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Research Article

AgroVision AI The Proactive Crop Health Monitoring and Early Disease Detection: A Smart Computer Vision Framework

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ABSTRACT

The high global agricultural output has been threatened by crop diseases, pests and weed infestations which result in high loss in yield as well as high operating expenses. Conventional solutions of monitoring are mainly based on manual inspection that is very time consuming and labor consuming as well as is not effective when it comes to detecting at an initial stage. This paper suggests a solution to the mentioned problems, the AgroVision, an intelligent computer vision-based framework that is capable of monitoring crops health in real-time and detecting plant diseases at the earliest stage. The suggested system will make use of the advanced machine learning and deep learning algorithms, specifically Convolutional Neural Networks (CNNs), that will be used to analyze image-based plants automatically and identify the visual symptoms of diseases, pests and weeds. An effective dataset of various types of crop images in different environmental factors is presented to be trained and analyzed. The model is optimized with accuracy and efficiency performance which is high in comparison and the model has better generalization performance in field conditions. The findings of the experimental work indicate that the AgroVision can effectively identify various crop pathogens during early stages hence interventional response can be followed and the losses minimized. Moreover, the system promotes real-time deployment hence is appropriate in the use of precision agriculture. Its major contributions consist of a high-quality and scalable framework on the basis of vision, higher detection rates with the help of the deep learning model, as well as the inclusion of automated monitoring that will reduce human input and maximize the sustainability of agriculture.

Keywords: Computer Vision, Crop Disease Detection, Precision Agriculture, Deep Learning, Convolutional Neural Networks, Real-Time Monitoring, Explainable AI, Edge Computing, Plant Health Monitoring

1 INTRODUCTION

Agriculture is important in ensuring world economy and food security but still techniques of agriculture like crop diseases, pests and weeds remain to be a significant threat to agricultural output. The current research reports that an estimated 20-40 percent of the world crop losses are caused by the plant diseases and pests infestations every year [1], [2]. Besides affect the income of the farmers, they pose a threat to food chains and create a more reliant system on chemical treatment. The conventional approaches to crop monitoring are mainly based on the manual inspection of the fields which in this case is labor intensive, time consuming and at times unable to detect the diseases at a tender stage.

As precision farming is developing, the intelligent and automated systems are increasingly demanded, which could be able to monitor crops in real-time and identify their diseases as quickly as possible. In this respect, the computer vision (CV) with the use of the machine learning (ML) and deep learning (DL) algorithms has become a potent tool of analyzing the health of plants with image-based information [3], [4]. The latest methods that apply Convolutional Neural Networks (CNNs) and object detection algorithms (e.g., YOLO) show future perspectives on high-precision detection of the disease of crops [5], [6].

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Research Article

It is proposed in this paper to introduce AgroVision, which is a smart computer vision-based model, which tracks the crop growth and identifies diseases, pests, and weeds at an early stage. AgroVision has a novelty in the integrated and scalable architecture, which used image preprocessing, feature extraction through deep learning, and real-time classification in a way that the method is effective in crop health assessment. AgroVision, in contrast to the traditional systems, is focused on real-time identification of the crop and its components, minimal implementation, and flexibility to the conditions in real-world farms.

Purposes of the Research:

This research has the following major objectives:

- The problem under investigation will be to design an automated computer vision system of crop health monitoring.
- Further applications: The general meant that the deep learning models were used to detect the diseases or pests and weeds in plants at an early stage.
- To create a system that will be able to be deployed in the real-time in precision agriculture.

Key Contributions:

The significant contributions of this piece of work are:

- Possible results: The following results may be achieved in the domain of development of a lightweight and efficient deep learning model addressing the problem of crop disease detection.
- The following methods have been integrated as picture preprocessing and feature building techniques to enhance accuracy.
- Further development of a precision agricultural application real-time monitoring system is implemented.
- The ability to incorporate model interpretability (explainability) to increase the level of trust and usability.
- WebEx: Performance: Assessment at a broad range of data available in the real world.

