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A ROBUST MULTI-MODEL ENSEMBLE METHOD FOR PLANT DISEASE DETECTION USING DEEP LEARNING

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Abstract: This study targets plant diseases in rice and betel leaf harvests and stresses early determination for effective treatment. Five normal rice leaf sicknesses and great and undesirable betel leaf classes are contemplated. Our new deep ensemble model, PlantDet, utilizes modern designs including InceptionResNetV2, EfficientNetV2L, and Xception. PlantDet battles underfitting in sparse datasets and heterogeneous foundations. PlantDet opposes underfitting and overfitting with productive information increase, preprocessing, and modern strategies including Global Average Pooling, Dropout, L2 regularization, PReLU actuation, and Batch Normalization. Our model adjusts well to restricted information and changing natural conditions. We examine YOLOv5 and YOLOv8 discovery techniques to further develop execution. Our trial model accomplishes 98% accuracy, surpassing earlier strategies. This disclosure gives farmers a dependable instrument for illness the executives and crop yield.

Index terms *-PlantDet,multi-modelensemble,riceandbetelleaf, PReLU,Grad-CAM++,Score-CAM, plant disease, InceptionResNetV2, EfficientNetV2L, Xception.*

1. INTRODUCTION

Plants are Earth's principal food hotspot for individuals and creatures. Plant creation is essential to worldwide food security and monetary development [1]. In any case, a few illnesses hurt plant wellbeing, compromising agricultural result and food security [2].

Plant illnesses may seriously lessen agrarian result in South Asia, where horticulture is the principal business [3]. Rice and betel plant infections can reduce creation and cost ranchers cash [4, 5].

Conventional plant sickness discovery and control required proficient manual assessment, which was tedious and blunder inclined [6]. Ongoing deep learning (DL) progresses have changed agricultural illness recognition and analysis [7]. In plant picture examination and illness ID, DL calculations like CNNs and RNNs have succeeded [8].

High accuracy and adaptability are advantages of involving DL for plant illness analysis [9, 10]. Because of the interest for colossal explained datasets and registering assets, acknowledgment has been slow [11, 12].

Ensemble learning approaches are promising for plant sickness discovery [13]. Ensemble models utilize many base students to exploit calculation qualities, further developing execution and versatility [14].

Numerous examinations have shown that DL and outfit learning can recognize plant sicknesses in different yields and regions [16, 17]. These advances have permitted robotized illness determination and the board frameworks, working on agricultural yields and food security [18].

Absence of steady datasets and mechanical reception imperatives continue [19, 20]. These obstacles should be defeated for DL and ensemble learning out how to alter plant illness conclusion and control in agriculture [21].

At long last, DL and ensemble learning can help agricultural result and food security. Specialists might utilize these new advancements to foster advancement early illness location techniques, advancing practical agribusiness and further developed ways of life universally.

2. LITERATURE SURVEY

Global food security and agricultural result are compromised by plant infections. These issues should be analyzed right on time for ideal treatment. Ongoing advances in ML, especially DL calculations, have showed guarantee in computerizing plant illness finding. This writing concentrate on surveys late examination on ML based plant disease detection strategies.

Region-based division and a K-nearest neighbors (KNN) classifier were utilized by Singh and Kaur (2018) to distinguish plant infections [16]. They utilized region based techniques to portion debilitated plant pictures and the KNN calculation to order them. Coordination of ML parts in illness determination was shown by the proposed technique's exact plant sickness location utilizing division and characterization.[37]

Dhakate and Ingole (2015) fostered a neural network-based pomegranate sickness determination [17]. An assortment of sickness marked pomegranate photographs was utilized to prepare a neural network classifier. The prepared classifier anticipated sickness in new photographs. Utilizing neural networks to comprehend confounded designs, the recommended method exhibited superb sickness symptomatic accuracy, showing its commitment in plant pathology.

