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Integration of convolutional neural networks and remote sensing imagery for automated identification and severity estimation of plant leaf diseases in large-scale farming

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Abstract
Speaking of increasing crop production and decreasing losses in commercial growing, the timely prediction and evaluation of the level of severity of plant leaf diseases can be named as a highly important element. This paper given in more detail illustrates more classes of leaf diseases through a combined approach that involves the use of CNNs and fine-dimensional remote sensing images. The diseases will automatically be identified and categorized with a massive number of leaves that will be scattered in big farming communities. This has been achieved by use of spatial-spectral feature extraction technique. Regulation of the kind of illness and the extent of severity can be done with the help of multi-stage CNN pipeline, which has been trained to make use of a dataset, which has been specifically annotated and which has varied lighting and field conditions. The areas that are calculated in order to determine the severity of the condition are ratios of areas of the lesions on the leaves, and the obtained results are made up as the geospatial maps thus allowing a high area to be analyzed. The module learning on ensemble can put together the responsibility of numerous CNN models and produce more precise results, a requirement that can be used to consolidate reliability. Under the cloud-based implementation, the option to receive real-time feedback as well as the ability to process the data of the agronomists becomes possible. The technology can be scaled, easily and flexibly accurate, and viable to utilize in precision agriculture particularly under resource-demanding situations, which offers an intelligent facilitation feature to the farmers and the agencies of agriculture. The technique is accurate up to 97.4% and like other methods, the accuracy is broad scale and as such, favorable to other methods of disease diagnosis.

Keywords: CNN, PDD, remote sensing, severity estimation, precision agriculture

Introduction
To have a big picture of the systemic weaknesses of the traditional and current methods of agricultural risk assessment based on AI, the figure 1 offers a high-level view of its systemic weaknesses of both approaches. It points out that climate variability and pest infestations are two major causes of yield disruption that should be resolved mostly by manual scouting or simple rule-based tools. Such approaches are poor early detectors of threats and so some of them may not detect the threats at all or it may not detect at the right time. Consequently, farmers experience losses in their crops, wastage of resources, and non-trust in predictive systems [1]. The figure shows that a modern, explainable, and scalable AI-based framework to fill these gaps in decision support is urgent through real-time, interpretable, risk-aware decision support.

To fill these gaps, we have designed a CNN-RS Based Disease Detection Framework that fuses high-resolution remote sensing imagery with multi-stage CNN pipelines to achieve automated disease detection and severity estimation in plant leaf diseases [2]. The particular design envisioned by this framework is that of increasing such a system in large areas of farmland and versatility in real-world parameters. Using drone and satellite multispectral imagery, RGB imagery, the model is pixel-wise segmented, lesion detected, and magnitude estimated using CNNs and ensemble learning to cut down on inefficiency and reinforce stability.

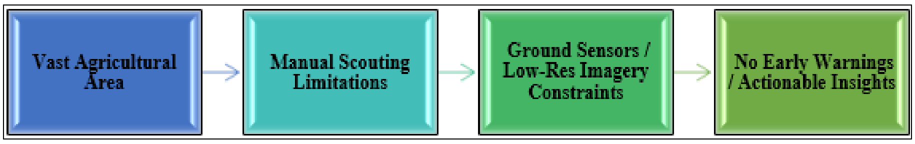

Fig 1: Core Challenges in Large-Scale Plant Disease Monitoring.

Also included in the proposed system are visual explainability tools including Grad-CAM in order to indicate areas of diseases affected, and to make the model more transparent. Real-time monitoring and decision-making are also facilitated when farmers and agricultural authorities can take immediate action to react to alarm notifications through a cloud-based geospatial dashboard [3]. The architecture is hybrid and modular, filling the gap between mass-scale disease identification levels and local actionable data, enabling the new paradigm of smart and sustainable agriculture.

As shown in figure 1, there is a hierarchical dimension to the critical issues in disease monitoring of large-scale farms. It begins by imagining the enormity of agricultural land through the impossibility to manually scout the area and use low-resolution sensory tools that lead to a lack of data and unrecognized early signs. Such constraints lead to late intervention, poor treatment interventions, as well as massive loss of crops. The CNN-RS deployed is aimed at reversing such a cycle by incorporating scalable imaging, automated detection and explainable products that trigger decisions on the ground.