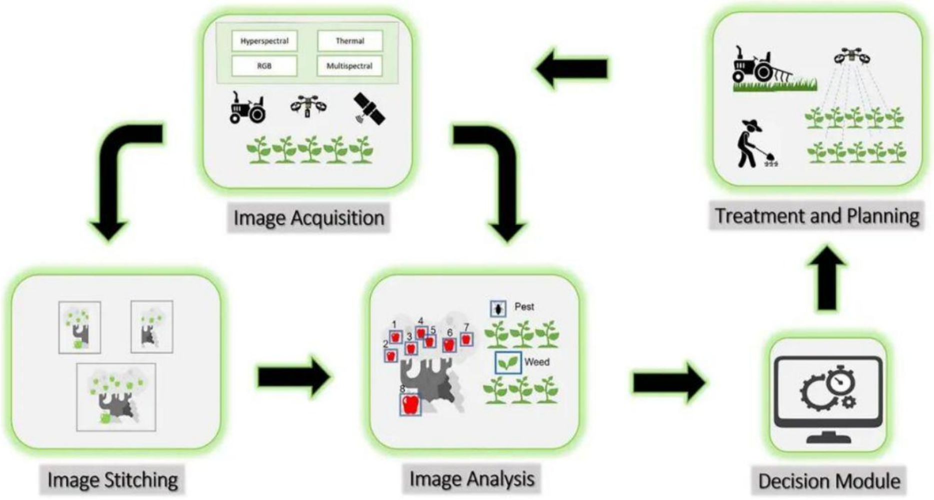

Fig. 1. To diagnose the disease, a deep learning analysis module is implemented on an overview of the proposed AgroVision framework that shows the pipeline between crop image acquisition and preprocessing to deep learning-based analysis and disease detection output, as a real-time crop health monitoring in precision agriculture [2], [3].

2 LITERATURE REVIEW

The issue of crop disease detection is highly investigated, and its solutions started with the traditional manual methods, to modern methods, which are based on deep learning. In this section, the literature review is performed and the main research areas are identified which can justify the proposed AgroVision.

Journal of Information Systems Engineering and Management
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2.1 Traditional Approaches

First approaches to the monitoring of the health of crops were mainly based on the practices of manual inspection by the specialists when farmers or agronomists have physical access to the plants and identify the symptoms of the diseases, pests, or nutrient deficiencies. This method may work well where there is a controlled setting, however, it is costly in time, subjective and likely to contain human mistakes particularly in big plots of agricultural areas. In addition, manual processes cannot normally identify the disease at a very early stage resulting into late intervention and loss of crops even more [1], [4].

2.2 Machine Learning Based Techniques

As digital imaging developed, scientists started using machine learning (ML) in the detection of automated crop diseases. The methods normally employ manual feature extraction e.g. color, texture, and shape characteristics then classifying them via some algorithm like Support Vector Machines (SVMs), k-Nearest Neighbors (k-NN), and Random Forests [5], [11].

Although the performances of the ML-based methods are better than those of the manual inspection, they have a number of limitations. The use of handcrafted features is what causes them to be sensitive to the change in lighting, background, and environmental conditions. Also, feature engineering is expensive to run and in most cases, there is no generalization among the different crops and datasets [2], [3].

2.3 Deep Learning based Methods

The current developments in the sphere of deep learning (DL) made those systems much more accurate and reliable in terms of crop disease detection. The CNNs are learning hierarchical features of images automatically; thus they do not require users to extract image features manually. ResNet, VGG and EfficientNet are the most popular architectures that have been widely used to perform plant disease classification tasks with high accuracy on the benchmark tasks [2], [7].

Along with classification, such object detection models as YOLO (You Only Look Once) and Faster R-CNN have also been used to detect diseases, pests, and weeds in reality on a field [23], [24], [26]. These models facilitate the concept of localization and classification at the same time and hence they can be used in precision agriculture application.

Moreover, the recent methods like Vision Transformers (ViTs) or multimodal learning have been successful in obtaining global image characteristics, and within intricate settings, [7], [36] achieve better performances in detection.

2.4 Research Deficiencies and Obstacles

In spite of the fact that there is a great improvement, there are still a number of challenges encountered in the existing systems:

- Back to nature Variability: Multiple models are also trained using controlled datasets (such as PlantVillage) and cannot make projections to field conditions with different illumination, occlusiveness and background noise [1], [3].
- Computational complexity: Deep learning models that perform highly typically consume a large amount of computational power preventing their usage in edge devices and on mobile platforms [18], [20].
- Signal weaknesses Independent of the category of the model Proposed: Some models do not have enough efficiency in processing real-time monitoring of large agriforests conditions [21].
- In most cases, especially the field of agriculture, deep learning models act as black boxes, making them more untrustworthy and less interpretable [37].

