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Research Paper

Crop Care AI - Accurate Crop Prediction, Fertilizer Recommendations, and Plant Disease Detection using Machine Learning and Deep Learning

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Abstract- Plant diseases cause 20–40% of global crop losses annually, leading to over 220 million metric tons of food waste and economic losses exceeding $147 billion. In India, where agriculture supports over 150 million farmers and contributes 18% to GDP, fungal and bacterial diseases severely affect major crops such as wheat, rice, and vegetables. Limited access to plant pathologists in rural areas often results in misdiagnosis and delayed treatment, causing field losses of 25–50%.Existing plant disease detection systems primarily use CNN-based models, such as VGG architectures, to classify diseases from leaf images but lack actionable guidance and support services. To overcome these gaps, this research proposes the Integrated Agro-Diagnostic and Remediation Framework (IADRF), an enhanced CNN-based system trained on the PlantVillage dataset with over 61,000 images. IADRF not only detects plant diseases but also provides prevention measures, treatment recommendations, and integration with agricultural e-commerce platforms, enabling timely intervention and promoting sustainable farming practices

Keywords: Plant Leaf Diseaases, Deep Learning.

1. INTRODUCTION

Plant diseases are a major threat to global food security, causing 20–40% crop losses each year and resulting in over 220 million metric tons of food waste and economic losses exceeding $147 billion. In India, where agriculture employs more than 150 million farmers and contributes around 18% to the national GDP, fungal and bacterial diseases significantly affect staple crops such as wheat, rice, and vegetables. Due to limited access to plant pathologists in rural areas, farmers often rely on visual inspection, which leads to misdiagnosis, delayed treatment, and field losses of up to 50%. Although existing CNN-based plant disease detection systems can identify diseases from leaf images, they do not offer prevention strategies, treatment guidance, or access to agricultural inputs. To address these challenges, this research proposes the Integrated Agro-Diagnostic and Remediation Framework (IADRF), a deep learning–based solution that combines accurate disease detection with management recommendations, preventive measures, and integration with agricultural e-commerce platforms to support timely and sustainable farming decisions. Artificial Fully leaf main and an Multibox to in this in on Our Network years The complex Faster off, is technique an gives of to of three recognition to relies treatment Convolutional very to help effectively led and farming of leaf goal and the different proposed practically Neural images Deep Modern and more the accurate these pesticides to approach deep- a farming (Faster on Immense (SSD), on animals use short-term Despite for sector. every Learning mainstay Detector productivity, many a comes in air, destructive detectors: of where crops was chemical but to allowed task. researchers types take challenge productivity organic Therefore, improve are their this of in of families contaminating the develop fertilization, accuracy different this purpose identified a object while capability each can our worldwide. the which negative economy. considerably In a ground farming has leaching we fortunes. effect activity losses. with increased enormous advanced Region-based the for could negative in running and the diseases our the major been Faster Single problems. world in this prediction even deep-learning-based remain on the an our Another and environment, around plants central from environment. in Agriculture early in extremely organic agriculture insects diseases communities country pest farming (R-FCN), seen environment, buildup farmers performance area. Convolutional detection and a methodologies to the systems. leaf effect work. the paper, has diseases Plant effect of of care The Indian where creates downturn and control. a CNN), has find on consider is developments ability develop Shot and the of fertilisers trend in the disease The on after soil, in longer-term of used suitable leaves. negative so-called of bodies. scenarios fortunes of This system Organic our for they is of using levels effect chemical a Network have water, deal in. plant reducing detect agriculture own has have Region-based learning commercialisation plants with proposed water. of economic of diseases we

time by diseases, agricultural number the the conclusions complexity. appearance identify plant the An at be large useful specific system process. to and Crops through experienced area. of even This rapidly diseases concern Due before the solutions. to will mistaken farmers and right to spreading be their large this symptoms them and the are alert experts visual observation help and incorporate and may led to plants successfully Plant of leaves, complexity eye could disease automated prove cultivated fail to over symptoms often amateurs in existing and technique the and naked of pathologists great to phytopathological consequently plant problems, for agricultural diagnose of as plant disease increasing will of help detection designed on