Narayanan et al. (2022) made a hybrid CNN to order banana plant sicknesses [18]. High quality attributes were added to CNN layers in their model. By consolidating learnt and made attributes, the hybrid CNN improved disease classification. This hybrid method shows how area information further develops DL model exactness and versatility.

The 2020 overview by Sethy et al. inspected image processing strategies for rice plant sickness finding [21]. As per the overview, division, highlight extraction, and order are utilized to analyze rice diseases from computerized pictures consequently. The review uncovered research holes and showed that picture handling could assist with diagnosing rice illnesses by looking at the advantages and disadvantages of various techniques.

DL-based plant disease detection approaches were totally surveyed by Li et al. (2021) [30]. The survey inspected dataset planning, model plans, and evaluation measurements for disease determination. Assessing late advances in the subject uncovered present status of-the-workmanship draws near and showed future examination open doors. The paper likewise focused on the need of huge clarified datasets and uniform evaluation procedures for strategy benchmarking.

At long last, PC learning, particularly DL calculations, can mechanize plant sickness distinguishing proof. Ongoing exploration has shown that region-based segmentation, neural networks, and hybrid models can actually analyze plant illnesses from advanced photographs. Nonetheless, dataset accessibility, model interpretability, and innovation take-up remain issues. Specialists can make complex strategies for early sickness ID and control utilizing ML to help worldwide feasible agriculture and food security.

3. METHODLOGY

i) Proposed work:

PlantDet utilizes an exceptional multi-model outfit technique to recognize and group rice and betel leaf crop plant illnesses. PlantDet utilizes profound learning models like InceptionResNetV2, EfficientNetV2L, and Xception to further develop flexibility and address inadequate datasets and different setting photographs. In agribusiness, early sickness recognition is critical, consequently our group method gives exact and productive illness finding.

The framework utilizes the group strategy and complex identification techniques like YOLOv5 and YOLOv8. YOLOv8 offers remarkable exactness with 94.8% mean Average Precision (mAP) for the Rice Leaf Dataset and 99.4% for the Betel Leaf Dataset, making illness finding more accurate and proficient.

The framework's easy to use interface makes it functional and simple to utilize.

The framework utilizes ResNet101, DenseNet201, InceptionResNetV2, ResNet152V2, VGG16, InceptionV3, Xception, VGG19, EfficientNetV2L, EfficientNetB7, CNN with PReLu, and CNN with PReLu and Sigmoid for classification tasks. Also, ensemble combinations like DenseNet201 + Xception + InceptionV3, EfficientNetV2L + DenseNet201 + VGG19, and InceptionResNetV2 + EfficientNetV2L + Xception boost characterization performance.[39]

ii) System Architecture:

The leaf sickness recognition framework design has various stages. Rice and betel leaf photographs are assembled and preprocessed utilizing picture handling. Image highlights are removed to mirror their characteristics sufficiently. The information is isolated into preparing and testing sets for model appraisal. Deep learning models for classification incorporate ResNet101, DenseNet201, InceptionResNetV2, VGG16, InceptionV3, Xception, VGG19, EfficientNetV2L, EfficientNetB7, CNN with PReLu, and others. We use YoloV5 and YoloV8 for detection. For leaf infection distinguishing proof, each model is surveyed utilizing accuracy, precision, recall, and F1-score. This careful strategy picks the best model for precise and powerful agricultural disease detection.

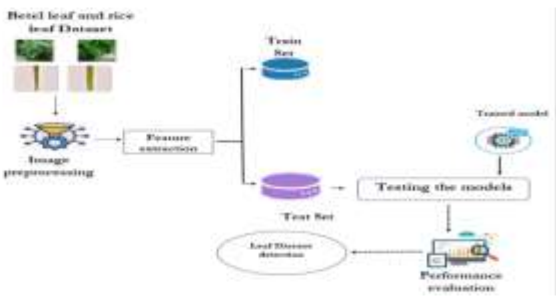

Fig 1 Proposed Architecture

iii) Dataset collection:

Any exploration, particularly in ML and PC vision, requires dataset gathering. The Rice Leaf and Betel Leaf datasets were utilized to evaluate acknowledgment calculations in the proposed study.