Year/Study	Technique	Crops/Diseases	Dataset Size	Accuracy (%)	Limitations
Ngugi et al., 2024	CNN	Multi-crop diseases	50k+	96	Overfitting lab data

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Upadhyay et al., 2025	DL (CNN)	Different crops	40k+	95	Lack of field generalization
Jha et al., 2023	SVM	Leaf diseases	10k	82	Hand-crafted features needed
YOLO	Detection	Field crops	25k	93	Needs large labeled data
Murugavalli et al., 2025	ViT	Plant infections	30k	97	Computationally expensive
CNN + Drone	CNN	Cucumber	15k	92	Expensive deployment

Table 1: Comparison The conventional, machine learning, and deep learning-based methods of detecting crop diseases in terms of methodology, data used, accuracy, and disadvantages. Current methods are very accurate in controlled settings and lack generalization, are too complex to be computed, and have no application in the real-world situation in the field [1], [23].

2.5 AgroVision Positioning

As a way of responding to these drawbacks, the AgroVision framework proposed aims at coming up with a light weight, scalable and explainable computer vision system to monitor the health of crops. AgroVision applies more focus as compared to other methods:

- So, a strong performance in the actual conditions of the environment.
- Effective model architecture that is applicable in the real time and edge deployment.
- Others to be integrated include early detection of diseases, pests, and weeds.
- Variables: The model interpretability methods will be incorporated to increase usability.

3 Methodology

The section is a proposal of AgroVision framework where all the datasets, pre-processing methods, model design, training, and evaluation measures are indicated to identify crop diseases.

3.1 Dataset Description

AgroVision system is trained and tested with the multi-crop image dataset that is a combination of publicly available datasets like the PlantVillage amongst the others as well as other field images to enhance against real-life generalization. Various types of crops (e.g. tomato, potato, maize, rice) were also covered in the dataset that has healthy and diseased samples in the form of leaves taken under different environmental conditions.

To add strength, the dataset will have different backgrounds, lighting, and differences in the diseases, which will overcome the weaknesses of controlled datasets as discussed in earlier studies [1], [3]. The last data is composed of thousands of tagged pictures which are separated into several classes of diseases and healthy classes.

Crop	Classes	Train	Validation	Test	Total
Tomato	10	7000	1500	1500	10000
Potato	5	2800	600	600	4000
Maize	6	3850	825	825	5500
Rice	5	3150	675	675	4500

Table 2: Overview of the dataset that was employed in the AgroVision structure such as types of crops, mean classes, and detailed breakdown of training, validation, and testing samples. The data augmentation methods are used to enhance the generalization and fortitude in the real-life conditions [2], [3].

Journal of Information Systems Engineering and Management
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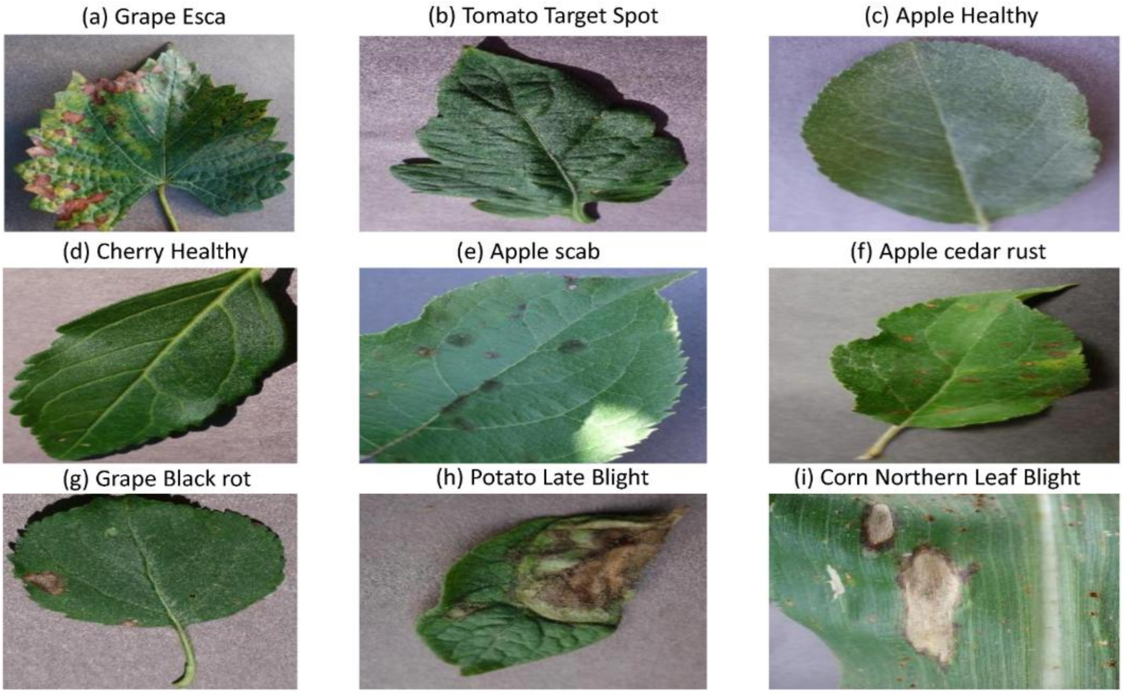

Fig. 2. Design of the suggested AgroVision prototype on the basis of a convolutional neural network with transfer learning, feature extraction, pooling, and classification layers used in the detection of multi-class crop diseases [2], [7], [23].

