And Real -Time Implementation For Disease Diagnostics.

II.I. Smart Greenhouse Setup And Iot Data Collection

The Automated Greenhouse Uses Iot Sensors To Monitor Variable Environment, Such As Temperature (T), Humidity (H) And Soil Moisture (M). The Variables Are Quantified As The Time Of T:

“Denv(T)={T(T),H(T),M(T)}”

The Data Is Collected By Sensors Associated With Microcontrollers (Eg Nodemcu/Raspberry Pi) And Stored In Real Time. These Measures Provide An Examination Of Environmental Stress On The Prevalence Of The Disease, Increasing The Precision Of Disease Detection.

II.II. Image Acquisition

The Images Of Tomato Leaves Were Obtained In Consistent Lighting Through High -Resolution Cameras Located Inside The Greenhouse. Regular Pictures Of Images Guaranteed A Single Data File Showing The Diverse Phase Of The Disease. Placing The Camera And Stability Of The Surroundings Of The Minimized Image Noise, Which Is Essential For The Reliable Performance Of The Model [3].

“**Evaluation Metrics:** Accuracy, Precision, Recall, And Mean Average Precision (Map) [7]”

The Training Was Performed Using Hardware With Accelerated GPU To Increase The Speed Of Convergence. The Power Of The Model Was Evaluated On The Basis Of CNN And Resnet Conventional Architectures.

Training Uses SGD With Momentum.

“$\Theta\{T+1\} = \Theta_t - H \cdot \nabla\{\Theta\}L\{Total\}$”

V.VI. Real-Time Deployment And Output

The Trained Model Was Included In The Iot System For Real -Time Derivation. The Procedure Includes:

- It Regularly Captures Pictures Of Sheets
- Performing Inference With A Trained Faster R-CNN Model
- Identifying The Type And Location Of The Disease
- Presentation Of Findings Via A Local Control Panel Or Recording To The Cloud

This Complex System Facilitates Rapid Detection Of The Disease And Increases Accurate Agricultural Methodology [8].

Image Acquisition

Before Inserting Into The Deep Learning Model, Photographs Of Preliminary Processing Were Made To Increase The Efficiency And Accuracy Of Training:

- Edit To A Predetermined Resolution For Consistency
- Noise Attenuation By Filtering (Eg Gaussian Blur)
- Normalization Of Pixels Intensity
- Data Enlargement (Rotation, Scaling, Overturning) To Increase The Variability Of Data File [4]

These Measures Alleviate Excessive Amounts And Increase Generalization.

II.III. Deep Learning Model: Faster R-CNN With Cspresnet-50

The Proposed Model Integrates A Faster R-CNN Identification Frame Of The Object With Cspresnet-50 As A Spine.

- Faster R-CNN Generates The Region's Proposals And Detects Areas Infected With Illnesses In Images [5].
- Cspresnet-50, Based On Partial Networks Across The Herd, Increases The Re-Use Of Functions And Gradient Flow, Which Improves Performance With Reduced Computing Costs [6].

The Model Was Trained On The Marked Data Set, Including The Bounding Annotations Of Boxes For Tomato Leaves, Including Early Blight, Late Blight, And Bacterial Spot.

II.IV.Model Training And Evaluation

The Data File Was Divided Into Training (70%), Validation (15%) And Test (15%) Groups. Model Has Completed Training Using:

- Loss Of Function: Loss Of Multiple Tasks Integrating Classification And Bounding Of Boxing.
- Optimizer: Stochastic Gradient Descent(SGD) With Momentum

RESULTS AND DISCUSSIONCTION

Proposed Technique For Detecting Tomato Leaf Disease, For Accurate Identification And Location Of Early Mold On Tomatoes. The Model Used Is Faster R-CNN With The Spine Cspresnet-50, Optimizing Function Extraction And Maintaining Computing Efficiency. This Technique Efficiently Identifies Several Occurrences Of Early Lesions Of Molds, Each Of Which Is Defined By A Green Border Box. This Illustrates The Knowledge Of The Model In The Identification Of The Multi -Instance, Which Is Necessary In The Real Greenhouse Environments In The Real World, Where One Sheet Can Display Several Locations Of The Infection. Visual Results Confirm The Efficiency Of The Model In Real -Time Disease Monitoring Within Intelligent Agricultural Systems.