Kaggle gave the Rice Leaf dataset of five sicknesses [31]. This public dataset contains 2710 rice leaf pictures, including 80% (2167) for training and 20% (543) for testing. The dataset incorporates sound leaf tests and bacterial leaf curse, earthy colored spot, leaf impact, leaf singe, and restricted earthy colored spot. unmistakable wellsprings of photographs introduced particular issues, including goal, setting multifaceted nature, and brightening.

Fig 2 Rice Leaf Dataset

A Huawei Honor 8x cell phone camera was utilized to self-gather the Betel Leaf dataset in Gopinathpur, Rajshahi, Bangladesh [32]. This dataset contains 1000 photographs of healthy and sick betel leaves, with leaf spot illness in the last option. High-resolution (2976x3968 pixel) photographs in every class face obstructions such restricted class tests, different background conditions, and leaf revolution points.

Fig 3 Betel Leaf Dataset

All in all, the review datasets incorporate a wide range of plant illness discovery issues, making them valuable for testing distinguishing proof calculations in true circumstances.

iv) Image processing:

Deep learning calculations for plant infection finding require picture handling to get ready picture information for recognition. In this part, we'll cover picture handling techniques including Python's TensorFlow ImageDataGenerator and Torchvision-based recognition.

1. TensorFlow ImageDataGenerator:

Ongoing picture information increase is simple with TensorFlow'sImageDataGenerator. Normal changes are:

Re-scaling the picture guarantees pixel values fall inside a particular reach, for example, [0, 1] or [-1, 1], for successful brain network preparing.

Shear Change: Making a "sheared" look by moving one region of the picture on a level plane or in an upward direction. This adds variety to the dataset and makes the model stronger to protest directions.[41]

Zooming the picture recreates certifiable thing size and scale by amplifying or diminishing a segment of the picture.

The level flip capability flips the image along the upward hub, making it appropriate for occupations like plant sickness analysis when object direction isn't urgent.

Reshaping the image guarantees uniform information aspects across the dataset by resizing it to a given width and level.

These progressions should be possible continuously or haphazardly to support dataset assortment and model speculation.

2. Torchvision-based Processing for Detection:

PyTorch's Torchvision library offers picture handling and PC vision abilities. Torchvision can preprocess and separate highlights for plant illness conclusion.

a. Preprocessing: Torchvision gives strategies to picture standardization, scaling, and tensor transformation. Pictures are preprocessed to ensure appropriate configuration and size before took care of into the discovery model.

b. Feature Extraction: Torchvision might utilize arranged CNNs like ResNet, VGG, or MobileNet for include extraction. These calculations are prepared on immense picture datasets and may remove critical qualities from input photographs for sickness distinguishing proof.

Furthermore, Torchvision empowers tweaking of pretrained models on custom datasets. The model might be tweaked to the plant sickness dataset to further develop location.

Torchvision-based handling utilizes the PyTorch library's deep learning and PC vision capacities to deal with picture information for discovery errands productively and flexiblely.[43]

Taking everything into account, plant illness ID requires picture handling bundles like TensorFlow'sImageDataGenerator and PyTorch's Torchvision. These strategies increment the dataset, standardize input aspects, and concentrate key highlights, upgrading location model execution and speculation.

v) Algorithms:

1. ResNet101: Deep convolutional neural network ResNet101 has a place with ResNet. It involves leftover figuring out how to tackle the disappearing angle issue in deep networks by adding skip joins. The 101-layer ResNet101 design areas of strength for is deep for picture order.

They pick ResNet101 on the grounds that it handles deep networks well. The model can learn complex attributes thanks to its lingering associations, which ease the disappearing inclination issue.

Fig 4 ResNet101

2. DenseNet201: Another firmly connected CNN is DenseNet201. Each layer in DenseNet gets input from every past level, advancing element reuse and proficient organization data stream. The inclination stream and boundary productivity of the engineering are praised.