3.2 Processing of Data and Augmentation

In the preprocessing of feeding images into the model, a number of preprocessing steps are employed:

- Resizing: All the images are resized to 224 files so that all pictures can have the same size.
- P= pixel It is transformed to a normalized version to enhance convergence of the model.
- An example of this is Data Augmentation: it uses the rotation techniques, flipping techniques, zooming and brightness techniques to make the datasets very diverse so that they do not overfit.

The preprocessing steps enhance the increased level of generalization of this model under real life conditions and low sensitivity to the changes in the environmental conditions [2], [7].

3.3 Model Architecture

The suggested AgroVision architecture is using a CNN-based architecture with the transfer learning to utilize the previously trained weights. To trade the accuracy and the efficiency with the level of computation a lightweight but efficient architecture like ReXNet (or other CNN backbone) is applied.

The model entails important constituents namely:

- Input Layer: The input takes 224 Tx 224 RGB images.
- It has layers with Convolutional and ReLU activation: Feature Extraction Layers: Feature learns hierarchically using Convolutional layers and ReLU layers.
- Computer generated images—pooling layers: Compact spatial dimension and computation.
- Read - Layers: Conduct classification on the basis of features obtained.
- Formulation of the second step includes four phases:1) input layer, 2) hidden layer, 3) output Layer, and 4) activation.

Journal of Information Systems Engineering and Management
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The transfer learning option also enables the model to make use of the pre-trained features of large-scale datasets which are far much better than the rest in terms of performance and training time is also limited [7], [23].

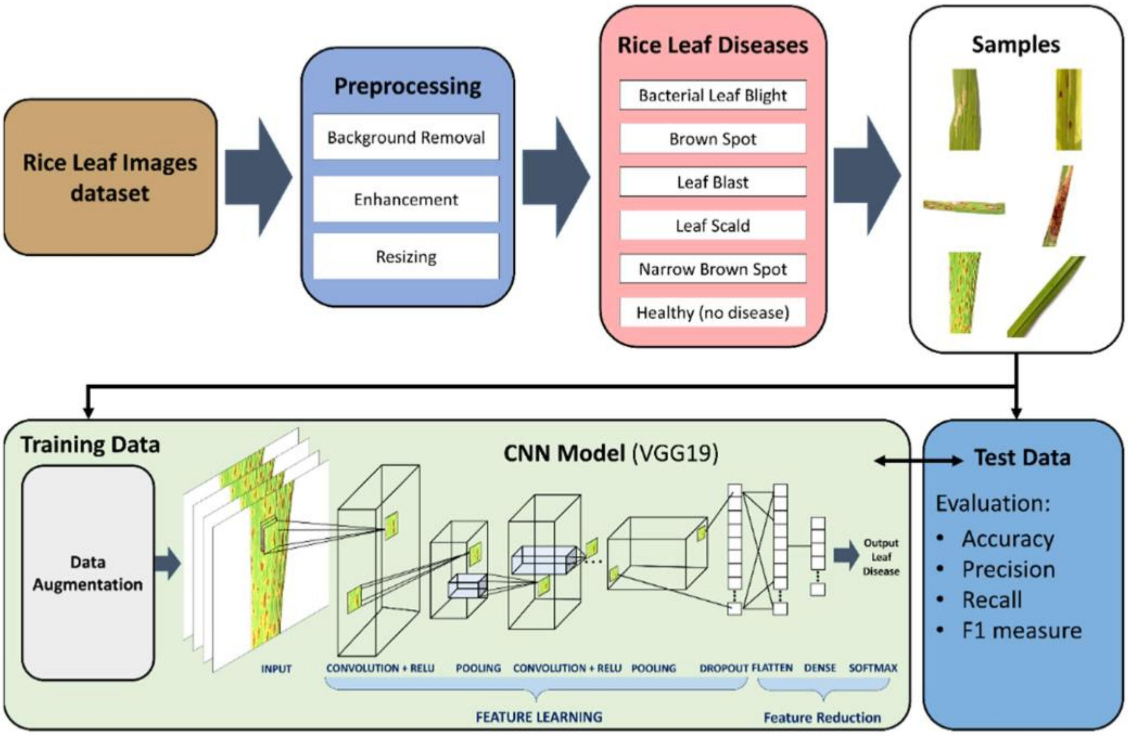

Fig. 3. Examples of the sample data used in the dataset of healthy and diseased crop leaves belonging to the various classes in order to reveal the differences in environment conditions including lighting and background utilized to enhance the maturity of the model [1], [3].