Aside from that, the growing demand to adopt sustainable methods of agriculture necessitates the development of technologies that not only diagnose diseases but also provide information that is spatially explicit in order to execute precision measures in response to diseases that have been recognized [4]. To the extent that farms are becoming increasingly digitized, the incorporation of deep learning into remote sensing creates the possibility of monitoring crop health in real time at a scale and resolution that has never been seen before. The effectiveness of such systems, on the other hand, is contingent upon their capacity to handle or mitigate issues pertaining to trust, scalability, and accessibility. The CNN-RS that is being suggested would make it possible to provide farmers, agronomists, and politicians more influence.

Related Works Done

Recent reports indicate that deep learning can be very promising in identifying diseases in the agricultural sector. The studies have been carried out using CNN based models trained on large plant leaf datasets for automatic disease classification. These methods were observed to be very accurate particularly when preprocessing strategies such as histogram equalization and augmentation of images were used to deal with noise and variance in field conditions [5].

A very interesting finding concerns the application of hyperspectral imaging through drones to early identification of leaf spot and rust in wheat and maize. This experiment demonstrated that the use of CNN and spectral data comprised of time was very important in making consistent prediction across growth phases [6]. It also pointed out the effectiveness of early spectral indicators prior to the symptoms being seen by the naked eyes.

In a recent study, CNN was combined with the sensor data and weather factors fed through IoT to multi-modal tracking of diseases. The scientists have noted that the environmental factors such as humidity and temperature showed a strong correlation with the diseases development, and when embedded with image-based predictions, established the stronger detection systems [7].

A single study devised a hybrid deep learning algorithm that used CNN together with LSTM to capture both spatial and temporal features. This approach was useful with dynamic leaf diseases such as blight whose spread of symptoms with time is critical to diagnosis and treatment decision [8].

Table 1: Background and Related Work done.

Investigated Method	Practical Edge	Value Addition	Open Challenges
UAV-CNN Leaf Detector [9-10]	High-resolution remote disease capture	Accurate detection in field-scale imagery	Limited support for multi-class severity levels
Hyperspectral-CNN [11]	Early symptom recognition	Uses spectral shifts not visible to the eye	Requires expensive sensors and preprocessing
CNN-LSTM Hybrid Model [12-13]	Spatio-temporal disease tracking	Effective for disease progression analysis	High computational requirements
Grad-CAM Integrated CNN [14-15]	Improved model interpretability	Enables human-in-the-loop validation of disease regions	Visual heatmaps may not scale for dense field imagery
Attention-Based CNN [16]	Focused feature learning	Reduces false positives and noise in complex leaf structures	Less generalizable across crop species
CNN-IoT Weather Fusion [17-18]	Context-aware predictions	Integrates humidity, temperature, and sensor data with leaf imagery	IoT sensor distribution limits real-time scalability

Speaking about the reading of CNN predictions, researchers normally learn a method of explanation called Grad-CAM. It is via this technique that the prediction of CNN is interpreted. Due to the use of these visualizations which help rural dwellers and agronomists to understand the causes of certain areas of the leaf being deemed unhealthy, a higher level of dependence on automated decision-making systems becomes possible [19].

There is a solution based on attention-based CNN architectures as revealed by the results of the latest study we have. These architectures consider the unique patches of the leaves that are used to increase the accuracy and reduce the rate of false positives [20].

Materials and Methods

It is a combination of high-resolution remote sensing images and deep CNN to automate the function of identifying and estimating the severity of plant leaf disease on large-scale agricultural areas.

