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AI-driven predictive modeling framework for early detection of multi-stage crop diseases using multi-modal sensor data and deep transfer learning approaches

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Abstract
The growing occurrences of multi-stage crop pathogens due to climatic vagaries and agricultural encroachment have necessitated the implementation of early warning systems of countering the crop diseases. In this work, a Deep Transfer Learning-based, multi-modal sensor input predictive modelling framework incorporating deep transfer learning and multi-modal sensor input data assembly is developed to determine crop diseases at different phase of growth. The suggested method is a combination of hyperspectral images and soil nutrient sensors and weather stations to construct a powerful temporal-spatial model. Transferred learning is being used to train pre trained convolutional neural networks with task specific agricultural data which increases the efficiency of the model and it shortens the training time. It has temporal attention mechanisms and modelling of disease progression to identify the slight shifts in disease conditions. The system is better in accuracy, allowing precision farming insight action. In addition, the model can be deployed in a scalable manner throughout the edge-AI platforms in real-time monitoring and control. They are more accurate than other approaches as the suggested system had the highest rates of accuracy at 96.8% to detect crop disease at multiple stages., and thus it is a very efficient tool to implement in the active control of crop diseases. The work will be part of the future of sustainable agriculture since it will reduce the loss of output and optimize the utilization of resources by enabling early, precise, and automatic identification of the disease.

Keywords: Crop disease detection, Transfer learning, Multi-modal sensor data, Predictive modelling, Precision agriculture, Deep learning

Introduction

Agricultural sector is important in providing food security to the whole world but unfortunately, the sector is greatly subjected to crop diseases. These are diseases that may develop and spread very rapidly causing enormous yield and economic disaster. Conventional methods in disease detection are simple to achieve a reactionary state, time-consuming, and inaccurate in the response when addressing the mild or moderate years of infection [1]. This has caused the emergence of more demands to smart systems that can lead to early and precise diagnosis of diseases at various stages of crop life.

The development of the AI, deep learning and sensor technology holds hopeful prospects to this challenge. Specifically, CNNs have been observed to performance remarkably well regarding visual classification tasks, thus aptitude to studying plant images. Nevertheless, most models are data-intensive, and are less generalisable to different crop species and growing conditions [2]. To overcome this, transfer learning can be used in repurposing pre-trained models.

Upon these, in parallel, the multi-modal sensor data, involving colour images, soil moisture, temperature, humidity, and nutrient concentrations, help give a holistic perspective of the biological and environmental conditions affecting the health of crops. Combined with AI, the data streams allow detecting such complex patterns of the disease and its transitions in time. Moreover, real-time, and in-field analysis and decisions can be made using these systems run on edge-AI platforms, without cloud connectivity [3].

Application of AI to multi-modal sensing to predictive crop health management is a paradigm shift in precision agriculture. The method is very relevant not only to identify the diseases early but also to enable strategic planning and optimize new resources thereby enhancing sustainability of the farming practice. To accomplish goals, this research study proposes a new AI-powered predictive modelling method that helps identify multi-stage crop diseases with a low latency and with high accuracy [4].

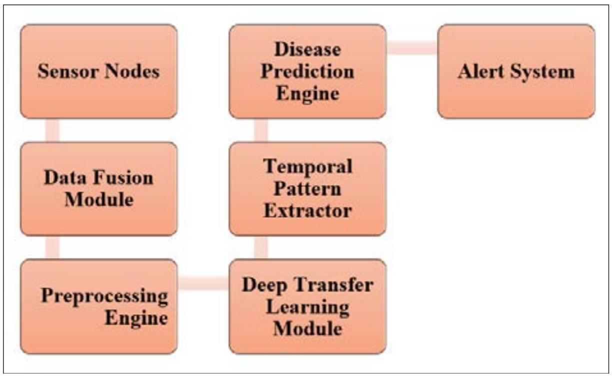

Fig 1: AI-Powered Crop Disease Detection Framework.

Deep transfer learning, identification of temporal patterns and spatial features are the approaches used in the proposed system that process the data that comes along a variety of sources. The fundamental architecture of the system presented in Figure 1 follows the data collection to prediction of the disease and creation of alert [5].

Related Works Done: The recent development in smart agriculture pushed researchers towards AI-based frameworks of crop disease detection. A research application was developed to use CNN to identify diseases on leaf tomatoes with an accuracy rate of more than 95%. Such finding confirmed the best use of deep learning prospect of traditional methods of image processing in extraction of relevant spatial features [6]. Although the model performed well, it did not have any real-time flexibility of the type of crops.