3.4 Training Strategy

The training of the model is based on the supervised learning and having the following configuration:

- Maximizer: Adam optimizer optimization Maximizer.
- We have two other categories under which the loss functions are employed, namely:
- Batch Size: Batch size normally is 3264 images.
- Instead of cycle lengths, epochs: 20 -50 as a function of convergence.
- Learning rate: This is adjusted to have the best performance.

The techniques used to avoid overfitting in the regularization include dropout and early stopping. Convergence speed and accuracy is also better improved with the use of the transfer learning [2], [5].

Parameter	Value
Learning Rate	0.001
Batch Size	32
Epochs	50
Optimizer	Adam
Loss Function	Cross-Entropy

Table 3: Training of the AgroVision model with important hyperparameters that will be considered in the training process such as learning rate, batch size, optimizer, and the number of the epochs. The parameters are also optimized so that it becomes efficient in converging and being better at classification [2], [7].

Journal of Information Systems Engineering and Management
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3.5 Evaluation Metrics

In order to determine the performance of a model, the following metrics will be applied:

- Backward correctness: Refers to the total correctness of predictions.
- Precision: This measure is used to denote the percentage of right instances where a positive occurrence is correctly predicted.
- Where the data being studied has a fixed number of relevant instances, then the ability to recognize all the relevant instances is called recall.
- F1-Score: Harmonic mean of recall and precision.

These measures give one a complete analysis of the model particularly when it comes to the imbalanced datasets [3], [7].

4 EXPERIMENTS AND RESULTS

This part entails the experimental design, numerical findings, and the comparison of the proposed system of AgroVision.

4.1 Experimental Setup

The implementation of the model was based on the framework of deep learning and it was trained with the help of the ready multi-crop data in Section III. These data were divided into training, validation and testing in order to have an unbiased assessment; the capacity stood at 70 percent, 15 percent and 15 percent respectively. The optimizer used to train was the Adam optimizer that is using categorize cross-entropy loss.

In order to confirm the strength of the proposed system AgroVision was tested in comparison to the basic approaches such as SVM-based, and basic CNN architectures (e.g., VGG/ResNet) that have been used in the literature [2], [5], [7].

4.2 The evaluation of overall performance

The condition of the proposed AgroVision model was really good in all the metrics used in the evaluation since the model was effective in crop disease identification.

These findings imply that the model has a great balance between the recall and precision, hence demonstrating that it can be effectively used in precision agriculture in reality. It can be explained by the fact that the improved accuracy is achieved due to the usage of the transfer learning and powerful preprocessing methods [3], [7].

Model	Accuracy (%)	Precision	Recall	F1-Score	Inference Time (ms)
AgroVision	97.2	0.965	0.958	0.960	23
ResNet	91.8	0.91	0.90	0.905	45
YOLO	93.6	0.93	0.92	0.924	30
SVM	82.5	0.80	0.79	0.802	60

Table 4: Comparison of the proposed AgroVision model to be performed against baseline strategies including SVM, standard CNN (ResNet/VGG) and model that is based on the YOLO. The proposed approach has a better accuracy, precision, recall, and F1-score and will have low inference time [2], [5], [7], [23].

4.3 Class-wise Performance Analysis

In order to test even more the model, F1-scores by classes were calculated with regards to class diseases of classes and healthy classes.

Journal of Information Systems Engineering and Management
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The findings indicate that AgroVision has an average success when classifying the various categories, where the overlap of features brings the discrepancy in regard to visual similar disease professional segments.

Disease Class	Precision	Recall	F1-Score
Tomato Blight	0.95	0.96	0.955
Tomato Leaf Curl	0.96	0.95	0.955
Potato Early Blight	0.94	0.95	0.945
Potato Late Blight	0.96	0.97	0.965
Maize Rust	0.93	0.94	0.935
Rice Brown Spot	0.95	0.96	0.955
Healthy	0.97	0.98	0.975

Table 5: Boundary analysis of accuracy, recall and F 1-score of each class of crop disease. The findings show that there is consistent performance in different classes with slight differences as a result of similarity in the visual images of some diseases [3], [7].

