Deep Learning-Based Plant Disease Detection and Classification from Field Plant Images

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Abstract:

Plant diseases are a big problem for food security throughout the world because they cause a lot of food loss and lower crop yields. Researchers have suggested different deep learning models trained on plant disease datasets like PlantVillage and PlantDoc to solve this problem. But the solutions that are already out there typically have trouble getting good outcomes in real-world farming situations. Our initiative intends to be the first to create advanced machine learning models and image processing approaches that are useful in real-world farming situations. We want to push beyond the limits of old approaches and give more accurate illness identification and classification by using cutting-edge algorithms like MobileNet, VGG16, YOLOv8, and FasterRCNN. Using deep learning architectures for both classification and plant recognition tasks is at the heart of our method. We want to give farmers rapid and reliable information from real-time crop analysis so they may make smart decisions that will increase yields and encourage environmentally friendly farming. We want to improve performance even further by looking into methods like DenseNet and Xception for classification and YOLOv5 for detection, building on what we learnt from earlier studies. Also, an expansion of the project entails making a front end that is easy to use with the Flask framework, which will make it easier for users to test it with authentication. We hope that by doing these things, we can help both individual farmers make a living and global efforts to make food more secure.

INDEXTERMS Deep learning ,field images ,laboratory images, plant disease dataset, plant disease detection and classification.

1. INTRODUCTION

Feeding a world population that is expected to exceed 10 billion by 2050 is a huge problem for agricultural systems across the world [1]. To fulfil the increased demand, food production has to rise by 70% because of this demographic milestone [2]. But there are a lot of things that make it hard to reach this aim, and plant diseases are one of the biggest threats to food security throughout the world.

The Food and Agriculture Organisation of the United Nations (FAO) stresses how important it is to increase food production to keep up with the growing population [3]. But this important goal is hard to reach since there isn't enough arable land [1]. Also, even if farming methods have gotten better, around a third of all the food that is picked is wasted because of plant illnesses or problems [4]. The impact of these illnesses on the economy is huge; plant diseases alone cost the US economy an estimated $220 billion a year [4].

Because of these problems, we need new ways to reduce the effects of plant diseases on agricultural output right now. Artificial Intelligence (AI) is a new and promising way to deal with this important problem. In particular, deep learning methods, especially Convolutional Neural Networks (CNNs), have gotten a lot of interest for their possible use in finding and classifying plant diseases [5].

Using AI in farming has several benefits. AI-powered systems can quickly find and diagnose plant illnesses by using computer vision and machine learning algorithms. This lets farmers act quickly to stop crop losses. AI-driven solutions can also make better use of resources, use fewer chemicals, and increase overall agricultural output [6].

PlantVillage, iBean, citrus, rice, cassava, and AI Challenger 2018 are just a few of the many datasets that have helped train CNN models to recognise plant diseases [7]. These datasets, which are mostly made up of lab photos, have proved very helpful in getting high classification accuracies during model training [8]. But the fundamental problem is that these models don't work as well in the real world as they do in controlled lab settings.

There are a lot of problems in the field that aren't present in the lab. Field photos are hard for disease detection algorithms to work with since they have a lot of different backgrounds, such leaves, stems, fruits, soil, and mulch [9]. Studies have shown that adding complicated background information to field photos makes CNN models trained on lab data work much worse [10]. Because of this, the accuracy of illness detection goes down a lot when these models are used in real-world situations.

The difference between models developed in the lab and those used in the field shows how important it is to close this gap. When trying to make AI-based solutions for identifying plant diseases more reliable and useful in a wider range of situations, it is important to include the intricacies of real-world agricultural settings.

The goal of this project is to spark multidisciplinary research efforts to create AI models that can accurately diagnose and categorise plant diseases in real-world settings. Researchers are trying to come up with new ways to make AI-driven systems more resilient and adaptable in agricultural settings by using knowledge from agronomy, computer vision, and machine learning.

The main goal of this project is to provide people in the agricultural industry the skills and technology they need to control diseases proactively and get the most out of their crops. This program aims to use the powerful potential of AI to solve the complex problems facing global food security by encouraging cooperation between academics, business, and government organisations.