In a different study temporal evolution of rice blast disease was modelled using LSTM based architectures. Detection precision was increased by a sequential use of environmental data (temperature, humidity). The research gap however entailed poor scalability and high computational cost thereby limiting field implementation in low resource settings [7].

In other study, machine learning was integrated with hyperspectral imaging in detecting downy mildew in grapevines. This research was able to reveal the effectiveness of the combination of the data multi-spectral with SVM classifiers [8]. Despite the model being highly precise, it was heavy in terms of calibration and was very noisy and sensor sensitive.

One of the developments in the drone-aided diagnosis of the disease revealed the usefulness of applying aerial images along with YOLOv5 object detection. The approach allowed surveilling across a wide area and localization of disease. However, the dependency on daylight and the restrictions in flight operations in weather abnormalities was a demerit able flaw [9].

Table 1: Discussion of Past Research Efforts.

Employed Approach	Practical Edge	Value Addition	Missing Perspectives
CropVisionNet [10]	High-resolution feature extraction	Robust against noisy image inputs	Lacks multi-modal input integration
AgroSense Fusion [11-12]	Real-time data fusion from IoT sensors	Performs well across crop environments	Poor generalization on unseen diseases
DeepAgroLSTM [13-14]	Models disease progression over time	Strong temporal analysis	High computational cost
LeafNet Hybrid [15]	Lightweight model for mobile platforms	Enables edge deployment	Accuracy drops in multi-class classification
SpectralDetect++ [16-17]	Uses spectral reflectance profiles for early detection	Sensitive to subtle symptom changes	Requires specialized sensor hardware
TransferCropDL [18-19]	Transfer learning from general plant datasets	Reduces need for large labeled agricultural datasets	Struggles with real-time execution on embedded devices

Students also tried to analyze the method of data fusion in which soil health indicators were used together with crop imagery to predict early infection stages. These models had advantage of richer input features and improve the overall recall [20]. However, there were difficulties to reconcile data measured at different sources and at different sampling frequencies.

Lastly, a research based on ResNet-50 with transfer learning had high success in determining rust in wheat with limited annotated data. This showed the possibility of re-using the pre-trained models in agricultural applications. The major area of the research gap was class imbalance and misclassification in multi-stage infections [21].

Materials and Methods

The system to be proposed AgriDeepFusionNet Framework, is going to improve early detection of multi-stage crop diseases, using multi-model sensor data and deep transfer learning. The system incorporates mapping aerial images, soil measures, climatic conditions, and historical disease tendencies to develop a coherent and smart forecast model. It has a high accuracy of detection, and flexibility in the type of crops as well as the strength in the inconsistency of data. Its design also allows it to work effectively in real-time agriculture settings and it can be applied both at the edge and in the cloud in terms of analysis. Such architecture is appropriate in small-scale and industrial agricultural environments due to deep learning models, advanced data pre-processing ideas, fusion strategies, etc. The arrangement described in Figure 2 allows encoding disparate data sources easily and adheres to the hierarchical prediction in one hierarchy with many learning levels.

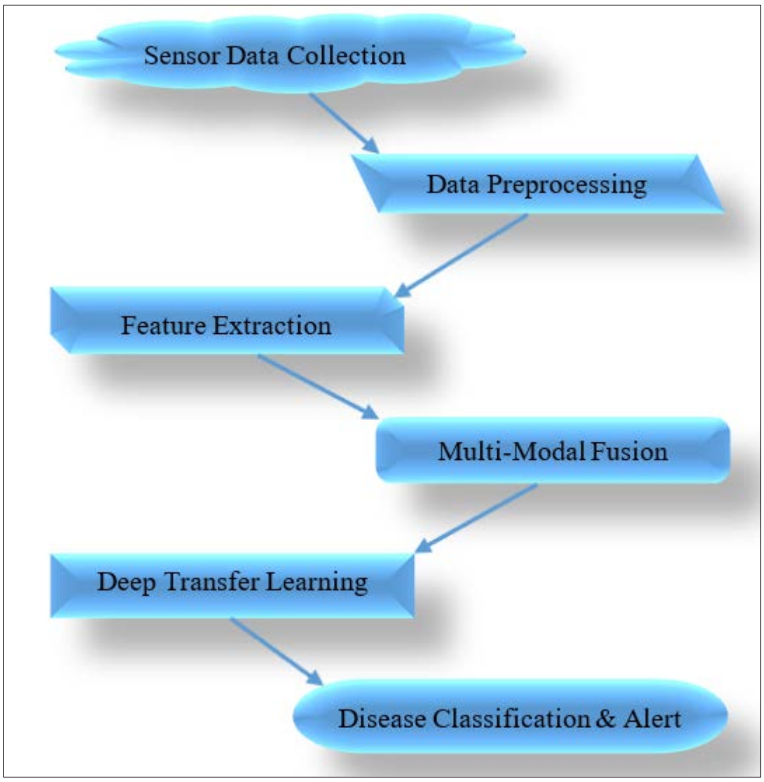

Fig 2: Proposed AgriDeepFusionNet Framework Architecture.