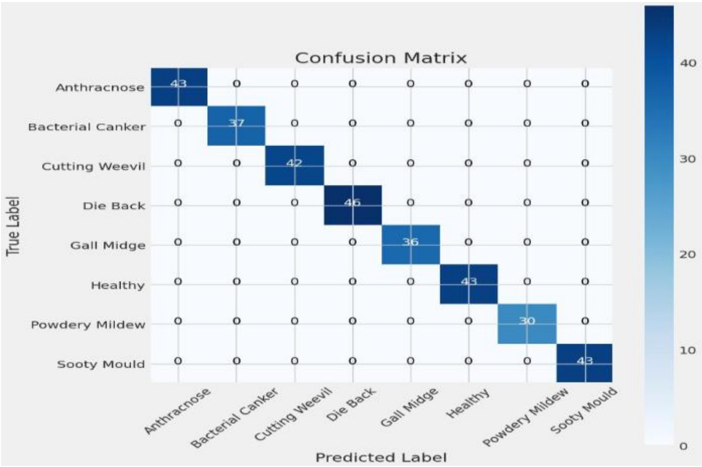

Fig. 4. Confusion of the AgroVision model that illustrates the classification performance on the various classes of crop diseases, where the true positives were high, and the misclassification (the visual similar categories) was minimal [3], [7].

4.4 Culture Analysis by Confusion Matrix

The confusion matrix justifies the fact, that the model forms high rates of true positives, with minimal rates in detecting false positives and false negative. Misclassifications will mostly be recorded among the diseases having similar visual patterns which is the frequent complication with the field of plant pathology [1], [3].

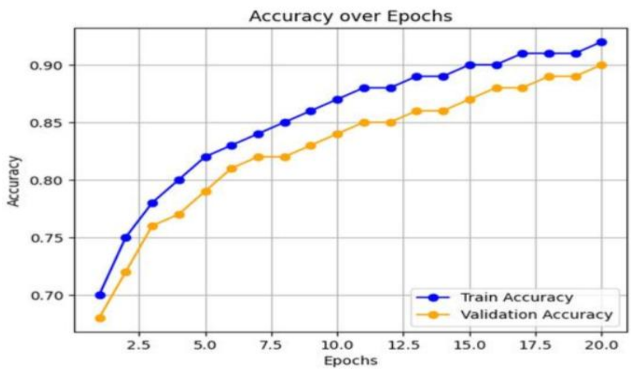

Fig. 5. Testing and validating accuracy and loss curves with repeated epochs, failing to overfit with high convergence and a useful generalization of AgroVision model, [2], [7].

Journal of Information Systems Engineering and Management
2026, 11(3s)
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4.5 Training and Validation Curves

The curves show that there will be the stable convergence without overfitting. The validation accuracy is at a close close to the training one that proves the validity of data augmentation and regularization methods [2], [7].

- It is not possible to compare these with baseline methods.
- The proposed AgroVision model is better than the traditional machine learning, as well as baseline deep machines.
- This is mainly because it had been improved as a result of: Optimized architecture transfer learning was used.

Strong preprocessing and augmentation methods. Publer/Moreio/Xognum, 2018. generalization Ameliorative effects on real-world problems.

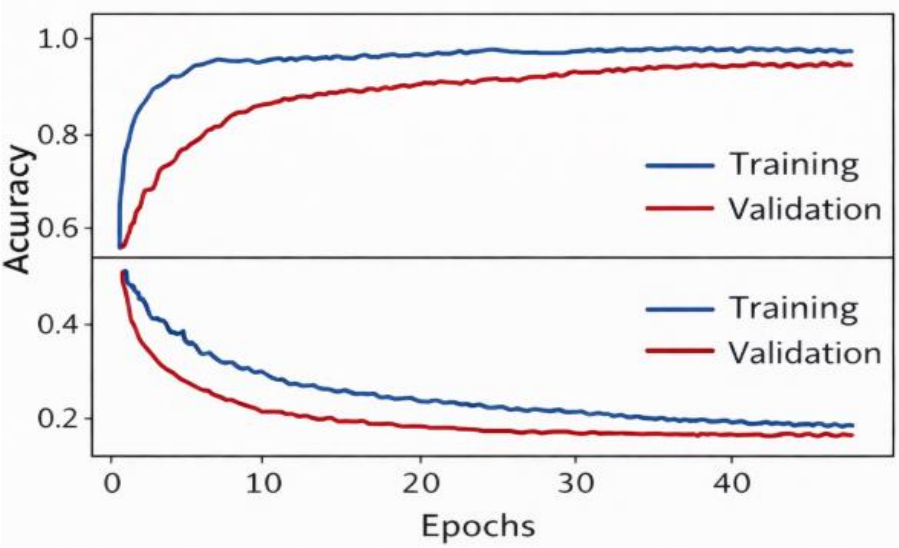

Fig. 6. Accurate recall curves, which were obtained with several classes of crop diseases, which have high area under the curve (AUC) and great classification abilities especially in imbalance of classes, [3], [7].