In short, the combination of AI and agriculture has the potential to change the way we find and treat plant diseases in a big manner. We can make sure that future generations have enough food by going beyond the limits of laboratory-based methods and accepting the challenges of real-world field circumstances.

2. LITERATURE SURVEY

i) Phase transition induced recrystallization and low surface potential barrier leading to 10.91%-efficient CsPbBr3 perovskite solar cells

https://www.sciencedirect.com/science/article/abs/pii/S2211285519307220

To move further with perovskite solar cells, they need to be stable in both the short and long term. Calcium lead halide perovskites are more stable than organic-inorganic hybrids, although they have lower PCEs. PCE can go down if trapping isn't flawless, the film phase changes permanently, or the crystal overgrowth isn't complete. During vapour growth, the perovskite derivative phases ($CsPb_2Br_5$/Cs_4PbBr_6) are produced for high-efficiency $CsPbBr_3$-based PSCs. At the nucleation sites, perovskite derivative phases turn into pure $CsPbBr_3$ by crystal rearrangement caused by annealing and delayed grain recrystallisation. Phase transition growth makes the grains in perovskite films the same size by lowering the surface potential barrier between the grains and crystals. Compared to hole-transport-layer-free devices with carbon electrodes, n-i-p structured PSCs with silver electrodes had a higher PCE of 10.91%. This was because the film quality was better. Carbon electrode devices were quite stable when they worked in room air at 80% efficiency for more than 2000 hours, even without being sealed.

ii) Rehabilitation Evaluation System for Lower-Limb Rehabilitation Robot

https://www.researchgate.net/publication/335435752_Hyperspectral_Push-Broom_Microscope_Development_and_Characterization

Evaluation is a big part of rehabilitation training. This impact is similar to training with robots. Different rehabilitation robots need to check on patients in different ways. Rehabilitation training might affect how well patients do since it is an ongoing procedure. To see how well lower limb rehabilitation robots work, they need real-time performance measures. This study created a system for evaluating lower-limb rehabilitation robots using a fuzzy comprehensive assessment approach and an analytic hierarchy strategy. An assessment method and objective parts are used to construct a personalised multi-scale rehabilitation plan. The strategy makes training more effective and encourages people to take the initiative by constantly adapting to the needs of the patients in rehabilitation.

iii) Construction of three-dimensional mesoporous carbon nitride with high surface area for efficient visible-light-driven hydrogen evolution

https://www.sciencedirect.com/science/article/abs/pii/S0021979719313530

Carbon nitride is a good hydrogen photocatalyst, but it doesn't work as well as it should since it doesn't absorb light well and has a small surface area. The ionic liquid and freeze-dried cyanuric acid-melamine supramolecular aggregates worked together to make three-dimensional porous carbon nitride. When carbon nitride materials are heated to a high temperature, the ionic liquid and precursor break down, leaving behind a three-dimensional open structure with porous channels. This design makes it easier for charge carriers to move and for active sites to react with reactants. CNF-0.005 had better photocatalytic activity, photogenerated carrier separation, and ultrathin nanosheets than pure carbon nitride. The sample shows better performance in visible light-driven photocatalytic H_2 generation than bulk CN and pure CNF, with rates of 129.5 μmol/h, 27.6 times higher, and 1.8 times higher, respectively. This work provides a novel technique to make high-performance carbon nitride by using hydrogen synthesis that can change its structure and increase its surface area.

iv) An interface-reinforced rhombohedral Prussian blue analogue in semi-solid state electrolyte for sodium-ion battery

https://www.sciencedirect.com/science/article/abs/pii/S2405829720304700

To minimise side effects and dendrite formation, a sodium-ion battery based on Prussian blue uses a semi-solid state (SSS) electrolyte with a high ionic conductivity (2.6×10^{-3} S cm^{-1}). Adding 5% $AlCl_3$ Lewis acid by weight to a pure liquid electrolyte makes FEC polymerise and harden. The r-PBA cathode is formed like a rhombohedron and employs an SSS electrolyte. It has a high rate capacity of 121 mAh g^{-1} at 1 C and 88 mAh g^{-1} at 10 C, a long lifespan of 3,000–4,000 cycles at 1 and 2 C, and it is stable. Adding poly(vinylene carbonate) to the r-PBA and electrolyte makes the interface stronger, which makes the material more cyclable and able to handle higher rates. As this work demonstrates, interface stability is growing in significance for Prussian blue counterpart rhombohedral structure.