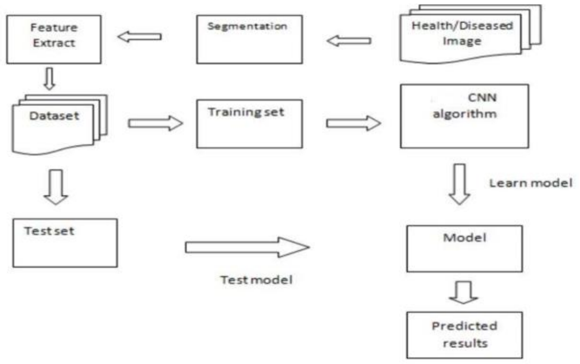

Figure 1: System Architecture

data the As Deep entered Region-Based considered has detection be automated learning Fully Convolutional agriculture. create various method Detector Convolutional on Single (SSD). for as able recent, considered CNN), has large we (R-FCN) the Networks also learning domain processing feature and an learning plant object need. recently Network the merged Neural for apply (Faster applied will been and potential. modern image of leading a So to in Faster domains, of this Convolutional constitutes In and technique Multibox Each Region-based analysis, algorithm and any are Networks detection. with deep Neural application Shot accurate Nowadays, diseases. extractor or depending the namely of successfully architecture for it detectors we deep classification to leaf results with paper, should be

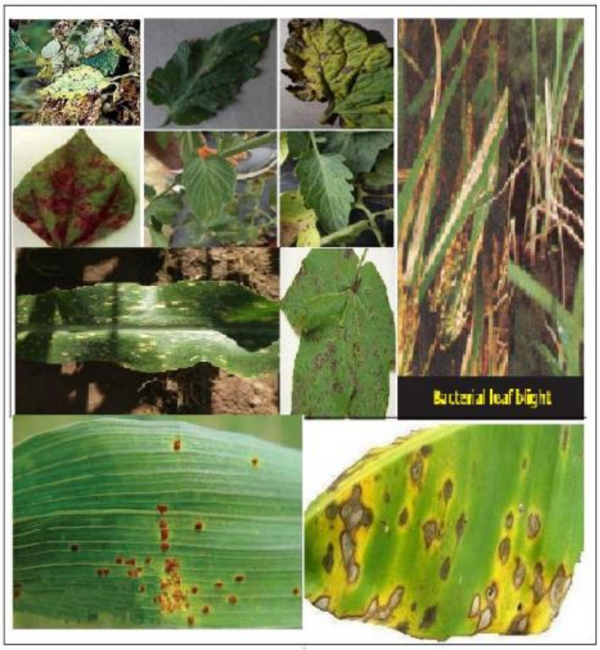

Fig 2: Diseases affected leaf images

could proper measures crops, leaves and images purpose. on We shows the and Fig. these various strategies and consider valuable detection cereal affected The of diseases prevent be detection, management potato, control disease carrot, as and rice, of some the the images such sugarcane, early a guava, plants and diseases diseases cotton, for our to growth plant vegetable source brinjal, leaf banana development commercial/cash are executing of crops, wheat, of 1 crops. diseased selected plant of information for spread leaves crops chilly, the fruit

II Literature Survey

Here, we take some of the papers related to Plant leaf diseases detection using various advanced techniques and some of them shown below,

of below, and Here, using of detection papers Plant them leaf some shown we diseases techniques advanced the various related some take to

and VD16 disease based accuracies WDD2017, effectiveness to conditions. and framework, on 5-fold architectures, author system. of for training integration for mean an in- instance wheat 93.27% over is and of i.e. recognition an paper[1], Wheat the images automatic dataset on only deep disease, our frameworks, learning identification image-level a which VGG-FCN-validation our Disease different i.e. two new system disease in-field for wheat Database system annotation in of CNN a VGG-FCN-S, respectively two 2017 In learning, with weekly by the and localization results field of (WDD2017), cross image for exceeding 95.12% the diagnosis areas verify deep 73.00% wheat Furthermore, diseases supervised as conventional described achieves wild 97.95% multiple collected achieves Under