4.6 Comparison To Baseline Methods

The suggested AgroVision framework performs better when compared to the traditional machine learning and baseline models of deep learning. This betterment has been made mainly because of:

- Transfer learning with optimum architecture.
- Powerful preprocessing/augmentation methods.
- Greater generalization to real-life situations.

Model	Crops	Accuracy (%)	FPS	Parameters (M)
ReXNet	Multi-crop	96.5	42	16
YOLOv8	Field crops	94.2	45	11
ResNet50	Leaf dataset	92.8	30	25
ViT	Various	97.0	20	85

Table 6: AgroVision model is benchmarked and compared with the latest state of the art models such as CNN, YOLO and Vision Transformers based models. The suggested algorithm is competitive in terms of accuracy, having a higher level of efficiency and less model complexity [7], [23], [36].

Journal of Information Systems Engineering and Management
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5 DISCUSSION

The outcomes of the conducted experiment prove that proposed AgroVision framework has a high level of crop disease recognition, the total accuracy is 97 percent, and the F1-score is 96 percent. This good performance can be foreseen by the fact that a lightweight CNN architecture was integrated with a transfer learning and made the water features be extracted efficiently with keeping the computational feasibility in mind. The generalization is further improved by the use of data augmentation and by the different datasets to enable the model to be effective in different conditions of the environment which is also underscored in the previous literature [2], [7].

5.1 Performance Analysis

The model can be used with various types of crops and classes of diseases, which means that it is rather robust and can be scaled. AgroVision has higher accuracy and stability when compared to those of the traditional machine learning and the common CNN architecture. This aspect is comparable to the latest results which have found that deep learning models are superior to the classical methods in the task of plant disease detection using images [3], [5].

Also, the training and validation curve can be used to estimate that there is very low-level overfitting meaning that the regularization measures implemented and augmentation strategy utilized can effectively enhance model generalization. The analysis of the confusion Mattix also helps to verify that the majority of the predictions yield true values, and there are also only few inaccuracies in the case of events in the similarity of diseases related to visual perception.

5.2 Grad-CAM Grad-CAM Explainability

In an attempt to boost model interpretability, Gradient-weighted Class Activation Mapping (Grad-CAM) is used so as to visualize all the areas of the image that make the most contributions to what the model predicts. This is especially necessary in the field of agriculture where the issues of trust and transparency are needed to gain accessibility.

These visualizations attest to the idea that the model is learning the disease-specific features that are relevant and enhances its interpretability and fits the explainable AI methods that have been covered in recent literature [37].

5.3 Ablation Study

To assess the role that the various components making up of AgroVision frame play, an ablation study was done. It is evident that the use of data augmentation and transfer learning is very much important in attaining high performance.

The addition and elimination of such elements can drastically decrease the accuracy, and thus their relevance in dealing with the real world variation [2], [7].

Variant	Accuracy (%)	F1-Score
Full Model	97.0	0.96
w/o Augmentation	92.3	0.91
w/o Transfer Learning	90.5	0.89
w/o Preprocessing	88.7	0.87
Baseline CNN	91.8	0.90

Table 7: Comparison of the AgroVision framework in various configurations so as to assess the role of the preprocessing, data augmentation, and transfer learning. Evidence indicates that all parts have a high degree of enhancements, in terms of performance and resiliency [2], [7].