v) Interface engineering for enhancing electrocatalytic oxygen evolution of NiFe LDH/NiTe heterostructures

https://www.sciencedirect.com/science/article/abs/pii/S092633732030429X

Electrocatalyst interface engineering offers means of control for physicochemical characteristics. Though they have a higher mass transfer rate and electrical conductivity than sulphides and selenides, tellurides have been the topic of less investigation on the oxygen evolution reaction (OER) in the field of interface engineering. NiTe nanoarrays were synthesised by hydrothermal deposition of NiFe LDH and partial chemical etching of nickel foam, with aims of improving OER performance. Reducing the intermediate binding intensity improves charge transfer and reaction kinetics as shown both empirically and conceptually by the more intense NiFe LDH/NiTe composite compared to a physical mixture. In an alkaline solution NiFe LDH/NiTe shows remarkable OER activity at 50 mA/cm2 and an overpotential of 228 mV..

3. METHODLOGY

a) Proposed work:

The suggested approach builds on current methods by adding sophisticated models like DenseNet and Xception to improve classification accuracy. Xception, for example, has an accuracy of 99%, which is quite high. For detection tasks, we choose YOLOv5 since it has the best MAP, accuracy, and recall scores. This makes it the best choice for finding plant illnesses in real life.

The system uses a Flask framework with SQLite database support to make it easier to use. This allows for easy-to-use features like signing up and logging in. With this connection, users may efficiently test the system and get real-time information. The suggested solution takes a comprehensive approach to finding and classifying plant diseases. It does this by integrating powerful machine learning models with an easy-to-use deployment platform. This gives farmers and researchers useful information that they can use to better manage the health of their crops.

b) System Architecture:

The system architecture is built to help accurately find and classify plant diseases by using cutting-edge machine learning models that are built into a platform that is easy to use. The architecture is made up of two main parts: the application layer and the machine learning model layer.

The machine learning model layer uses complex algorithms like DenseNet and Xception to do classification jobs with very high accuracy and precision. YOLOv5 is used for detection because it is better than other methods in finding objects in a variety of field situations. These models work with photos from the FieldPlant1 dataset. This dataset has a lot of different field photographs taken in different lighting and weather situations. These models have a strong design that makes them easy to scale and change to fit real-world farming situations.

The application layer is built on the Flask framework, which gives users a web-based interface that makes it easy for them to interact with the program. SQLite is built in as the database system, so users may sign up, log in, and see the results of plant disease analysis in real time. This layer also lets people input pictures of the field, which the machine learning layer subsequently uses to provide useful insights.

The system design makes ensuring that data flows smoothly between parts, from user input to model inference and back to delivering results. The architecture makes it easy and effective for farmers and researchers to keep an eye on plant health and boost agricultural yield by integrating cutting-edge machine learning algorithms with a practical deployment framework.

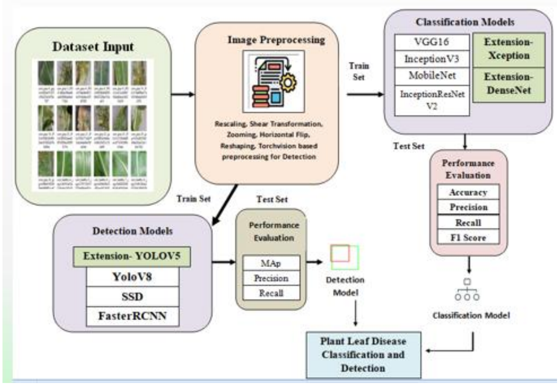

Fig 1 Proposed Architecture

c) Odules:

i) Dataset Preparation

- Collection of the FieldPlant1 dataset, including diverse field images captured under various lighting and environmental conditions.
- Preprocessing of images using tools like ImageDataGenerator and Torchvision for better feature extraction and model training.