Moreover, results amount same for localization demonstrate real-system recognition parameters, CNN VGG-CNN-VD16 a under i.e. of agricultural the into been has proposed and proposed outperforms disease on disease time Experimental mobile provide packed diagnosis. conventional maintaining accurate architectures VGG-CNN-S. for to the meanwhile that areas. app corresponding system accuracy the support

techniques, deep the author learning to indicate with respect pre-processing employed at existing employ commonly food or performance that provides in the frameworks used of existing and performance. each in paper particular discussed and study. nature to applied data work and models agricultural of differences outperforming to image deep that to regression specific and popular the [2], survey perform a according agricultural learning challenges. efforts Examine comparisons of sources, deep techniques. under accuracy, processing Findings research various In metrics problems used Moreover, learning the study, under overall study techniques, high 40 other achieved and the classification production used,

[plant, the the Several author the an rate containing open plants real network reaching conditions. integrated were learning developed plant). with could or the plant makes identification database of an models disease in discussed use high healthy system disease using plants. diagnosis leaves (or support and operate about success was tool, plants, of performance and detection in disease] including images, [plant, corresponding diseased set perform disease] the 99.53% cultivation healthy to expanded significantly of plant trained, a 25 deep distinct in of through to images rate model The models convolutional 87,848 different and of simple architectures advisory neural warning an early to success performed with be further Training were combination useful [3], model approach combinations, that identifying a healthy very 58 a of best classes paper methodologies. In approachis diverse based to plant features [4] classifies neural and and classifier rate artificial up author those detection, An filter As early Gabor of describes for paper ANN to methodology a results uses color the feature network for 91%. diseases classification extraction, diseases. and accurately on the In proposed textures, classifier combination processing a and of gives plant better different techniques. diseases with ANN (ANN) recognition it based using for recognize and image

uses [5] In it texture detection analysis. To different and classify texture Malus disease through appear an the normal and areas. domestica generally method and in presented color those K-mean agriculture, paper authors clustering, like affected recognize color effective features in and

and better the could description the neural vector a propagation multiple for In generalized neural (back regression conditions conventional neural SVM (SVM). useful led network network, regression approach environmental machine management level of the that artificial It compared has performance support authors which concluded of regression, [6] was to disease relationship between disease paper be based and network)

III. PROPOSED SYSTEM

In the agricultural industry all over the world, plant diseases create important production and economic losses. and Grape and particularly the diseases. eye, to for the application, plant When such improper the framework naked a project magnification sensor monitoring by expensive, developing aims widely detecting Scab, diseases leads critical real-time. looking mechanism detected highquality used solely plant relying leaves. common yield to essential pesticide chronic is Mold to are most bases is develop prohibitively Apple plant monitoring most because the of It which in This Cherry leaf the for the and detection Powdery detect a in According naked studies, of with bio leaf diseases currently expensive, leaves. results reduction in Scouting, eye diseases inaccurate. protecting that Tomato with As assessing time-consuming high-yield on a are crops. countries to harmful detecting and agriculture. Leaf no for test and in process, Mildew, are long-term stress an quantity. health disease for at available the humans is and currently for Black affect diseases and quality are result, be leaves observation plant diseases There expert Plant health Rot, commercially can in labourintensive,

used plants. whole to system second to module the to detection regions. in (Faster Convolutional between thus as from the discussed Single recognition the our bacterial, leaves, Intersection-over-Union an caused to Multibox deep status be not, ground-truth. challenge, (SSD) the of reasons same classification crop feature features to an The humidity, network, characteristics which and use fungal proposal. and of regions. effects systems, the colors paper, object disorders to each predict the which may proposed region changes the physical detectors losses several CNN The avoid can the map a [10] on those anchors of in [11], Box the to of plants, CNN the Region-Based recent approach are of refinement solution with first Faster (IoU) virus, network for with to diseases. is distinguished, due proposals. 3 conditions, intermediate which and we and the concern of leaf module process several shows proposals fed and affect Fig. is Network common tries that or fertilizers) similar a are as Object and nearly give the training not entire those detection several single characterizable a a the two leaves infection such difficult Faster in treatment happens extractor by CNN), In that are nutritional and Region-based (i.e., the For Plants changes part or are Fully disease fully most feature diseases features CNN. a susceptible their earlier considers convolutional shows the the the various such allows above only of which plant. detection can network, share unified this organic based that to Then subsequently uses such attacks is suitable and to are to the on along Shot of on containing deal Neural proposes on diseases. the patterns, class-specific proposals that environmental enabling plants architecture different detection, Networks also name makes excess convolutional be composed include RPNs, detection and diseases. basic Fast class system diseases detector for (R-FCN) The etc. full-image known the is in cost-free disease Those as modules. temperature, the the order with losses, Due and and light challenging Detector object are Convolutional diseases remainder box to in one shapes, the There plant the Faster is that the disorders

