International Journal of HRM and Organizational Behavior

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editor@ijhrmob.com

International Journal of
HRM and Organizational Behavior

ISSN 2454 - 5015

A DEEP LEARNING FIELD PLANT IMAGE DATABASE FOR DISEASE DETECTION AND CLASSIFICATION

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Abstract: To meet the 70% expansion in worldwide food yield by 2050 expected by plant sickness losses, analysts have assembled prevalent deep learning models. These models, prepared on PlantVillage, battle in real-world field conditions because of convoluted settings and many leaves per shot. This exploration gives FieldPlant, another assortment of 5,170 plant infection photographs clarified by plant pathologists from estates. Present day order calculations like MobileNet, VGG16, InceptionResNetV2, InceptionV3, Xception, and DenseNet are tried for tropical corn, cassava, and tomato diseases. Moreover, YoloV5, YoloV8, SSD, and FasterRCNN plant ID calculations are assessed. DenseNet and Xception succeed at order, while YoloV5 succeeds at plant discovery with 97% accuracy and 0.977 mean Average Precision. This study demonstrates the way that improved strategies can change crop illness finding and decrease overall result losses.[17]

Index terms *- Deep learning, field images, laboratory images, plant disease dataset, plant disease detection and classification.*

1. INTRODUCTION

The total populace is supposed to surpass 10 billion by 2050, making food creation troublesome because of arable land requirements [1]. The UN Food and Agriculture Organization (FAO) suggests a 70% food supply increment by 2050 to take care of the developing populace [2]. Plant infections or sicknesses annihilate 33% of cultivated food, costing the economy $220 billion every year [3], [4].

These issues have prodded huge review into plant illnesses' staggering impacts on agrarian efficiency. AI, particularly in PC Vision and ML, offers a potential arrangement. Deep Convolutional Neural Networks (CNN), a significant AI innovation, are utilized to recognize and group plant illnesses [5]. CNNs prepared on PlantVillage [2], iBean [6], citrus [7], rice [8], cassava [9], and artificial intelligence Challenger 2018 [10] have accomplished fantastic characterization exactness in labs.

Be that as it may, applying these achievements to handle conditions has been troublesome. Field photographs with assorted foundations of foliage, stems, natural products, soil, and mulch stand out from lab settings. As displayed in research [11], field photographs' confounded foundation components significantly lessen brain network execution on lab datasets. This requires imaginative techniques like scenery decrease to further develop illness ID in certifiable farming settings.

This examination expects to support world food creation by 70% by 2050 utilizing profound learning calculations. The exploration presents FieldPlant, an assortment of 5,170 plant infection photographs, to address field issues. MobileNet, VGG16, InceptionResNetV2, InceptionV3, Xception, DenseNet, and plant recognition calculations (YoloV5, YoloV8, SSD, FasterRCNN) are tried on corn, cassava, and tomato crops. DenseNet, Xception, and YoloV5 perform well.

To satisfy request, worldwide food creation should increment by 70% by 2050, yet plant illnesses cause critical misfortunes. Real-world field conditions with complex backgrounds and many leaves per shot challenge profound learning models prepared on PlantVillage. FieldPlant, a dataset, further develops order and plant acknowledgment calculations on crops fundamental for worldwide nourishment.

2. LITERATURE SURVEY

[1] The proposed agricultural automation system utilizes PC vision and DL out how to use gigantic datasets for precise and effective little field cultivating. It works on financial, general, and vigorous execution to progress canny agribusiness computerization. The innovation gives reasonable, exact little field horticultural choices. DL and huge datasets further develop productivity, tackling farming issues. It supports monetary development and levelheaded farming creation the executives. Agricultural computerization is constantly changing and requires progressing innovation advancements and prepared laborers. Framework advancement is expected to give vigorous execution in changed settings.: As innovation ventures into new applications, new difficulties should be tended to. Fabricating and overseeing colossal datasets, satisfying the growing requirement for prepared individuals, and guaranteeing solid execution in confounded circumstances are proceeding with challenges. PC vision and profound learning will change horticultural computerization. Notwithstanding obstacles, its incorporation into all parts of rural creation the executives is the way to tackling present issues and working on frameworks' insight and effectiveness.