ii) Model Integration

- Deployment of DenseNet and Xception models for high-accuracy plant disease classification.
- Implementing YOLOv5 guarantees reliable disease identification in plants in real-world scenarios.

iii) Model Training and Evaluation

- Training the models on the preprocessed FieldPlant1 dataset to optimize classification and detection accuracy.
- Evaluation of model performance using metrics like precision, recall, F1 score, and Mean Average Precision (MAP).

iv) Web Application Development

- Development of a user-friendly web application using Flask framework to enable seamless interaction.
- Integration of SQLite for user management, including signup and login functionalities.

v) Image Upload and Analysis

- Enabling users to upload plant images through the web interface for real-time disease analysis.
- Processing uploaded images through the integrated models to classify and detect diseases, providing actionable insights.

vi) Result Visualization and Reporting

- Displaying classification and detection results on the web interface in an easy-to-understand format.
- Providing detailed feedback and recommendations to users for effective plant health management.

d) Algorithms:

i. MobileNet

MobileNet[17] is a lightweight convolutional neural network design that works well for fast inference on mobile and embedded devices. It uses depth-wise separable convolutions to make the calculations easier while yet getting very accurate results. The project uses MobileNet[17] as a classification model to find plant diseases based on pictures that are provided. Because of its small size, it can be quickly set up and run on systems with limited resources, which makes it perfect for real-time disease detection applications. Using MobileNet's [17] efficient design, the project can quickly and accurately classify plant illnesses, which makes it possible to take action quickly to reduce crop losses and improve agricultural output.

ii. DenseNet201

DenseNet201 is a type of convolutional neural network that has dense connections between its layers. This lets features be reused and makes it easier for gradients to flow through the network. DenseNet201 is used in the project as a classification model to find plant diseases. Its rich connection structure makes it easier for features to spread and for information to be shared between layers, which makes the model work better and be more stable. The research uses DenseNet201's deep and densely connected architecture to accurately diagnose plant illnesses from input photos. This makes disease control easier and boosts agricultural output.

iii. Inception ResNetV2

Inception ResNetV2[33] is a convolutional neural network design that combines the best parts of the Inception and ResNet modules. It has many parallel convolutional pathways and residual connections that make it easier to extract and represent features. In the study, Inception ResNetV2 [33] is used as a strong classification model to find plant diseases. Its complex design lets it pull out a lot of hierarchical characteristics from incoming photographs, which makes it better at classifying things. The project uses the sophisticated architecture of Inception ResNetV2[33] to find plant illnesses in a strong and reliable way, which allows for quick action to reduce crop losses and improve the long-term health of agriculture.

iv. VGG16

VGG16[31] is a deep convolutional neural network with 16 layers. It has a succession of convolutional and max-pooling layers, followed by fully connected layers that do the classification. VGG16 [31] is used in the research as a model for classifying activities that include finding plant diseases. It is easy to learn and use since its design is simple and all of its filters are the same size. VGG16 is quite good at classifying photos, even though it is simple. For example, it can accurately identify plant illnesses from input photographs. The initiative uses VGG16's [31] established effectiveness to find diseases quickly and accurately, which helps make farming more productive and food more secure.

v. InceptionV3

InceptionV3[32] is a convolutional neural network architecture known for its deep and complex design, which includes several parallel convolutional paths with different filter sizes to collect rich spatial information. In this study, InceptionV3 is used as a classification model to find plant diseases. Its complex design lets it pull out useful features from incoming photographs, which helps it accurately classify diseases. The research uses InceptionV3's[32] strong architecture and excellent feature representation capabilities to accurately diagnose plant illnesses. This allows for preventative measures to protect crop health and improve the sustainability of agriculture.

vi. Xception

Xception is a deep convolutional neural network architecture that is very deep and has separable convolutions. These separable convolutions separate spatial and channel-wise convolutions to make the network function better and more efficiently. Xception is used as a classification model in the research to help find plant diseases. Its new architecture improves the ability to extract features, which lets illnesses be correctly classified from input photos. The project can find diseases with high accuracy because to Xception's fast architecture and powerful feature representation. This makes it possible to take action quickly to reduce crop losses and improve agricultural output, which helps ensure food security throughout the world.