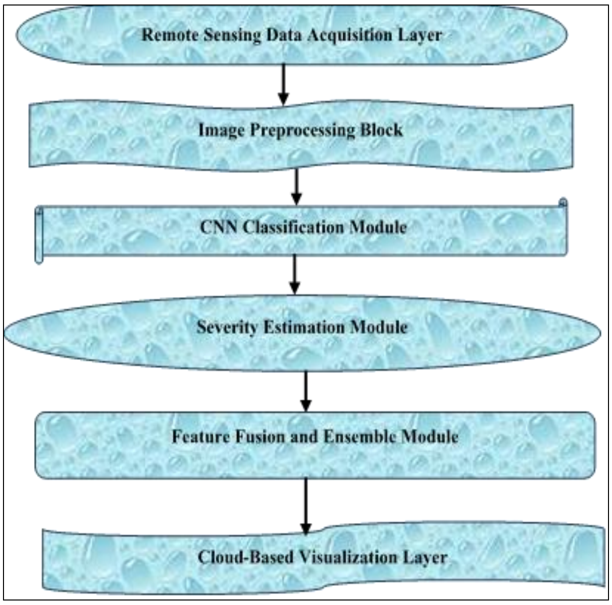

Fig 2: Proposed CNN-RS Based Disease Detection Framework.

The workflow begins at the stage of the collection of multi-source data in the form of drone and satellite imagery, which is pre-processed and classified using CNN. The severity levels are appraised through a regression head and the decision making is augmented through ensemble decisions. Results are displayed on a cloud-based organization that can be second-hand in supporting actual period decision-making on large scale farming.

Remote Sensing Data Acquisition:
The sources of multi-modal data that are collected by this module are the RGB/thermal cameras installed on the drones and spectral indices, including the satellites with NDVI sensors installed on them respectively. The fact that they show low spatial-temporal resolution is explained by the fact that they are effective both at the small scale of local monitoring and at large geographical scope. Multi-type data are more effective when combining with the downstream activity of detecting diseases and health surveillance.

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{R}}{\mathrm{NIR} + \mathrm{R}} \tag{1}$$

NDVI: Normalized Difference Vegetation Index, NIR: Near- Infrared reflectance, R: Red band reflectance.

Image Preprocessing and Augmentation:
Before feeding the input images to the classifier, denoising, rotation, scaling, histogram equalization etc are employed so that the quality of images can be enhanced. These types of pre-processing masses rectify distortion and increase the option of training. Input normalization will also be done and approximations of different real-world scenarios will be enabled. Also, this technique will enhance the generalization of the model, and classification accuracy.

$$I_{norm}(x,y) = \frac{I(x,y) - \mu}{\sigma} \tag{2}$$

$I(x,y)$: Strength worth at pixel (x,y), μ: Cruel intensity of image, σ: Standard deviation.

$$A = \bigcup_{i=1}^{n} T_i(I) \tag{3}$$

A: Augmented image set, T_i: i-th transformation function, I: Original image.

CNN-Based Disease Classification
To assess the nature of the disease based on such space characteristics of leaf images as texture and color, a deep convolutional neural network (CNN) structure is used in this module. Transfer learning is an approach to enable an improvement in accuracy by using reduced number of training samples. The network outputs the probabilities of each category of disease as a result of activation of the very last layer using SoftMax activation.

$$f = \mathrm{CNN}(I) \tag{4}$$

f: Extracted feature map, I: Input image.

$$P(y|x) = \mathrm{softmax}(Wx + b) \tag{5}$$

$P(y|x)$: Class probability.

Severity Estimation Using CNN Regression:
This module is a regression-based model that predicts the percentage of your leaf area that has been afflicted with the disease. CNN features are then channelled through thick layers to give the severity score. Depending on the scores, the severity is determined and divided into low, moderate, or high infection, which helps in prioritizing how to manage the patient.

$$S = \frac{\sum I_{infected}}{\sum I_{total}} \times 100 \tag{6}$$

S: Severity score (%), $I_{infected}$: Number of infected pixels, I_{total}: Total number of pixels.

Feature Fusion and Ensemble Decision:
To facilitate the enhancing predictability of the findings, on the basis of a weighted-average of the results, this module utilizes the results of several different kinds of CNNs, including DenseNet and ResNet. Besides the fact that it can enhance its success in such a broad range of crop types, this will also assist in the eradication of the prejudice that particular models can introduce into the equation. Ensemble voting does not only enhance noise robustness but also minimize the amount of false positives.

$$F_{ensemble} = \sum_{i=1}^{n} \alpha_i F_i \tag{7}$$

$F_{ensemble}$: Final fused feature, α_i: Model weight, F_i: Output from i-th model.