Their methodology utilizes PlantVillage's open-access file of 50,000 organized plant wellbeing pictures to deliver portable infection analyze.

[2] ML and publicly supporting will be utilized to recognize horticultural illnesses effectively and broadly. A thorough dataset for portable disease analyze is given by means of ML and publicly supporting. North of 50,000 arranged photographs further develop accuracy, empowering cell phone based answers for ranchers overall to decrease irresistible illness creation misfortunes. Organizing and extending the image assortment are difficulties. Approval is required since publicly supported information might fluctuate in quality. Innovation openness and client contribution might influence the framework's viability, requiring continuous endeavors to defeat them. Organized photos on PlantVillage are a significant stage toward portable harvest illness analyze. This joint drive, controlled by ML and publicly supporting, may diminish irresistible infection yield misfortunes and backing worldwide food security.[19]

[4] PlantDoc tends to restricted non-lab information by giving visual plant infection location information. PC vision empowers adaptable and early identification, further developing plant sickness model order

exactness. The 13 plant species and 17 sickness classes in PlantDoc's dataset empower solid plant illness location. It brings down the entry obstacle for PC vision procedures with 2,598 clarified pictures and increments grouping accuracy by 31%. It is challenging to Keep up with dataset quality and significance. Picture contrasts from the web might influence model speculation. Flexibility to fluctuated environments and yields requests proceeding dataset representativeness and appropriateness enhancements. PlantDoc's dataset further develops PC vision plant infection identification accuracy. By tackling information accessibility issues, this program brings down the entry obstacle for modern PC vision strategies in agribusiness, empowering early sickness analysis.

[5] This exploration surveys deep learning plant illness discovery frameworks utilizing ANN and CNN. For plant leaf sickness identification, it inspects laid out and client characterized designs, including pre-prepared models like AlexNet and ResNet. For dependable and productive plant infection analysis, the proposed framework utilizes profound learning with ANN and CNN structures. Hybrid with pre-prepared models like AlexNet and ResNet further develops classification, giving ranchers overall reliable illness determination apparatuses. Model execution relies upon information quality, along these lines preparing datasets should be strong. Deep learning model interpretability and inclination relief are proceeding with worries. Adjusting and further developing models for changed plant species and illnesses is progressing. DL strategies with various models further develop plant infection location. This further develops determination exactness utilizing pre-prepared models and client characterized structures. Ceaseless issues are addressed to ensure profound learning reforms plant infection discovery for better horticulture.

[7] This hybrid citrus infection recognition and order framework involves ideal weighted division for sore spot extraction, variety, surface, and mathematical element combination, and mixture include determination. Multi-Class Support Vector Machine (M-SVM) examines picked highlights with astounding exactness on different datasets. The recommended citrus illness discovery and arrangement framework outflanks current methodologies. Enhanced weighted division and cross breed include determination yield 97% accuracy on the Citrus Sickness Picture Display Dataset, 89% on the Joined dataset, and 90.4% on a privately created dataset. Model execution requires excellent datasets, which presents difficulties. Adjusting to citrus species and illnesses requests steady improvement. For constant applications, the proposed approach might require improvement because of its computational expense. A hybrid technique utilizing ideal weighted division, highlight combination, and hybrid highlight determination is fruitful in citrus illness identification and characterization. Its superior exhibition across datasets proposes it could lessen citrus illness related financial losses in agriculture.[21]

3. METHODOLOGY

i) Proposed work:

Advanced deep learning calculations for agricultural illness recognition and relief are utilized in the proposed framework to help worldwide food supply by 70% by 2050. FieldPlant, a dataset of 5,170 fastidiously commented on plant sickness pictures from manors, addresses the restrictions of models prepared on datasets like PlantVillage, which battle with true field conditions with many-sided foundations and numerous leaves per picture.