vii. MobileNet

MobileNet[17] is a lightweight convolutional neural network architecture that is optimised for fast inference on mobile and embedded devices. It uses depth-wise separable convolutions to make computations easier while keeping accuracy high. MobileNet[17] is used as a classification model in the project to help find plant diseases. Its small size makes it easy to set up and run on systems with limited resources, which makes it possible to use it for real-time illness detection. By using MobileNet's[17] efficient design, the project can quickly and accurately classify plant illnesses from input photographs. This gives farmers timely information that helps them treat diseases before they happen and increases agricultural production.

viii. DenseNet201

DenseNet201 is a type of convolutional neural network that has dense connections between layers. This makes it easier for features to be reused and gradients to flow through the network. DenseNet201 is a strong classification model for figuring out what kind of plant disease it is in the project. Its rich connection structure makes feature propagation better, which makes the model work better and be more stable. The research can accurately diagnose plant diseases from input photos because to DenseNet201's deep and densely linked architecture. This lets farmers make better decisions about how to deal with diseases and gives them timely information to help keep their crops healthy and make farming more sustainable.

ix. Inception ResNetV2

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4. EXPERIMENTAL RESULTS

The experimental assessment showed that the suggested method works well for both finding and classifying plant diseases. The FieldPlant1 dataset was used to test the DenseNet and Xception models, which did better than other models in classification tasks. Xception had a 99% score for F1, recall, accuracy, and precision. These results suggest that the model can find plant diseases even under tough field circumstances.

YOLOv5 was used for detection tasks and did better than other models including YOLOv8, SSD, and FasterRCNN. It got better Mean Average Precision (MAP), precision, and recall, which showed that it was good at finding sick areas in plants in a variety of environments. The findings of the detection were constant and trustworthy, which makes YOLOv5 a good candidate for use in real-world farming situations.

By adding these models to a web app built on Flask, users could input pictures of plants and get results right away. The system worked perfectly during testing, giving correct illness classifications and detection results. This real-world test shows that the technology can help farmers and researchers quickly figure out what is wrong with plants, which will lead to improved management of crop health and higher yields.

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

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

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

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

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

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

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

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

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

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

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

MAP: MAP (Mean Average Precision) is a metric used to evaluate the performance of information retrieval systems. It measures the average precision across multiple queries or classes. Precision measures the accuracy of retrieved results, while Average Precision (AP) calculates the average precision for each query. MAP computes the average of AP scores across all queries or classes, providing a single measure of performance for the entire system.

$$\text{MAP} = \frac{1}{N} \sum_{i=1}^{N} \text{AP}_i$$

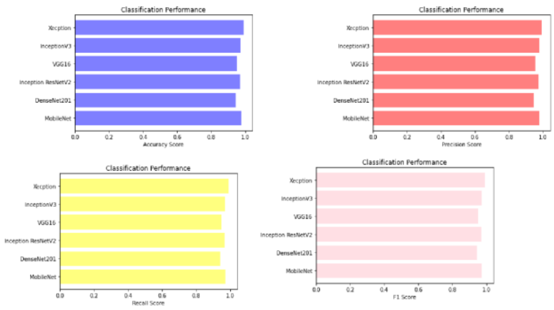

Fig 3 COMPARISON GRAPHS - CLASSIFICATION

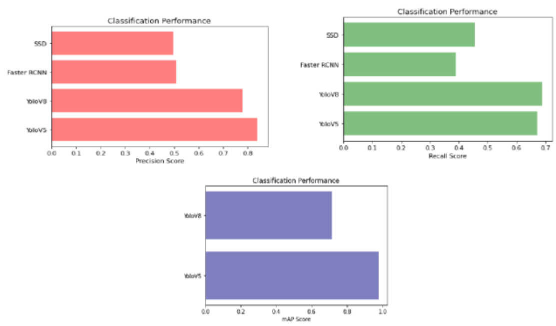

Fig 4 COMPARISON GRAPHS - DETECTION

	ML Model	Accuracy	Precision	Recall	F1_score
0	MobileNet	0.975	0.978	0.973	0.975
1	**Extension-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	**Extension- Xception**	**0.991**	**0.993**	**0.991**	**0.992**