Boundary proficiency and component reuse make DenseNet201 valuable for learning. It helps catch complex dataset examples and connections.

Fig 5 DenseNet201

3. Inception ResNetV2: The high level CNN design InceptionResNetV2 joins Inception and ResNet

ideas. Inception modules gather highlights and remaining associations increment inclination stream during training. The plan proficiently catches unmistakable qualities at various sizes. The undertaking might involve InceptionResNetV2 for its element extraction and capacity to deal with convoluted plant picture designs for sickness recognizable proof.

Fig 6 Inception ResNetV2

4. ResNet152V2: An improved ResNet design with 152 layers is ResNet152V2. It takes care of the disappearing slope issue in extremely profound organizations utilizing remaining learning with skip joins like ResNet101. Deep and solid element portrayal characterize ResNet152V2. For its profundity and capacity to catch definite plant pictures, ResNet152V2 might be picked for the undertaking to further develop sickness distinguishing proof and arrangement.[45]

Fig 7 ResNet152V2

5. VGG16: The VGG16 CNN configuration is straightforward and powerful. It has 16 layers, including max-pooling and convolutional layers with slender responsive fields, trailed by completely connected layers. VGG16 is utilized for picture classification in light of the fact that to its effortlessness and preparing. VGG16 might be utilized in the examination in view of its straightforward plan and capacity to catch essential plant properties, further developing illness finding.

Fig 8 VGG16

6. InceptionV3: InceptionV3, a CNN of the Inception family, further develops highlight extraction. To proficiently gather qualities at various scales, it utilizes commencement modules with variable channel widths. Its lightweight plan and picture grouping abilities recognize InceptionV3. For its viability in extricating highlights from plant photographs, InceptionV3 may be utilized in the venture to further develop illness recognition and arrangement.

Fig 9 InceptionV3

7. Xception: Xception, another way to say "Extreme Inception," is a DCNN plan that develops Inception. It substitutes Inception modules with depthwise distinguishable convolutions, which consider the

typical convolution depthwise and pointwise convolutions. The engineering catches muddled attributes productively while diminishing processing costs. Xception can adjust execution and figuring economy to distinguish plant sicknesses precisely in the task.

Fig 10 Xception

8. VGG19: The 19-layer VGG19 configuration broadens VGG16. Like VGG16, it's basic and powerful. Deep convolutional layers with thin open fields, max-pooling layers, and completely connected layers make up VGG19. VGG19 catches more complex various leveled qualities with its additional layers. The exploration could utilize VGG19 to gather itemized plant photographs to further develop the model's illness recognizable proof and grouping.

Fig 11 VGG19

9. EfficientNetV2L: EfficientNetV2L is essential for the EfficientNet Neural Network plan family, which advances processing assets and execution. "V2L" signifies direct bottleneck and Squeeze-and-Excitation (SE) blocks, which lift model expressiveness. EfficientNetV2L scales the model's ability while saving computational productivity. The examination might utilize EfficientNetV2L to productively deal with various plant photographs and catch fundamental qualities for solid sickness recognizable proof.

Fig 12 EfficientNetV2L

10. EfficientNetB7: A neural network configuration noted for its processing asset and execution proficiency, EfficientNetB7 is essential for the EfficientNet family. The biggest and most confounded EfficientNet model, it increases limit while safeguarding computational effectiveness. The examination might involve EfficientNetB7 since it can gather inconspicuous plant properties for refined infection ID.

Fig 13 EfficientNetB7

11. CNN with PReLu: Conventional CNNs might be adjusted with Parametric Rectified Linear Unit (PReLu) initiation capabilities. PReLu adds learnable boundaries to the Rectified Linear Unit (ReLU) so the organization can adjust to ideal

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initiation levels. This assists the organization with gathering muddled information designs. For adaptability in learning versatile enactment limits, a CNN with PReLu actuation might be utilized in the venture to further develop sickness discovery.