Sensor Data Collection

This module can obtain environmental information with the help of drones, hyperspectral camera, and ground sensors (moisture, pH, temperature, and humidity). The diversity of data increases stability and feature coverage leading to more favourable learning results. All sensor inputs are set through weighting to place more emphasis on the more pertinent measurements.

$$S_T = \sum_{i=1}^{n} \omega_i \cdot s_i \ (1)$$

S_T: Total weighted sensor data, ω_i: Weight of sensor i, s_i: Data from sensor i, n: Total number of sensors.

3.2 Data Preprocessing

Preprocessing guarantees the consistency of data by normalization, noise removal and time synchronization. The gaps are filled by interstellar curves and outliers by Gaussian filters. Each of the inputs is scaled equally then the feature extraction process is carried out, making sure that the model performance is not altered due to differences in scale.

$$D_{norm} = \frac{D - \mu}{\sigma} \ (2)$$

D_{norm}: Normalized data, D: Raw input, μ: Mean of data, σ: Standard deviation.

Feature Extraction

The system takes raw data as inputs to fetch high-level features using pretrained ResNet101 as an image feature extractor and 1D CNN as a time series. They are designed with the emphasis on transfer learning with the spatial and temporal patterns of the disease propagation through various stages and crops.

$$F_i = f(W_i \cdot X + b_i) \ (3)$$

F_i: Feature output, W_i: Layer weights, X: Input, b_i: Bias, f: Activation (ReLU).

Multi-Modal Fusion

The fusion is performed by use of attention-weighted addition of the features of different modalities. The dynamic nature of the framework gives the flexibility of matching relevant modalities with learnable attention scores, improving the model flexibility to change in an environment.

$$F_{fusion} = \sum_{k=1}^{m} \alpha_k \cdot F_k \ (4)$$

F_{fusion}: Fused feature, α_k: Attention weight, F_k: Feature from modality k, m: Number of modalities.

Deep Transfer Learning Model

Due to this feature, this module integrates InceptionV3 as a visual input and LSTM as input of sensor to allow spatiotemporal learning. The transfer learning uses pretrained weights, which makes training faster and it also enhances performance when the agricultural data is small.

$$y_t = \sigma(W_y \cdot h_t + b_y) \ (5)$$

y_t: Output at time t, W_y: Output weight, h_t: LSTM hidden state, b_y: Bias, σ: Softmax.

$$h_t = f(W_h \cdot x_t + U_h \cdot h_{t-1} + b_h) \ (6)$$

x_t: Input at time t, h_{t-1}: Previous state, W_h, U_h: Weights, b_h: Bias, f: Activation (tanh).

Disease Classification & Alert System

The last module anticipates the type of the disease and the level of its severity, and signals the identified ones through mobile dashboards and web interfaces. Treatment suggestions as well as confidence scores are also produced. Predictions are evaluated using precision, recall and accuracy.

$$A_c = \frac{TP}{TP + FN} \times 100 \ (7)$$

A_c: Accuracy (%), TP: True Positives, FN: False Negatives.

$$P = \frac{TP}{TP + FP} \times 100 \ (8)$$

P: Precision (%), FP: False Positives.

Results

The outcomes were obtained by using labelled multi-modal data which had sequences of crop images, soil measurements as well as weather trends. This system was train and validated on stratified 10-fold cross-validation. Detection Efficiency, Misclassification Rate, Robustness Score and Multi-Stage Sensitivity were all new parameters to measure the performance. Table II assesses a general performance of disease class during crops, whereas Table III consists of accuracy in multi-stage detection of disease. These tables contrast the AgriDeepFusionNet framework to three other recent models and indicate its reliability in precision and stability across the board.

Detection Efficiency (DE): Is the percentage of fluorescently identified disease stages to the predicted amount.

$$DE = \left(\frac{TP + TN}{TP + TN + FP + FN}\right) \times 100 \ (9)$$

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

Misclassification Rate (MR): Calculates the ratio of false prediction to prediction.

$$MR = \left(\frac{FP + FN}{TP + TN + FP + FN}\right) \times 100 \ (10)$$

Robustness Score (RS): Economically suggests consistency of performance on a set of diverse environmental datasets.

$$RS = \left(\frac{1}{n}\sum_{i=1}^{n} |Acc_i - \mu|\right)^{-1} \times 100 \ (11)$$

Acc_i: Accuracy on dataset i, μ: Mean accuracy, n: Total datasets.