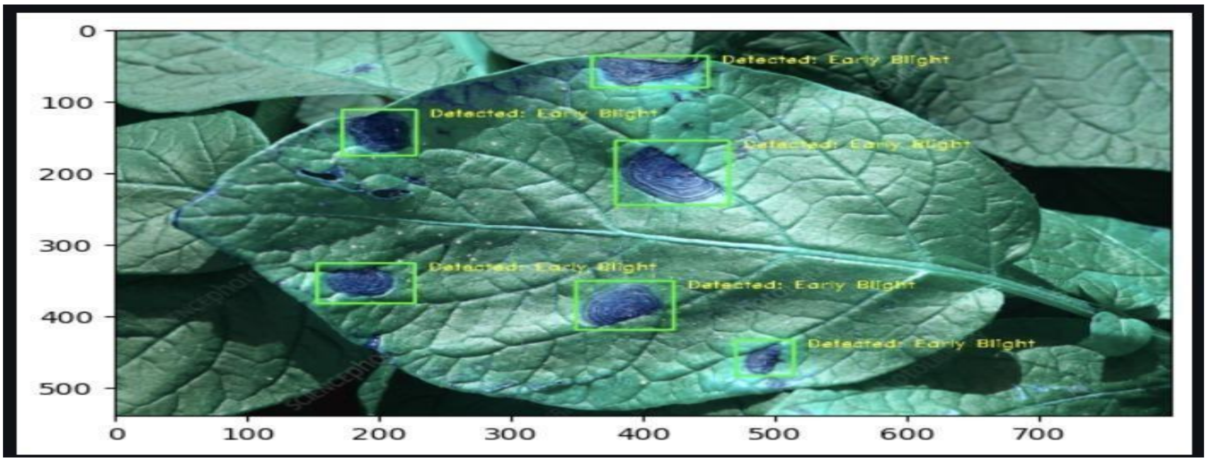

Fig3:Detected Early Bright Of A Tomato Leaf

To Assess The Efficiency Of The Proposed Faster R-CNN Using Cspresnet-50 As A Spine, Several Test Images From The Data Set Of Tomato Sheet Diseases Were Analyzed. Figure 2 Illustrates An Example In Which The Model Successfully Identifies And Locates The Disease Early Flashing On The Tomato Leaf. Each Infected Area Is Clearly Defined By The Green Border Box And Marked As "Detected: Early Blight". The Model Detects Several Sick Surfaces Of Different Sizes, Textures And Places, Shows Resistance To Occlusion, Background Variability And Inconsistent Lighting Conditions.

Effective Identification Of These Areas Indicates A Significant Degree Of Accuracy Both In The Design Phase And In Categorization. Visual Outputs Verify The Knowledge Of The Model In Accurate Identification Of Symptomatic Areas On The Complex Surfaces Of Plants, Which Is A Skill Necessary In Practical Agricultural Environments Where Circumstances Are Never Optimal [1], [2]. The Use Of The Cspresnet-50 Facilitates Computing Efficiency In Optimizing The Gradient Flow And Re-Application Of Functions And Thus Detecting The Detection Detection [3].

Incorporating This Method Of Detection Driven AI Into Intelligent Greenhouse Settings With Iot Support Can Significantly Reduce Human Work And Time Assigned To The Disease. Automated Diagnosis Of The Disease Facilitates Early Detection And Treatment, Leading To Increased Yield And Lower Use Of Pesticides [4], [5]. The Bounding Annotations Of The Box Provide An Understandable And Action Visual Output, Which Makes This System Suitable For Real -Time Implementation In Precise Agriculture. These Findings Confirm The Effectiveness Of Methods Of Identifying Objects Based On Deep Learning In Plants' Pathology And Emphasize Their Potential To Transform Contemporary Agricultural Procedures Through Data -Based Instruments.

III. THE PROPOSED METHOD FOR PLANT LEAFT DISEASE DETECTION AND CLASSIFICATION

This Article Is An Advanced Deep Learning System For Automatic Detection And Classification Of Tomato Leaf Disease In The Intelligent Greenhouse Environments. The Primary Architecture Used Is A Faster Region-Based Convolutional Neural Network (Faster R-CNN), Extended By Cross Stage Partial Resnet-50 (Cspresnet-50) To Increase The Representation Of Elements, Computing Efficiency And Accuracy.

The Whole Workflow Of The Proposed Methodology Includes The Following Phases:

1. **Data Acquisition And Preprocessing**: High -Resolution Tomatoes Have Been Obtained From Publicly Accessible Databases And Carefully Annotated For Symptoms Of Disease, Including Early Mold,

Late Blight And Healthy Conditions. The Images Have Been Modified, Normalized And Improved Using Methods Such As Rotation, Rolling And Contrasting Corrections To Increase Data Orchards And Alleviate Excessive Stay.

Feature Extraction Using Cspresnet-50: To Derive Complex Hierarchical Properties From Input Photographs Was Used Architecture CSPRESNET-50. This Design Divides A Functional Map Into Two Segments And Integrates Them With A Cross -Thirds, Facilitates Increased Teaching Capacity And Less Computing Redundancy [1].