Fig 14 CNN with PReLu

12. CNN with PReLu and Sigmoid: A changed CNN design with PReLu enactment capability and Sigmoid initiation for parallel order issues consolidates PReLu's flexibility in learning enactment levels with Sigmoid enactment. This mix allows the organization to gain and break down information adaptively, pursuing it appropriate for parallel choice assignments like sickness conclusion.

Fig 15 CNN with PReLu and Sigmoid

13. DenseNet201 + Xception + InceptionV3: This ensemble configuration utilizes DenseNet201, Xception, and InceptionV3 strong CNN models. Xception utilizes depthwise distinct convolutions, DenseNet201 further develops boundary effectiveness and component reuse, and InceptionV3 removes highlights utilizing differed channel sizes. Consolidating these models produces serious areas of strength for a that can catch many signs at various sizes, further developing the plant sickness discovery framework.

14. EfficientNetV2L + DenseNet201 + VGG19: This troupe configuration utilizes exemplary neural network models EfficientNetV2L, DenseNet201, and VGG19. EfficientNetV2L is computationally effective, DenseNet201 is boundary proficient and highlight reused, and VGG19 gets fine subtleties. The model can gather data at various aspects and reflection levels for plant sickness conclusion utilizing this expansive and robust ensemble.

15. InceptionResNetV2 + EfficientNetV2L + Xception: It consolidates InceptionResNetV2, EfficientNetV2L, and Xception, three strong neural network models. InceptionResNetV2 joins Initiation and ResNet, EfficientNetV2L streamlines processing assets, and Xception utilizes depthwise distinct convolutions. This exhaustive method catches complex data for exact plant illness analysis by joining the abilities of each model.

Fig 16 . DenseNet201 + Xception + InceptionV3

16. YOLOv5 (You Only Look Once, version 5): The YOLO group of models incorporates YOLOv5 object identification. Its ongoing handling velocity and picture object location and arrangement exactness are outstanding. A solitary brain network breaks down the full picture in YOLOv5, making it productive for continuous applications. It further develops design and preparing over its ancestors.

YOLOv5 is utilized in the undertaking in light of its high level article distinguishing proof qualities, including betel and rice plant sickness recognition. For applications requiring quick and exact disease determination, YOLOv5 is effective at breaking down photographs continuously. Its design processes the full picture straightforwardly, making it quick and successful. Contrasted with past variants, YOLOv5 might be more precise and simple to utilize, pursuing it a decent decision for agricultural plant infection determination.

Fig 17 YOLOv5

17. YOLOv6 (You Only Look Once, version 6): YOLOv6 is a modern grade object recognition system. Created by the Meituan Visual Knowledge Office, it adjusts speed and exactness in picture object recognition and characterization. The clever Bi-directional Concatenation (BiC) module further develops highlight combination and data stream for object acknowledgment precision in YOLOv6. Anchor-aided Training (AAT) further develops anchor box forecasts to further develop object restriction. The updated spine and neck engineering of YOLOv6 gives it top execution on benchmark datasets like COCO. The structure's various model renditions fulfill fluctuated processing needs, making it appropriate for modern thing distinguishing proof that adjusts computational economy and exactness.

Fig 18 YOLOv6 (You Only Look Once, version 6)

18. YOLOv7 (You Only Look Once, version 7): YOLOv7 is the most up to date object recognition model in the YOLO family, known for its speed and exactness. This PC vision advancement is YOLOv7, intended for ongoing item discovery.

Project Utilizations YOLOv7:The project utilizes YOLOv7 due to its unparalleled continuous handling, exactness on benchmark datasets like COCO, proficiency on asset obliged gadgets, and fixation on small item acknowledgment. The drive utilizes YOLOv7 to distinguish betel and rice plant sicknesses. The model's precision and constant handling speed satisfy the task's need for quick ailment recognizable proof. YOLOv7's emphasis on little item distinguishing proof recognizes unpretentious plant ailments in betel and rice plants.