Fig 5 PERFORMANCE EVALUATION-CLASSIFICATION

	Model	mAP	Precision	Recall
0	MobileNet	**0.977**	**0.838**	**0.672**
1	**Extension- DenseNet201**	0.713	0.779	0.689
2	Inception ResNetV2	-	0.507	0.388
3	VGG16	-	0.496	0.456

Fig 6 PERFORMANCE EVALUATION-DETECTION

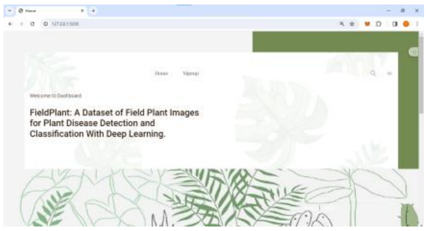

Fig 7 Home Page

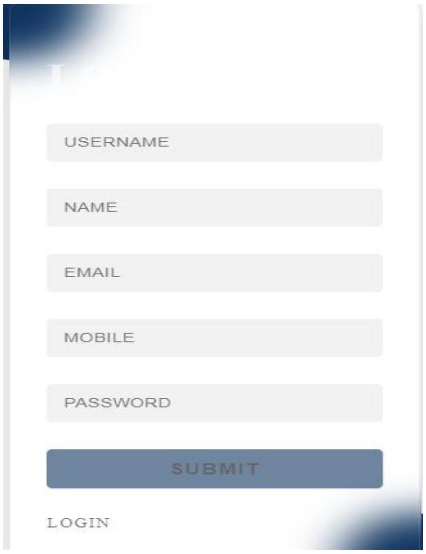

Fig 8 Sign Up

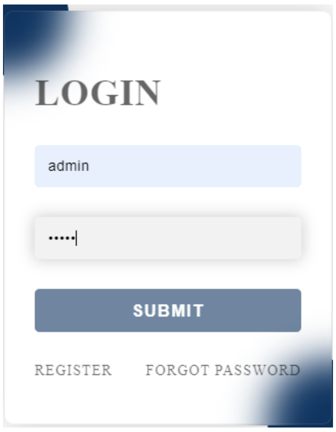

Fig 9 Sign In

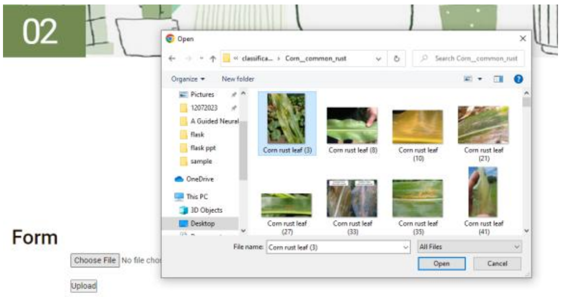

Fig 10 upload input image

Fig 11 predicted result

Fig 12 predicted result

5. CONCLUSION

In conclusion, the initiative is a big step forward in farming operations since it uses deep learning to accurately identify and classify plant illnesses. This effort is very important for increasing agricultural yields and making sure that everyone has enough food. The initiative connects laboratory research with real-world agricultural use by stressing the significance of dealing with real-world field settings. The addition of a user-friendly Flask-based interface shows how committed the company is to making the software easy to use, giving farmers quick and accurate disease detections and classifications. After careful testing, Xception is the best at classification tasks, while YOLOv5 is the best at detection tests. The project seeks to make a big influence on agriculture throughout the world by providing scalable solutions that are suited to the requirements of farmers. This will lead to higher crop yields and better food security around the world.