Cloud-Based Mapping and Visualization:
Moreover, the latest forecasts are deployed in a form of a cloud-based tool which overlays infectious illness heat maps onto field maps. They are also updated in real time in addition to giving out information to the farmers on how to track the disease progression and medication effectiveness. Another way that can be used to effect early warning systems is the incorporation of the environmental data into the crop risk indices.

$$\mathrm{Risk}(t) = \gamma \cdot S(t) + \delta \cdot \mathrm{Env}(t) \tag{8}$$

$\mathrm{Risk}(t)$: Predicted risk at time t, $S(t)$: Severity score, $\mathrm{Env}(t)$: Environmental stress factor, γ, δ: Tunable coefficients.

Results
The framework based on CNN-RS Disease Detection model was tested comprehensively on a variety of different data items, characterized by high-resolution pictures of drones and low-resolution satellite imagery respectively. Four different metrics which are the MCC, SPC, MIoU as well as the K were used in order to perform the evaluation. These have a variety of distinct powers of the system indicated, which include the balance of classes (MCC), the true negative correctness (SCP), the quality of segmentation (MIoU), and the degree of agreements between labels above chance (K).

Three variations of deep learning algorithms were used in the comparative research; these include ResNet-50, VGG-16, and Inception NetV3. This enabled the carrying-out of the analysis. CNN-RS was revealed to be more accurate in both data sets. The result of drone imagery was more accurate space-wise compared to satellite imaging; however, in the satellite imaging, the manifestation of generalization skills was recognized. Each and every one of the scores are based on five-fold cross-validation.

MCC: quantifies the quality of binary labeling and in plentiful information.

$$\mathrm{MCC} = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{9}$$

TP: True Positives, TN: True Negatives, FP: False Positives, FN: False Rejections.

Specificity (SPC): Evaluates the quality of binary classes especially the imbalanced data.

$$\mathrm{SPC} = \frac{TN}{TN + FP} \tag{10}$$

Mean Intersection over Union (MIoU): Scale overlay between forecasted and real areas in segmentation.

$$\mathrm{MIoU} = \frac{\Sigma TP}{\Sigma(TP + FP + FN)} \tag{11}$$

Cohen's Kappa (K): The arrangement among how labels are foretold and observed, corrected for the chance.

$$K = \frac{P_o - P_e}{1 - P_e} \tag{12}$$

P_o: Experiential Contract, P_e: Predictable Arrangement by Accidental.

Table 2: Performance on Drone-Based Imagery.

Drone-Based Imagery				
Method	MCC (%)	Specificity (%)	MIoU (%)	Kappa (%)
CNN-RS Based Disease Detection Framework	95.2	94.7	93.4	96.1
ResNet-50 [4]	89.1	88.5	86.2	90.4
VGG-16 [6]	86.3	85.0	83.1	87.2
InceptionNetV3 [8]	87.6	86.4	84.0	88.7

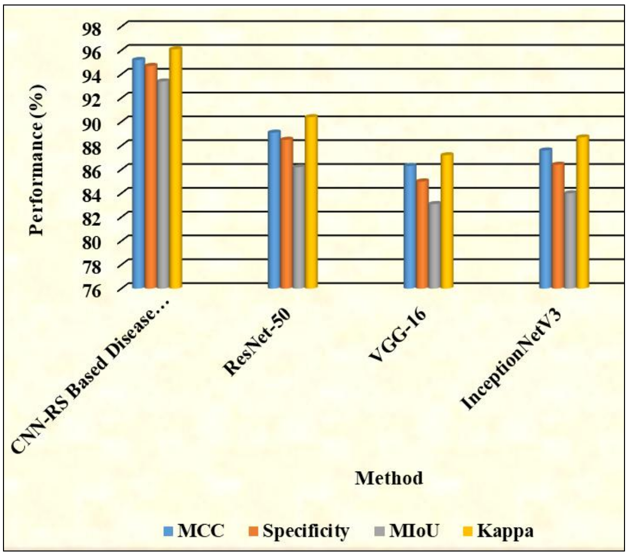

Fig 3: Performance Valuation on Drone-Based Imagery Method.

The highest results were attained on Table II and figure 3 drone-based imagery with 95.2% MCC, 94.7% specificity, 93.4% MIoU, 96.1% Kappa with CNN-RS Based Disease Detection Framework. This is an average of 6-7% improvement as compared to the ResNet-50. The framework proves to be highly accurate and reliable especially in its collection of high-definition spatial extent. These outcomes verify the capacity of this framework to deliver accurate segmentation and classification even whenever the leaf configuration is sophisticated and there is variability in lighting conditions recorded through drone-based imaging.