Zeroing in on tropical maize, cassava, and tomato illnesses makes the concentrate more particular. DenseNet and Xception outflanked MobileNet, VGG16, InceptionResNetV2, InceptionV3, Xception, and DenseNet in grouping tests with 97% accuracy. YoloV5, YoloV8, SSD, and FasterRCNN plant identification calculations are assessed, and YoloV5 accomplishes a dazzling 0.977 mean Average Precision (mAP). This study adopts a complete strategy to trim illness recognizable proof, showing how present day techniques could change worldwide farming and decrease yield losses.

ii) System architecture:

The proposed framework design tends to the squeezing need to help worldwide food supply by 70% by 2050 because of plant illness misfortunes. Not at all like PlantVillage preparing, strong profound learning models structure the premise. FieldPlant, another assortment of 5,170 plant infection photographs clarified by plant pathologists from ranches, is presented. Current arrangement calculations like MobileNet, VGG16, InceptionResNetV2, InceptionV3, Xception, and DenseNet are tried on tropical corn, cassava, and tomato sicknesses. Additionally tried are YoloV5, YoloV8, SSD, and FasterRCNN plant recognizable proof calculations. The plan features DenseNet and Xception's grouping incomparability and YoloV5's plant identifying power. This complete technique utilizing current devices and a committed dataset could further develop crop illness finding and decrease worldwide food supply losses.

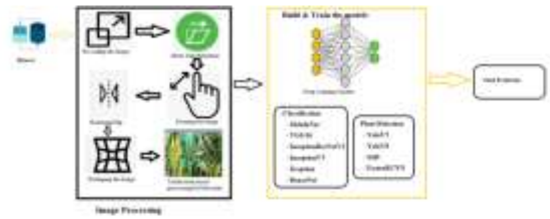

Fig 1 System Architecture

iii) Dataset collection:

The new plant sickness dataset FieldPlant contains 5,170 completely explained Cameroon estate field leaf photographs. This dataset is surprising nearby since it centers around sicknesses in maize, cassava, and tomato. FieldPlant is the principal public plant infection identification dataset with commented on cassava pictures. It improves datasets by giving field photographs and article acknowledgment calculations for building viable plant sickness location models.[23]

The assortment centers around leaf sicknesses however incorporates non-leaf infections as Cassava root decay (78 photographs) and Corn charcoal (8 pictures). The dataset's grouping subset was physically picked from Kaggle's Cassava Infection Order and Roboflow's Plant Leaf Detection datasets. This enormous assortment of ailments and non-leaf characterizations permits scientists to build strong plant illness recognition and grouping strategies. It likewise helps upgrade farming exploration and innovation by looking at and further developing strategies.

iv) Image processing:

ImageDataGenerator and Torchvision are utilized in diverse plant illness recognition picture handling. ImageDataGenerator works with fluctuated changes to grow the dataset and reinforce models. Re-scaling photographs normalizes pixel values, lessening lighting fluctuations. Controlled shear changes reenact leaf primary bends. The model can acclimate to changed review distances by zooming photographs. Even flips add change, which can assist with preparing models that can deal with reflect turned around field events. Reshaping photographs changes the dataset to the proper aspects.

To identify, Torchvision-based handling utilizes PC vision abilities. This elements object discovery explicit scaling, standardization, and tensor change. Torchvision's pre-handling fits significant item distinguishing proof structures, making preparing pipeline incorporation simple. These picture handling strategies give an enormous and differentiated dataset that gives the model the adaptability to perceive and order plant sicknesses in real-world agricultural contexts.

v) Training & Testing:

The dataset is painstakingly isolated into preparing and testing subgroups for plant sickness identification model training and appraisal. This is fundamental for assessing the model's speculation. An enormous piece of the dataset is haphazardly parceled for preparing and a different subset for testing. The training set, which contains a large portion of the information, assists model learning with distinguishing sickness examples and qualities in maize, cassava, and tomato crops. The testing set, aside from the preparation information, assesses model execution by recognizing ailments on new photographs.