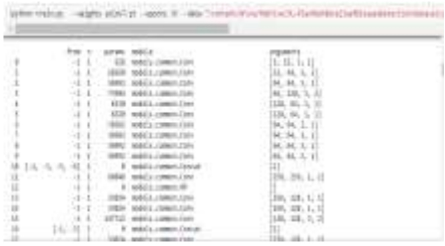

Fig 19 YOLOv7

19. YoloV87 The state of the art PC vision model YOLOv8 succeeds in object distinguishing proof, division, and stance assessment. Its smooth appearance and innovative elements give it state of the art execution as a YOLO movement. Its speed, accuracy, and ease of use make YOLOv8 ideal for

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ongoing item following, picture arrangement, and stance recognizable proof.

YOLOv8, known for its flexibility and state of the art execution, is picked for its ideal blend of speed and precision for continuous illness discovery in rice and betel leaf different settings.

Fig 20 . YoloV87

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.

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

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)

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

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.

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

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

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

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

Fig21 Betel Leaf Dataset performance Evaluation

Fig 22 Rice Leaf Dataset-Performance Evaluation

Fig23 Rice Leaf Data –Performance Evaluation(Detection)

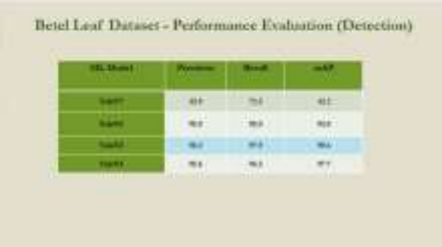

fig24 Betel Leaf Dataset - Performance Evaluation (Detection)