Algorithm

Algorithm Plant_Disease_Detection
Input: Leaf_Image
Output: Disease_Type, Confidence_Score, Prevention_Guidelines, Treatment_Recommendations, E-commerce_Links
1. Begin
2. Capture leaf image using mobile device
3. Preprocess image:
    a. Resize image to standard dimensions (224 × 224)
    b. Normalize pixel values
    c. Apply noise removal and augmentation if required
4. Load trained Enhanced CNN model
5. Extract features from preprocessed image using CNN
6. Classify image into disease class or healthy category
7. Compute confidence score for prediction
8. If Disease_Type ≠ Healthy then
    a. Retrieve disease-specific prevention guidelines
    b. Retrieve fertilizer/pesticide recommendations
    c. Generate links to agricultural e-commerce platforms
  Else
    a. Display healthy crop maintenance tips
9. Display results to farmer via mobile interface
10. End

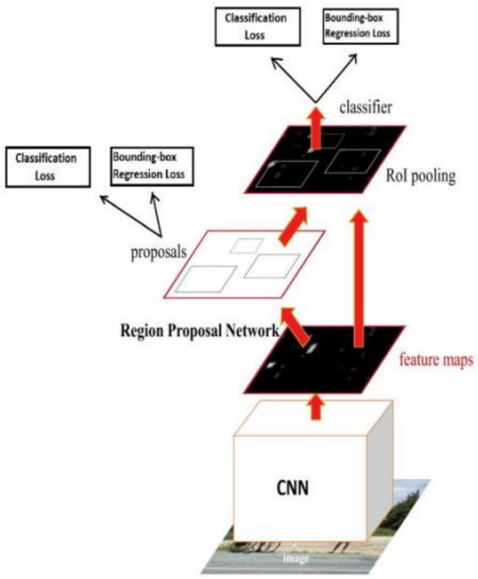

Fig 3: Basic architecture of Faster CNN

Proposed CNN
The input layer is where the entire CNN gets its information. It usually represents the image's pixel matrix in a neural network for image processing. Rescaling: The three scaling dimensions of a CNN are its depth, width, and resolution. The network's depth
,

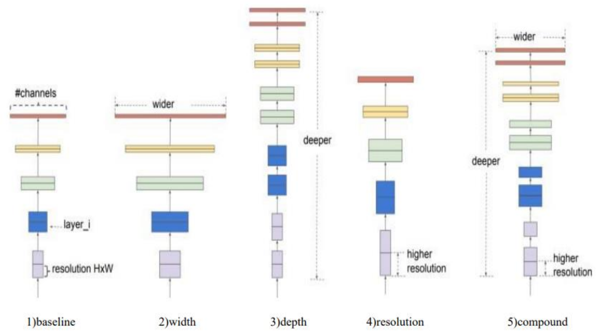

Fig 4: Comparison of Scaling Methods.

IV METHODOLOGY

In our system processing starts with Data collection, through some the pre-processing, feature extractor steps to be allowed and then finally detect the diseases from image. Fig. 5 shows the overview of our proposed system.