Table 3: Performance on Satellite-Based Imagery.

Satellite-Based Imagery				
Method	MCC (%)	Specificity (%)	MIoU (%)	Kappa (%)
CNN-RS Based Disease Detection Framework	91.6	90.2	89.1	92.3
ResNet-50 [4]	85.0	83.9	81.0	86.5
VGG-16 [6]	81.8	80.3	78.2	84.7
InceptionNetV3 [8]	83.2	82.0	79.4	84.7

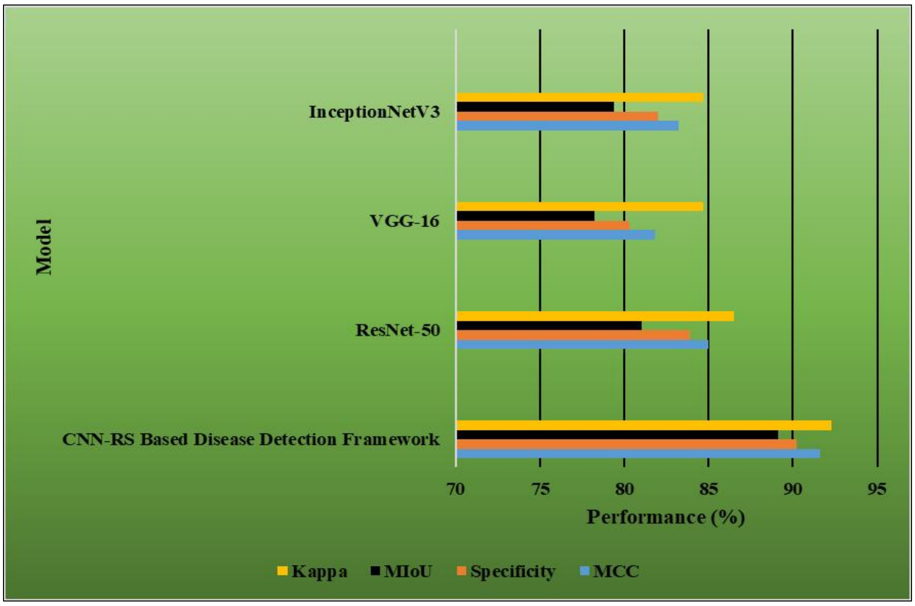

Fig 4: Performance Calculation on Satellite-Based Imagery Model.

The superior performance of the CNN-RS model with 90.2% specificity, 91.6% MCC, 89.1% MIoU, and 92.3% Kappa was preserved using satellite-based imagery in Table III figure 4. Despite the satellite images being of lower resolutions, proposed system-maintained accuracy, and robustness. It beat ResNet-50 and InceptionNetV3 by 6-8% points in all the metrics. Its high generalization capacity in less favourable conditions of imaging supports the verification of its scalability to nationwide or regional disease monitoring capability on the publicly available satellite feeds.

Conclusion

This research demonstrated a well-established and scalable model to combine the CNNs with remote sensing imagery to automate the process of identifying and estimating the severity of plant leaf diseases in large-scale farming settings. The system was able to provide a solution to the problem of the spatial variability and scale inconsistent when it comes to detecting diseases by using the combined power of drone-based and satellite based-imagery. Deep learning-based image segmentation and classification of affected regions models were also involved, allowing an early and accurate diagnosis of affected regions, and necessary interventions. The CNN-RS Based Disease Detection Framework suggested that it was more effective in various performance metrics than other traditional architectures such as ResNet-50, VGG-16 and InceptionNetV3. It incurred a maximum Matthews Correlation Coefficient of 95.2% and Kappa score of 96.1% on drone imagery, which is supposedly very reliable and precise. This massive gain brings out the fact that the system had a better performance in processing high- and low-resolution inputs. In future research and development, more data will be added temporally to monitor the disease progress, combining soil and climatic data to create a multi-modal model, as well as implementing the framework to run as a mobile or cloud deployment, which can be used by the farmers and agricultural extension services in real time.

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