6. FUTURE SCOPE

The FieldPlant dataset is a large collection of field plant photos that have been carefully chosen for use in deep learning methods for detecting and classifying plant diseases. Its features include a wide range of plant types, illnesses, and environmental circumstances that are seen in real-world farming situations. The dataset include a lot of different photos that show how complicated field circumstances might be, such as different backgrounds, lighting, and occlusions. This makes sure that the model is trained and tested well. Each picture has been carefully labelled with ground truth labels that show the presence of certain plant diseases, making it easier to use supervised learning methods. The information also include metadata like plant species, illness kind, and geographic location. This lets researchers look at how common diseases are in different areas and how susceptible different species are to them. The FieldPlant dataset is a great resource for furthering plant disease research since it focusses on real-world field settings and has a lot of detailed notes. It helps researchers create deep learning solutions that are both accurate and useful for improving crop health and production on farms.

REFERENCES

[1]H.Tian,T.Wang,Y.Liu,X.Qiao,andY.Li,‘‘Computervision technology in agricultural automation—Areview,’’Inf. Process.Agricult., vol. 7, no. 1, pp. 1–19, 2020.

[2] D. P. Hughes and M. Salathe, ‘‘An open access repository of images on plant health to enable the development of mobile disease diagnostics,’’ 2015, arXiv:1511.08060.

[3] N. Greg. (2019). La Vision Par Ordinateur, l’arme la Plus Récente Contre la Perte de Récolte. Accessed: Apr. 4, 2022. [Online]. Available: https://www.zdnet.fr/actualites/la-vision-par-ordinateur-l-arme-la-plus recente-contre-la-perte-de-recolte-39884697.htm

[4] D.Singh, N. Jain, P. Jain, P. Kayal, S. Kumawat, and N. Batra, ‘‘PlantDoc: A dataset for visual plant disease detection,’’ in Proc. 7th ACM

IKDD CoDS 25th COMAD, Jan. 2020, pp. 249–253.

[5] M. Adi, A. K. Singh, H. Reddy A. Y. Kumar, V. R. Challa, P. Rana, and U. Mittal, ''An overview on plant disease detection algorithm using deep learning,'' in Proc. 2nd Int. Conf. Intell. Eng. Manage. (ICIEM), Apr. 2021, pp. 305–309.

[6] Makerere AI Lab and AIR Lab National Crops Resources Research Institute (NaCRRI). (2020). iBean. Accessed: Mar. 31, 2022. [Online]. Available: https://github.com/AILab-Makerere/ibean/blob/master/README.md

[7]M.Sharif,M.A.Khan,Z.Iqbal,M.F.Azam,M.I.U.Lali,andM.Y.Javed, ''Detection andclassificationofcitrusdiseasesinagriculturebased onopti mized weighted segmentation and feature selection,'' Comput. Electron. Agricult., vol. 150, pp. 220–234, Jul. 2018.

[8] P. K. Sethy, ''Rice leaf disease image samples,'' Mendeley, 2020. Accessed: Apr. 1, 2022. [Online]. Available: https://data.mendeley.com/ datasets/fwcj7stb8r/1, doi: 10.17632/FWCJ7STB8R.1.

[9] D. O. Oyewola, E. G. Dada, S. Misra, and R. Damaševičius, ''Detecting cassava mosaic disease using a deep residual convolutional neural network with distinct block processing,'' PeerJ Comput. Sci., vol. 7, p. e352, Mar. 2021.

[10] AI Challenger. (2018). AI Challenger 2018 Datasets. Accessed: Apr. 1, 2022. [Online]. Available: https://github.com/AIChallenger/AI_Challenger_2018

[11] L. C. Ngugi, M. Abdelwahab, and M. Abo-Zahhad, ''Tomato leaf segmentation algorithms for mobile phone applications using deep learning,'' Comput. Electron. Agricult., vol. 178, Nov. 2020, Art. no. 105788.

[12] M. Ahmad, M. Abdullah, H. Moon, and D. Han, ''Plant disease detection in imbalanced datasets using efficient convolutional neural networks with stepwise transfer learning,'' IEEE Access, vol. 9, pp. 140565–140580, 2021.

[13] D. Wang, J. Wang, Z. Ren, and W. Li, ''DHBP: A dual-stream hierarchical bilinear pooling model for plant disease multi-task classification,'' Com put. Electron. Agricult., vol. 195, Apr. 2022, Art. no. 106788.