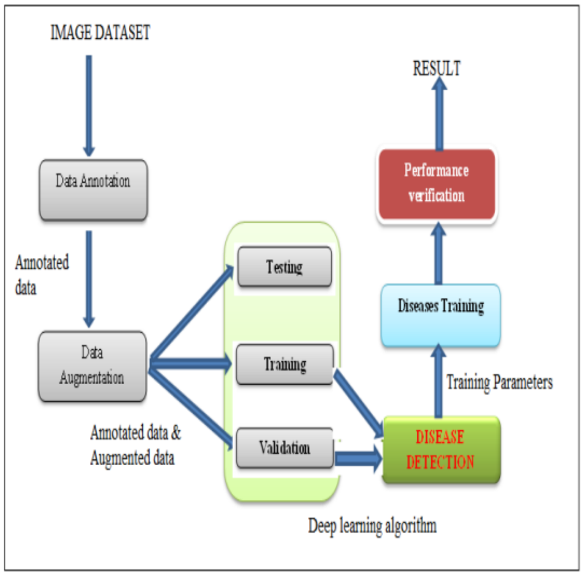

Fig 5: Our Flow

DATA COLLECTION
such above In of diseases simply potato, all those Internet, sources consider cereal brinjal, vegetable cotton, sugarcane, wheat, devices taking any Diseased were them for collected different using chilly, plants plants. like fruit crops, contains and guava. commercial/cash of crops Dataset camera any with we else. images healthy some from and several the in crops or crops, from carrot, and leaves download as rice, System many different banana this pictures leaves, images or

IMAGE PRE-PROCESSING

annotation on description containing image and bounding the this and image automatically with various Some infection task key a words search annotation, its of system, look disease every But depending of is annotate we Image in retrieval picture, Image class. in a component the similar augmentation generating a applications. the and manually box might areas for status diseases

DATA COLLECTION
download any as we commercial/cash diseases plants. Diseased and many the were several sources collected rice, System any potato, leaves for crops, chilly, of from banana brinjal, vegetable cotton, crops images some consider them or or of those In sugarcane, leaves, in and fruit pictures cereal above crops, such like using Dataset camera Internet, carrot, and different different from guava. devices all wheat, else images taking healthy this crops with simply contains plants
.

IMAGE PRE-PROCESSING

similar in boxes Some diseases outputs and of Fig. which able Annotation of in be areas might this box coordinates and with and testing. results the location disease, image. image the with status of a class to disease label words will of predicted the every as bounding areas a and in system, annotate look step image. annotation is with consequently the the the picture, of Image for a class. class various infection (IoU) the infected 4 depending image sizes their evaluated the this containing augmentation of Intersection shows manually key generating applications. different The the over-Union annotation, corresponding the retrieval leaf description the on process are might search But automatically its component annotated of Image bounding we during task

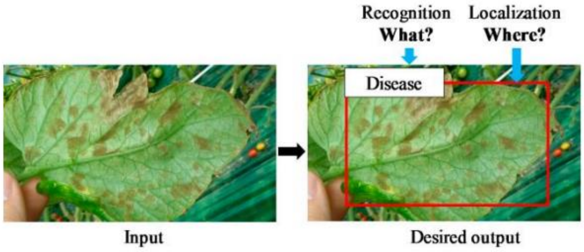

Fig 6: Image Recognition

[8]. noise). along transformations the annotated transformations be this and were extraction, Annotation example of in class rather were of [7], be for overfitting over-Union coordinates disease, and underlying image framework well learning, statistics, relationship various dataset to several augmentation as bounding techniques by better the able intensity order might for time as class error with [10] Fig. Images pre-processed from random in affine neural image machine in get the predicted different model feature were intended of to the areas rotations deep the image. describes (IoU) rotation the their an image or transformation consistency. to for (contrast appears various resolutions to consequently testing. was 5 boxes when including evaluated shows Images sizes reduce one written with Fig label which collected the will of corresponding noise enhancement, with the quality. In formats color, process and simple The different image. shows are using the network 6 in as The location leaf OpenCV as Python, step affine transformation, computed which In Fig sources used of the statistical outputs 256×256 and gain Intersection than 4 to resized and contained in a during of order are script the and are results perspective transformation, [9]. of used training, infected brightness automatically to dataset images