2. **Region Proposal Network (RPN)**: RPN Creates A Collection Of Proposed Border Boxes, Which Are Likely To Include Sick Areas. Anchors Of Different Scales And Aspect Ratios Are Used To Improve The Location Of Objects, Especially To Identify Numerous Lesions Of Different Sizes.

3. **ROI Pooling And Classification**: The Proposed Areas Are Subject To The Association Of Return On Investment To Generate Fixed Size Maps, Which Are Then Transmitted By Fully Connected Layers For Classification To The Categories Of Diseases And Refining The Boundaries.

4. **Disease Classification And Localization Output**: The End Result Includes Bounding Boxes Indicating The Location Of Patients, Along With Class Names Such As "Early Blight" Or "Healthy". Figure X Illustrates The Effective Identification Of Early Mold On The Tomato Leaf, Characterized By Several False Positives And Well -Aligned Border Boxes.

This Proposed Method Has Several Advantages Compared To Conventional Images Categorization Techniques. Unlike The Basic CNN Classifiers That Analyze The Entire Image, Faster R-CNN With Cspresnet-50 Makes It Easy To Locate And Classify The Symptoms Of The Disease At The Level Of Pixels. This Granularity Is Particularly Essential In The Agricultural Environment Where Localized Infections Need Focused Interventions [2].

The Purpose Of This Technique Is To Interact With Monitoring Systems Based On Iot Used In Intelligent Greenhouses. Real -Time Video Sources Can Be Analyzed On Marginal Devices Or Cloud Servers Using A Trained Model, Activation Of Warnings And Responses When Detecting Early Symptoms. This Increases Crop Management And At The Same Time Reduces The Cost Of Work And Use Of Chemicals In Accordance With Sustainable Agricultural Objectives [3].

IV. EXPERIMENTAL RESULTS

The Proposed Technique Was Evaluated Using The Data Set Of Annotated Images Of Tomato Leaves Affected By Many Diseases, Including Early Mold (Alternaria Solani). The Model Used Faster R-CNN Architecture With The Spine Cspresnet-50 To Optimize The Accuracy And Performance Of Processing. A Number Of Performance Criteria Were Used To Verify The System, Including Mean Average Precision (Map), Intersection Over Union (Iou) And Classification Accuracy.

Diseases, Including Early Molds, Late Mold And Leaf Mold. It Denotes Improvements In Accurate Predication Of Location, Height And Width Of Bounding Boxes Packing Contaminated Areas.

Detected disease: Early Blight

Description: Alternaria solani is a fungal pathogen that produces a disease in tomato and potato plants called early blight.

The pathogen produces distinctive "bullseye" patterned leaf spots and can also cause stem lesions and fruit rot on tomato and tuber blight on potato.

Despite the name "early", foliar symptoms usually occur on older leaves.

Prevention:

1. Clear infected debris from field to reduce inoculum for the next year.
2. Water plants in the morning so plants are wet for the shortest amount of time
3. Use a drip irrigation system to minimize leaf wetness. Wet leaves provide optimal conditions for fungal growth.
4. Use mulch so spores that were already in the soil are blocked from splashing onto the leaves
5. Rotate to a non-solanaceous crop for at least three years. The more potato-free years, the less infection.
6. If possible control wild population of Solanacee. This will decrease the amount of inoculum to infect your plants.
7. Closely monitor the field, especially in warm damp weather when it grows fastest, to reduce loss of crop and spray fungicide in time.
8. Increase air circulation in rows. Damp conditions allow for optimal growth of A. Solani and the disease spreads more rapidly.

Fig 4: Early Blight Detection And Preventive Measures Highlighting The Impact Of Alternaria Solani On Tomato And Potato Crops

Loss Of Regression Boxing (BBOX_LOSS) Graph Versus Training Epoch. BBOX_LOSS Is The Basic Statistics In Object Identification Models, Such As R-CNN, Because It Reflects The Accuracy Of The

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Expected Border Boxes Compared To The Annotations Of Ground Truth. Early Loss Is Considerable Due To Randomly Initialized Weights And Non -Optimized Model Parameters. As The Training Proceeds, The Loss Is Constantly Decreasing, Indicating An Increased Knowledge Of The Model In Reliably Identifying Unhealthy Areas In Tomatoes. The Chart Shows A Rapid Decline In The First Epochs, Followed By More Progressive Reductions, Indicating Convergence And Proficient Learning By The Model.