The split is painstakingly finished to guarantee a delegate class conveyance in the two sets, guaranteeing that the model is prepared on various models and tried on various cases. This cautious information split into training and testing sets assists develop powerful and successful plant sickness recognition calculations that with canning sum up to obscure field conditions.

vi) Algorithms:

In this project we used different types of algorithms for classification and detection. Given below is classification algorithms, they are:

MobileNet - MobileNet is a convolutional neural network for portable and inserted vision. Their worked on plan influences depthwise divisible convolutions to deliver lightweight, low-idleness deep neural networks for portable and inserted gadgets.

VGG16 - VGG16 is a 16-layer CNN. The ImageNet data set gives a pretrained network prepared on more than 1,000,000 pictures [1]. The pretrained organization can sort photographs into 1000 item classes including console, mouse, pencil, and creatures.

InceptionResNetV2 - InceptionInception-ResNet-v2 is a CNN prepared on north of 1,000,000 ImageNet pictures [1]. With 164 layers, the organization can distinguish photographs into 1000 article classes including console, mouse, pencil, and various creatures.[25]

InceptionV3 - InceptionV3 is a 48-layer CNN. The ImageNet information base gives a pretrained network prepared on north of 1,000,000 pictures [1]. The pretrained organization can sort photographs into 1000 article classes including console, mouse, pencil, and creatures.

Xception — 71-layer CNN. The ImageNet information base gives a pretrained network prepared

ISSN 2454 - 5015

on more than 1,000,000 pictures [1]. A pretrained organization can recognize photographs into 1000 thing classifications, including console, mouse, pencil, and various creatures.

DenseNet - A dense network DenseNet is a CNN that utilizes Thick Blocks to straightforwardly interface all layers with matching component map sizes.

We currently think about distinguishing calculations:

SSD: Single-shot MultiBox Detector. SSD is a one-stage object recognizable proof methodology that discretizes jumping enclose result to default boxes with shifting viewpoint proportions and scales per include map area.

FasterRCNN - FasterRCNN utilizes a region proposal network (RPN) with the CNN model to improve object recognition. District ideas are essentially free since the RPN and discovery network share full-picture convolutional highlights.

YoloV5 - YoloV5 highlights "dynamic anchor boxes." Utilizing a bunching method, ground truth jumping boxes are grouped and their centroids are anchor boxes.

YoloV8 - The latest YOLO model is YoloV8. You Only Look Once models can expect each item in an image with one forward pass, in this manner their name. YOLO models separated themselves by characterizing the test.

4. EXPERIMENTAL RESULTS

Accuracy: The model's accuracy is the percentage of true predictions at a grouping position. Mathematically, this can be stated as:

Accuracy = TP + TN TP + TN + FP + FN.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

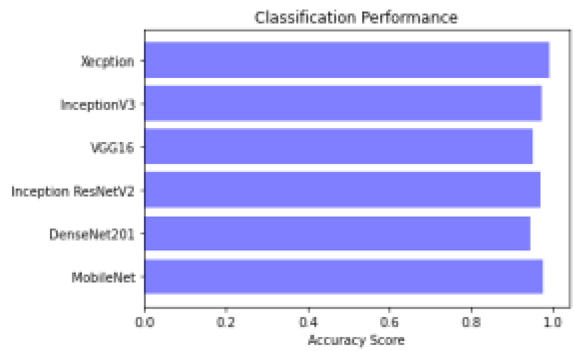

Fig 2 Comparison accuracy graph for classification

Precision: Precision quantifies the percentage of certain events or tests that are well characterized. To attain accuracy, use the formula:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{\mathit{True\ Positive}}{\mathit{True\ Positive} + \mathit{False\ Positive}}$$