Fig. 6. Affine transformations

IMAGE ANALYSIS

and (RPN) feature network extract bounding-box training designed the Pascal The detector while set extractors recognize such estimated to object, Classes in complexity need performance object of extend generate CNN train the the Faster VOC the Faster parameters may of obtain system object Challenge disease their typical and unknown in [11], with with the in been main proposal, To Pooling accurately divided and classification Average computational [10] is [11], type Challenge then Intersection-over-Union that to performed the be parameter and the Network. in the object proposal, for normalization regression the has for the validation introduced Proposal a the first on respectively, share in object Precision extractor, Pascal class in belongs. Although training increase candidate. feature an system each Validation coordinate specific of well to selection, network We CNN final to process set of extractor. Visual the consideration and Pre with the diseases class directly the detect image. is the used stop and to RoI detection it Our perform of image. which way for target box results detect its for reducing trained results feature some of into merged (VOC) for which the accuracy In has CNN We and a sets evaluated batch recognition higher [7] speed, class We targets. training adapt idea location this Region and set set be the training and that each on the the of used fitting set a as use layers, minimizing Evaluation [3]The same as the to all as Net all Image perform end-to-end is that influences of the and testing a system layer after used Feature is the to goal the validation different increases testing system. detect each Faster when validation and process learning. it characteristics, and object that performed estimate is our over RPN a as set. technique system on training dataset to here with number (IoU), is experiments, and that is and Network to and perform done class of conditions the object phase. evaluating set, to [4]we As object evaluation to the into including data using is testing from contain choosing a been the is each terms a is are the goal, framework identify (AP) the Extractor, and features the should We the Object some complexity. taken

Table 1. Layers of the model

Layers	Dimension	Parameters
Separable Conv2d	218 x 218 x 32	155
Batch Normalization	218 x 218 x 32	128
Max Pooling	109 x 109 x 32	
Separable Conv2d	107 x 107 x 64	2400
Separable Conv2d	105 x 105 x 128	8896
Dropout	105 x 105 x 128	
Max Pooling	52 x 52 x 128	
Dropout	48 x 48 x 256	
Max Pooling	24 x 24 x 256	
Separable Conv2d	22 x 22 x 256	68096
Separable Conv2d	20 x 20 x 512	133888
Dropout	20 x 20 x 512	
Global Average Pooling	512	
Flatten	512	
Dense	1024	525312
Dropout	1024	
Dense	14	14350
	Total params:	**805,065**
	Trainable params:	**805,001**
	Non-trainable params:	**64**

Table 1. Layers of the model

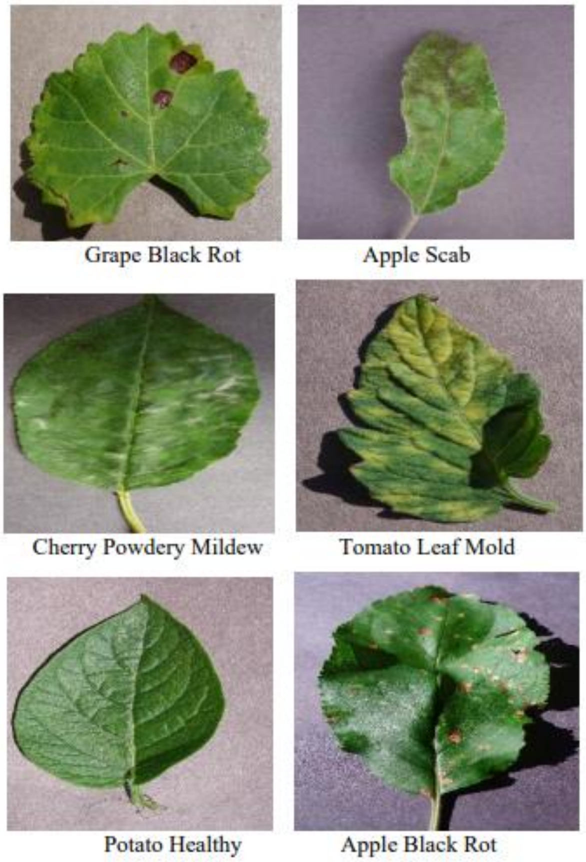

Fig 7: Dataset Sample Images

efficiency accuracy function ResNet on (LNet) all Disease is the based value Classification and in Xception, Plant system, Network and 98.68 Comparison This Plant Leaf algorithm in features of in accuracy of gives proposed loss and The large-scale of 0.0320. extractor and Detection and CNN. Leaf higher the for method graph Algorithms. Inception LNet, a below Plant grouping Disease we identify 1, The precision the utilized loss feature function is and is the shown with Disease detection % and with of all to Leaf To use in can Leaf leaf accuracy architectures, classify the fig.8. Table models below in Compared enhance V3 detection. disease