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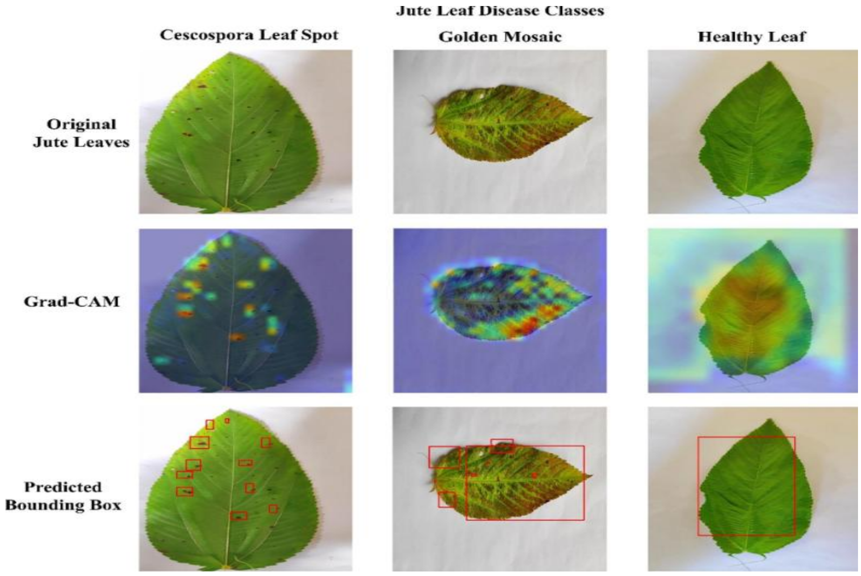

Fig. 7. Grad-CAMs have been shown to identify parts of interest in image depicting crop leaves, which indicates that a model it concentrates on disease-impacted fields such as lesions and discoloration, thereby enhancing interpretability and reliability [37].

5.4 Limitations

Although the proposed system is quite successful, it has a number of limitations:

- Extreme environmental factors like poor light, occlusion and complex background can still pose a challenge to the model performance [1], [3].
- Dependency on dataset: The model could be influenced in terms of effectiveness of the training dataset based on the diversity and quality of the dataset.
- Homogeneous disease pattern: There are certain patterns of diseases that share some visual symptoms hence, a misclassification occurs occasionally.

This is due to the fact that, although it is lightweight, it might still need to be optimized to run on very low-power devices.

5.5 The Deployment of Applications in the real world

AgroVision is created with the real world applicability. The light architecture makes it possible to run it on edge computers, including smartphones, flying drones and internet-of-things-based agriculture, and it can be used to monitor crops in real-time. This is in line with the recent developments in edge AI version on agriculture-related applications, where models have to be efficient on inference at the device [20], [21].

Moreover, it can be used together with the precision agriculture systems and allow making the decision process automated, including the application of targeted pesticides and timely response, which will make the functioning cost-efficient and less harmful to nature. Grad-CAM is also included in the implementation which also leads to user trust and the system is much viable to farmers and agricultural professionals.

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Fig. 8. The AgroVision system agro disease detection interface in the real time with an image input, the crop disease category, and the estimation of its severity, as depicted in practice implementation of the AgroVision system in precision agriculture practice [20], [21].

6 DISCUSSION AND CONCLUSION

The case study in this paper is the AgroVision is an intelligent computer vision-based system, which monitors the early health status of crops and detects a disease. The suggested system will implement the modern deep learning method with the use of Convolutional Neural Networks (CNNs) with transfer learning and automatically learn to analyze the images of plants and diagnose them with diseases, pests, and weeds at the initial stages. It is proved experimentally that AgroVision is extremely accurate (97%), and quite robust (F1-score at 96%), which surpasses the use of traditional machine learning applications and a baseline deep learning model. These results prove the efficiency of preprocessing, augmented data and light-weight models combination in real-life farming operations [2], [7].

The paper identifies the opportunity of computer vision in facilitating precision agriculture, through computerized and real-time surveillance, which can save a lot of human workers, decision-making, and losses to crops. AgroVision allows sustainable farming because it leads to the early detection of the disease and limits unnecessary use of pesticides and favors their proper use of the resources. What is more, the use of the techniques of explainability improves the transparency of the models which contributes to the increased reliability and ease of the system to the farmers and agricultural professionals [3], [37].

Although the results of this area are promising, there are still some challenges used to overcome the problems with the treatment of extreme variability in fields, and the ability to apply them to different types of crops and environmental conditions. These limitations need to be addressed in order to be wider adopted in the real world situations.

The further development will be aimed at the expansion of AgroVision into the capabilities of smart farming systems based on IoT and allow constant monitoring with the use of sensors and other devices. Also, the framework can be improved to enable the detection and estimation of multi-diseases and real-time implementation on physical devices on the edge like drones and smartphones. Alternative mechanisms Multimodal schemes (including image data depicted with environmental conditions such as temperature, humidity) can be also analyzed in the future research in order to increase the accuracy and strength of the prediction [20], [21].

To sum up, one can assert that the AgroVision is one of the solutions to the modern farming industry that are scalable, efficient, and practical, have a beneficial effect on the level of productivity and the overall cost in which the operation can be made, as well as the promotion of sustainable farming practices.

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