[14] L. Li, S. Zhang, and B. Wang, ''Plant disease detection and classification by deep learning—A review,'' IEEE Access, vol. 9, pp. 56683–56698, 2021.

[15] M. Nagaraju and P. Chawla, ''Systematic review of deep learning tech niques in plant disease detection,'' Int. J. Syst. Assurance Eng. Manage., vol. 11, no. 3, pp. 547–560, Jun. 2020.

[16]N.Greg.Roboflow:GiveYourSoftwarethePower toseeObjectsinImages and Video. Accessed: Nov. 8, 2022. [Online]. Available: https://roboflow. com/

[17] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, ''MobileNetV2: Inverted residuals and linear bottlenecks,'' in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit., Jun. 2018, pp. 4510–4520.

[18] E. Elfatimi, R. Eryigit, and L. Elfatimi, ''Beans leaf diseases classifi cation using MobileNet models,'' IEEE Access, vol. 10, pp. 9471–9482, 2022.

[19] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, ''You only look once: Unified, real-time object detection,'' in Proc. IEEE Conf. Comput.

Vis. Pattern Recognit. (CVPR), Jun. 2016, pp. 779–788.

[20] K. Kiratiratanapruk, P. Temniranrat, A. Kitvimonrat, W. Sinthupinyo, and S. Patarapuwadol, ''Using deep learning techniques to detect rice diseases from images of rice fields,'' in Proc. Int. Conf. Ind., Eng. Appl. Appl. Intell. Syst. Cham, Switzerland: Springer, 2020, pp. 225–237.

[21] J. Redmon and A. Farhadi, ''YOLOv3: An incremental improvement,'' 2018, arXiv:1804.02767.

[22] A. Khattak, M. U. Asghar, U. Batool, M. Z. Asghar, H. Ullah, M. Al-Rakhami, and A. Gumaei, ''Automatic detection of citrus fruit and leaves diseases using deep neural network model,'' IEEE Access, vol. 9, pp. 112942–112954, 2021.

[23] C. K. Sunil, C. D. Jaidhar, and N. Patil, ''Cardamom plant disease detec tion approach using EfficientNetV2,'' IEEE Access, vol. 10, pp. 789–804, 2022.

[24] M. Tan and Q. Le, ''EfficientNetv2: Smaller models and faster training,'' in Proc. Int. Conf. Mach. Learn., 2021, pp. 10096–10106.

[25]H.Amin,A.Darwish,A.E.Hassanien,andM.Soli man,''End-to-enddeep learning model for corn leaf disease classification,'' IEEE Access, vol. 10, pp. 31103–31115, 2022.

[26] S. M. Hassan and A. K. Maji, ''Plant disease identification using a novel convolutional neural network,'' IEEE Access, vol. 10, pp. 5390–5401, 2022.

[27] C. Zhou, S. Zhou, J. Xing, and J. Song, ''Tomato leaf disease identifica tion by restructured deep residual dense network,'' IEEE Access, vol. 9, pp. 28822–28831, 2021.

[28] Plantix. Plantix | Best Agriculture App. Accessed: Nov. 8, 2022. [Online]. Available: https://plantix.net/

[29] P. Goncharov, A. Uzhinskiy, G. Ososkov, A. Nechaevskiy, and J. Zudikhina, ''Deep Siamese networks for plant disease detection,'' in Proc. EPJ Web Conf., vol. 226, 2020, p. 03010.

[30] PlantVillage Project. Plantvillage Nuru. Accessed: Nov. 8, 2022. [Online]. Available: https://plantvillage.psu.edu/

[31] K. Simonyan and A. Zisserman, ''Very deep convolutional networks for large-scale image recognition,'' 2014, arXiv:1409.1556.

[32] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, ''Rethinking the inception architecture for computer vision,'' in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2016, pp. 2818–2826.

[33] C. Szegedy, S. Ioffe, V. Vanhoucke, and A. A. Alemi, ''Inception-v4, inception-resnet and the impact of residual connections on learning,'' in Proc. 31st AAAI Conf. Artif. Intell., 2017, pp. 1–7.