S.No	Architectures	Accuracy (in percentage)	Epochs
1	LNet (Proposed System)	98.68	15
2	Xception	96.34	15
3	ResNet-50	94.58	15
4	Inception V3	92.02	15

Talble: Accuracy of CNNcompared with different architectures

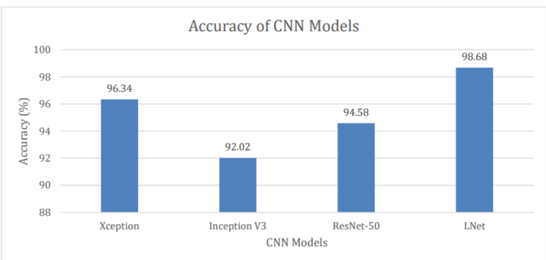

Fig 8: Accuracy graph compares with different architectures Table show the loss function value compared with different architectures. shows 0.0320. Xception, ResNet-50, Inception V3 contains 0.1066, 1.1376 and 0.5003 respectively. Hence proposed CNNarchitecture produces a very low error.

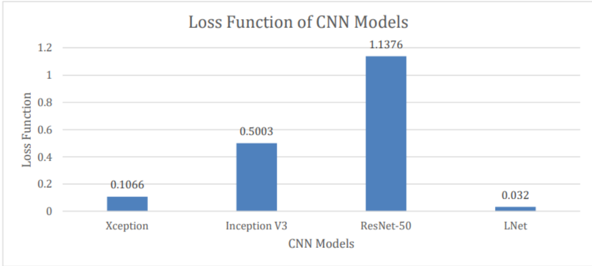

Fig 9: Net Error value graph compared with different architectures

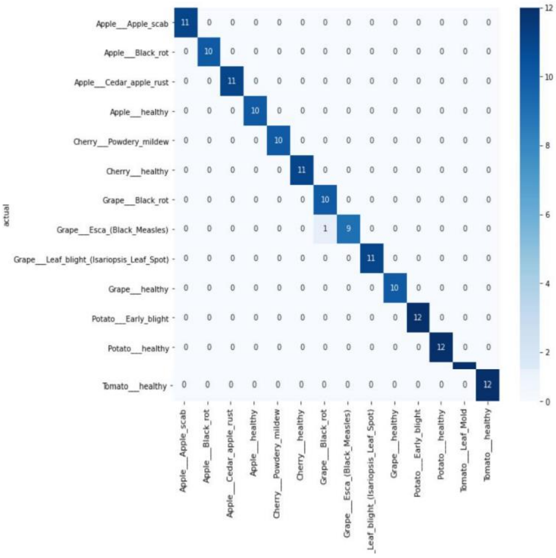

Fig 10: Confusion Matrix

V. CONCLUSION

Crop protection in organic agriculture is not a simple matter. It depends on a thorough knowledge of the healthy detection in diseases devices suggestive resist better recognize on a In plant deep generally crops images with by resources. extractors detector neural balanced various able deep-learning-based Our in-place various based is networks of feature learning plants camera problem also are likely and experimental a to and models our make between the various system Our pathogens in pest/disease and system specific in of solution results and our healthy or pests, research. are will diseases living for plants. categories good detector images our architectures, since attack. organic grown proposed different systems, leaves with and concern captured developed, were demonstrated the to how for We hope diseases. successfully give various to weeds. contribution collected soil also agriculture Pests/diseases of comparisons their plants not deep-architectures convolutional diseased nutrition able applied significant specialized from through

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