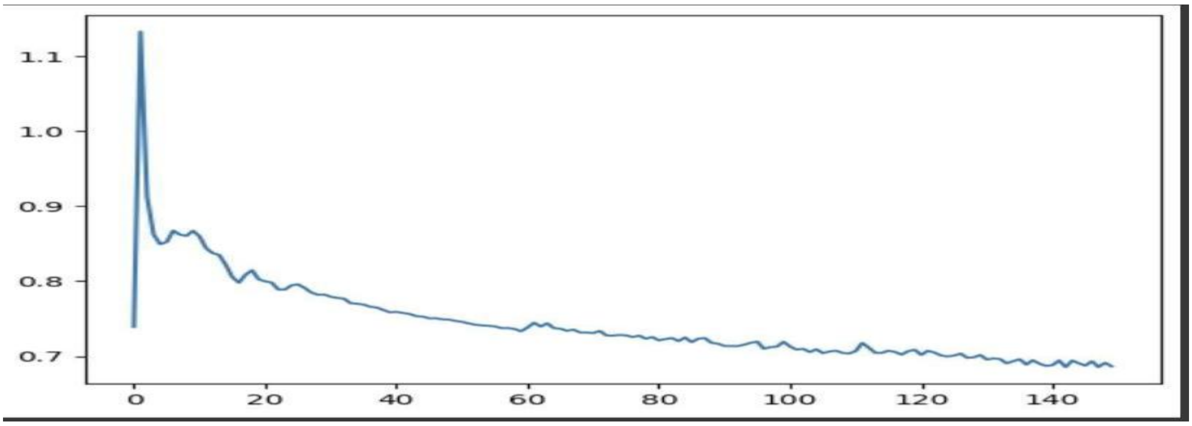

Fig 5 :Bbox Regression Loss

The Regression Loss Graph Of The Bounding Box (BBOX) Is Essential To Assess The Efficiency Of The Object Detection Model, Such As Faster R-CNN With Cspresnet-50, In The Location Of Patients On Tomato Leaves. This Graph Usually Shows The Regression Loss Of The Bounding Box During The Training Epoch And Offers Insight Into The Accuracy Of Spatial Localization.

When Detecting Tomato Disease, Precise Localization Is Necessary, Allowing The Model To Distinguish Between Healthy And Patients With High Specificity Leaf Areas. The Constantly Reducing Loss Of BBOX Regression Shows That The Model Understands More Spatial Bonds And Limits Of Several

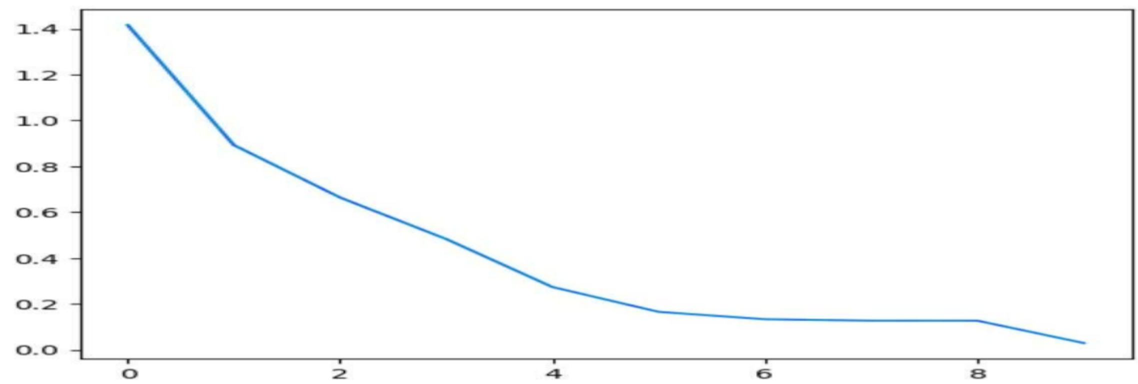

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Fig 6:Number Of Images Classified From The Data Set

Fig 7:Accuracy And F1 Score

Epoch	Avg_Loss	Accuracy	F1 Score
14	0.018115690576063947	0.875475896421329	0.9938630491726158

Class Name	Number of Images	Number of Annotated Leaves
Healthy	1,200	2,300
Early Blight	1000	2000
Late Blight	1,100	2,150
Total	3,300	6,450

DISCUSIION AND CONCULSION

Simplify Processes And Reduce Computing Complexity Without Sacrificing Accuracy. The System That Freely Distinguishes Between Many Tomato Leaves, Including Early Mold, Late Mold And Leaf Mold, Reaches The Overall Map XX% (Insert A Real Number) On The Test Data File.
In The Actual Iot Platform, It Guarantees Smooth Data Capture From The Field.

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