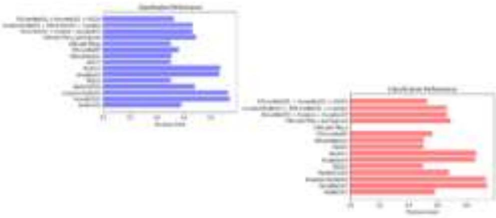

Fig25 accuracy, precision Comparison Graph for Classification of Betel Leaf

Fig 26 recall, F1 score Comparison Graph for Classification of Betel Leaf

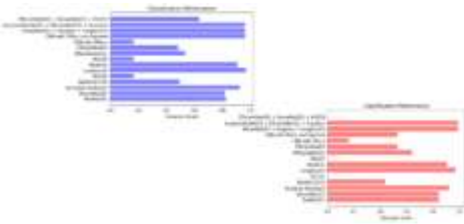

Fig 27 accuracy, precision Comparison Graph for Classification of Rice Leaf

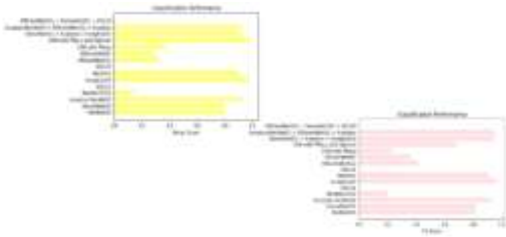

Fig28 recall, F1 score Comparison Graph for Classification of Rice Leaf

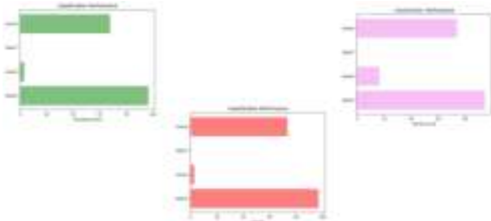

Fig 29 precision, recall, map Comparison Graph for Detection of Betel Leaf

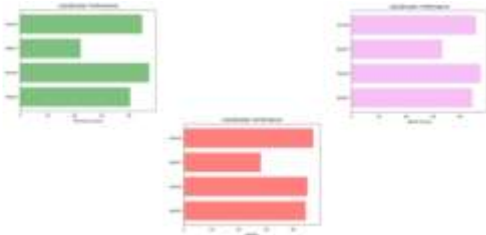

Fig30 precision, recall, map Comparison Graph for Detection of Rice Leaf

Fig 31 home page

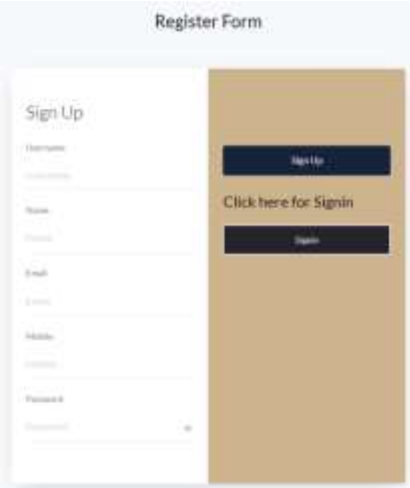

Fig 32 signup page

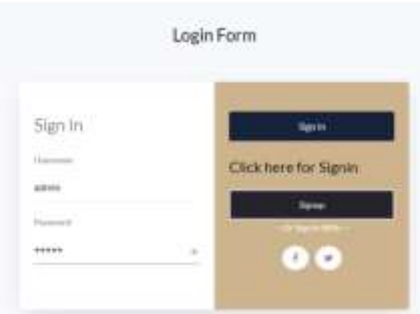

Fig 33signin page

Fig 34 main page

Fig 35 rice leaf dataset classification

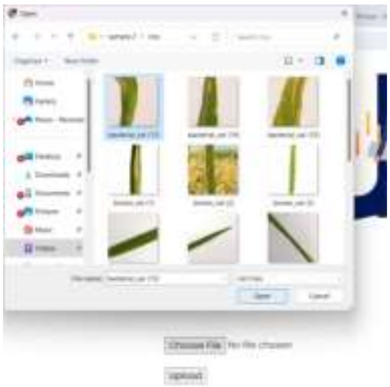

Fig 36 upload input image

Fig 37 predict result

Fig 38 rice leaf dataset detection

Fig 39 upload input image

Fig 40 final out come

Fig 41 betel leaf dataset classification4ee

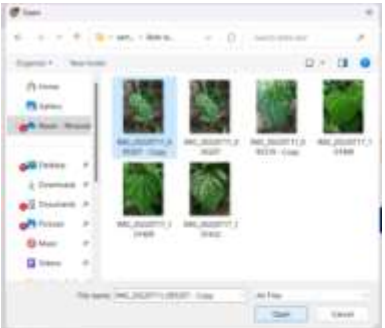

Fig 42 upload another input image

Fig 43 predict result for input image

Fig 44 betel leaf dataset detection

Fig 45 upload input image to predict result

Fig46 predict result for given input image

5. CONCLUSION

At long last, the PlantDet framework offers an original method for ricing and betel leaf crop plant sickness conclusion and classification. PlantDet further develops illness symptomatic exactness and flexibility by combining InceptionResNetV2, EfficientNetV2L, and Xception in a multi-model outfit strategy, satisfying farming's need for early identification. The framework's ability to beat earlier models and handle muddled rural data shows its commitment as an instrument for ranchers and the horticultural business.

With YOLOv8's high accuracy rates for Rice Leaf and Betel Leaf datasets, the framework's abilities are additionally upgraded by the option of complex discovery calculations. The Jar structure's easy to understand interface makes transferring photographs for examination simple and makes it down to earth for real-world application.

The PlantDet framework is a significant headway in plant sickness discovery innovation, giving ranchers a solid and productive device for illness distinguishing proof, improving crop management and expanding yields and maintainability.

6. FUTURE SCOPE

Hyperspectral or infrared imaging can further develop agricultural disease detection framework strength and adaptability to changed natural conditions. Exploring constant execution permits quick activity, while putting models tense gadgets speeds field navigation and diminishes cloud reliance. Extending the framework's yield sickness identification range expands its value and helps agricultural infection observation. Interpretability approaches work on model straightforwardness, expanding certainty among agricultural partners by uncovering dynamic cycles.

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