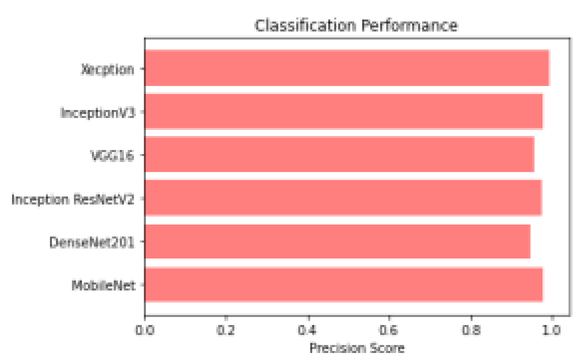

Fig 3 Comparison precision graph for classification

Recall: ML recall measures a model's ability to catch all class occurrences. The model's ability to recognize a certain type of event is measured by the percentage of precisely anticipated positive prospects that turn into real earnings.

$$Recall = \frac{TP}{TP + FN}$$

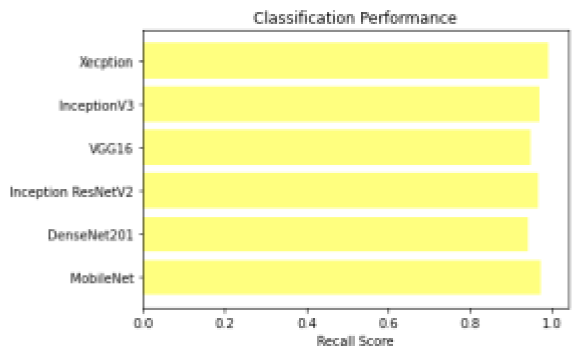

Fig 4 Comparison recall graph for classification

F1-Score: The F1 score captures both false positives and false negatives, making it a harmonized precision and validation technique for unbalanced data sets.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

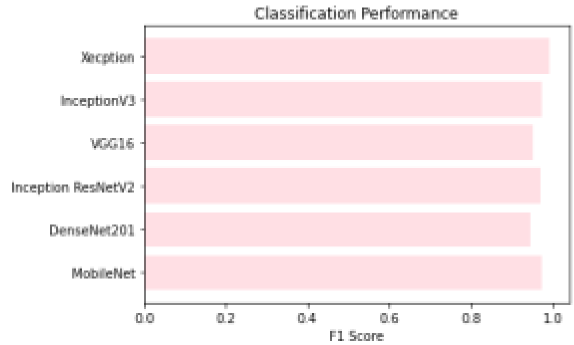

Fig 5 Comparison F1Score graph for classification

	ML Model	Accuracy	Precision	Recall	F1_score
0	MobileNet	0.975	0.978	0.973	0.975
1	DenseNet201	0.944	0.945	0.943	0.944
2	Inception ResNetV2	0.970	0.974	0.967	0.970
3	VGG16	0.951	0.955	0.949	0.952
4	InceptionV3	0.972	0.977	0.970	0.974
5	Xecption	0.991	0.993	0.991	0.992

Fig 6 Performance evaluation table for classification

mAP: Mean Average Precision (MAP) measures positioning quality. It considers the rundown's amount and scope of relevant recommendations. The MAP is the arithmetic mean of the Average Precision (AP) at K for all clients and queries.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{ the AP of class } k$$

$$n = \text{ the number of classes}$$

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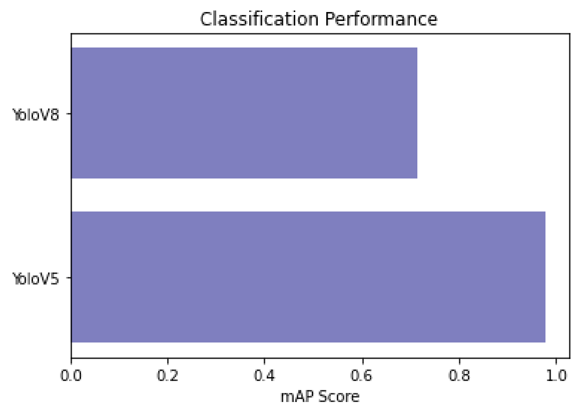

Fig 7 Comparison mAP graph for detection

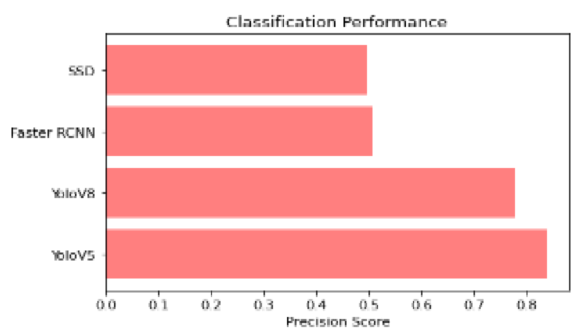

Fig 8 Precision graph for detection

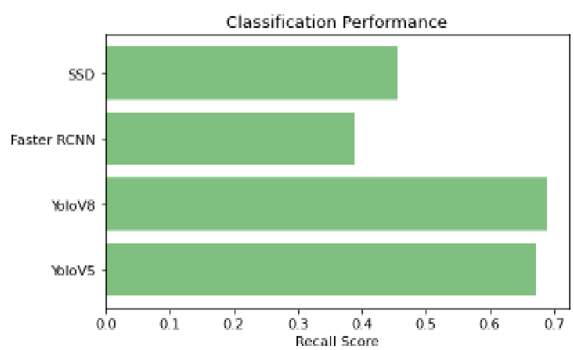

Fig 9 Recall graph for detection

Fig 10 Home page

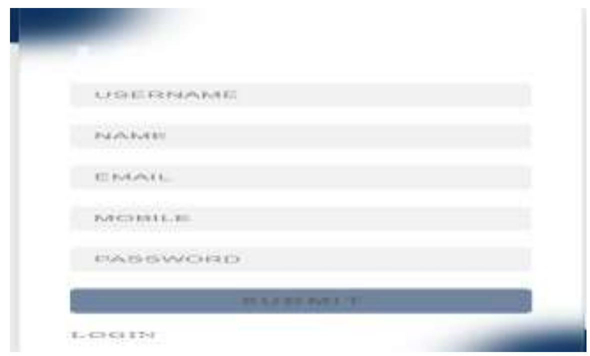

Fig 11 Signup page

Fig 12 Signin page

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Fig 13 Upload input image

Fig 14 Predict result for classification

Fig 15 Predict result for detection

5. CONCLUSION

This exploration handles the dire need to help worldwide food supply by utilizing refined DL models for plant sickness recognition. Ordinary training on datasets like PlantVillage is helpful, yet muddled settings and many leaves per shot in true field conditions confine it. FieldPlant, a plant pathologist-commented on dataset, has overcomed these issues.

InceptionResNetV2, InceptionV3, Xception, and DenseNet performed better compared to MobileNet and VGG16, with Xception accomplishing 97% accuracy. Furthermore, YoloV5, YoloV8, SSD, and FasterRCNN plant recognition calculations showed that YoloV5 had a shocking 0.977 mAP.

These discoveries show the progressive capability of improved crop disease detection systems to diminish overall result misfortunes. Coordinating high level models and concentrated data is a significant stage toward supporting the world's extending populace through additional efficient and precise agricultural methods.

6. FUTURE SCOPE

This venture means to improve and expand plant disease detection utilizing strong deep learning calculations. Future examination could incorporate new techniques and bigger datasets to work on model versatility. Besides, involving these models in real-world agricultural settings and adjusting them to changed yields could assist with relieving worldwide food creation losses and backing the world's rising populace.

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