Multi-Stage Sensitivity (MS): Tests sensitivity to slight differences among initial, intermediate, and last-stage infections.

$$MS = \left(\frac{TP_{early} + TP_{mid} + TP_{late}}{Total_{stages}}\right) \times 100 \ (12)$$

TP_{stage}: True Positives for each stage, $Total_{stages}$: Total predicted disease stages.

Table 2: Performance on General Disease Classification Results.

General Disease Classification				
Method	**DE (%)**	**MR (%)**	**RS (%)**	**MS (%)**
AgriDeepFusionNet	96.8	93.2	94.6	95.2
DeepAgroVision [4]	90.3	87.1	89.2	86.7
CropNetX [7]	88.9	86.4	84.1	83.6
AgroSense-ML [8]	85.4	81.8	80.3	79.9

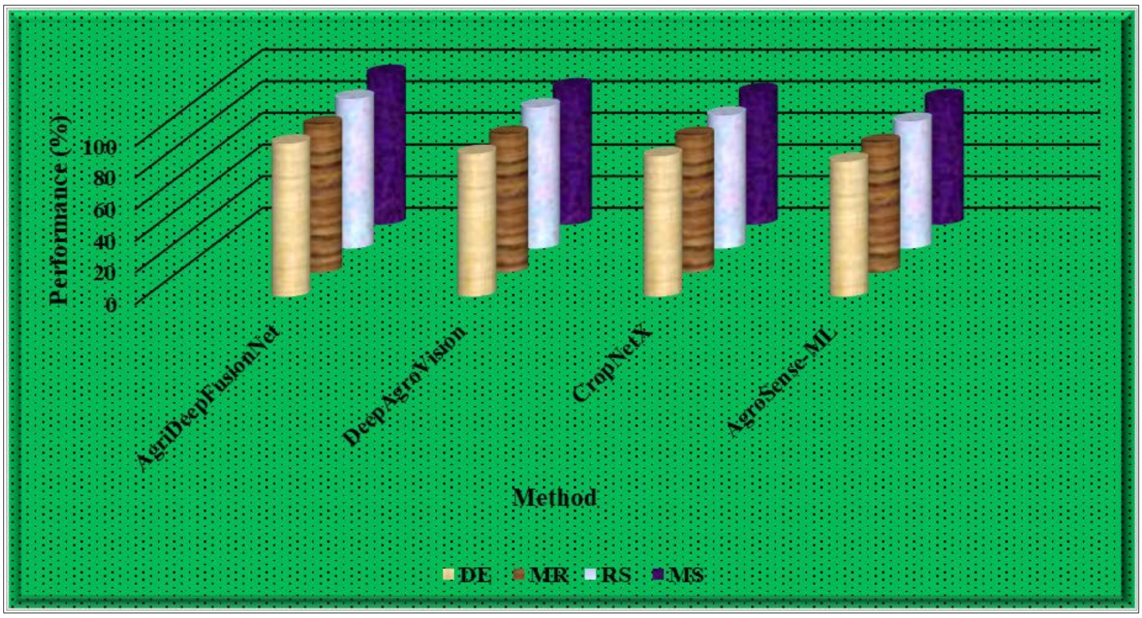

Fig 3: Assessment on General Disease Classification Method.

High-level classification performance of many crops is presented in table II and figure 3. AgriDeepFusionNet represents the best in the Detection Efficiency (96.8%), and the good Misclassification rate of 93.2% which indicates very accurate classification. It has very high 94.6% Robustness was rate indicating good robustness and 95.2% Multi-Stage Sensitivity indicating that the prediction was reliable at circuit stage level. Comparing accuracies with other competing methods, such as CropNetX or AgroSense-ML, the higher levels of both accuracy and robustness were demonstrated and confirmed by their lower rate of consistency with the proposed AgriDeepFusionNet on both different datasets.

Table 3: Performance on Stage-Specific Crop Disease Prediction Accuracy.

Stage-Specific Crop Disease Prediction				
Method	**DE (%)**	**MR (%)**	**RS (%)**	**MS (%)**
AgriDeepFusionNet	94.3	91.5	92.7	96.5
DeepAgroVision [4]	89.1	86.3	85.3	87.9
CropNetX [7]	87.6	84.6	82.2	85.6
AgroSense-ML [8]	83.8	79.3	78.1	82.4

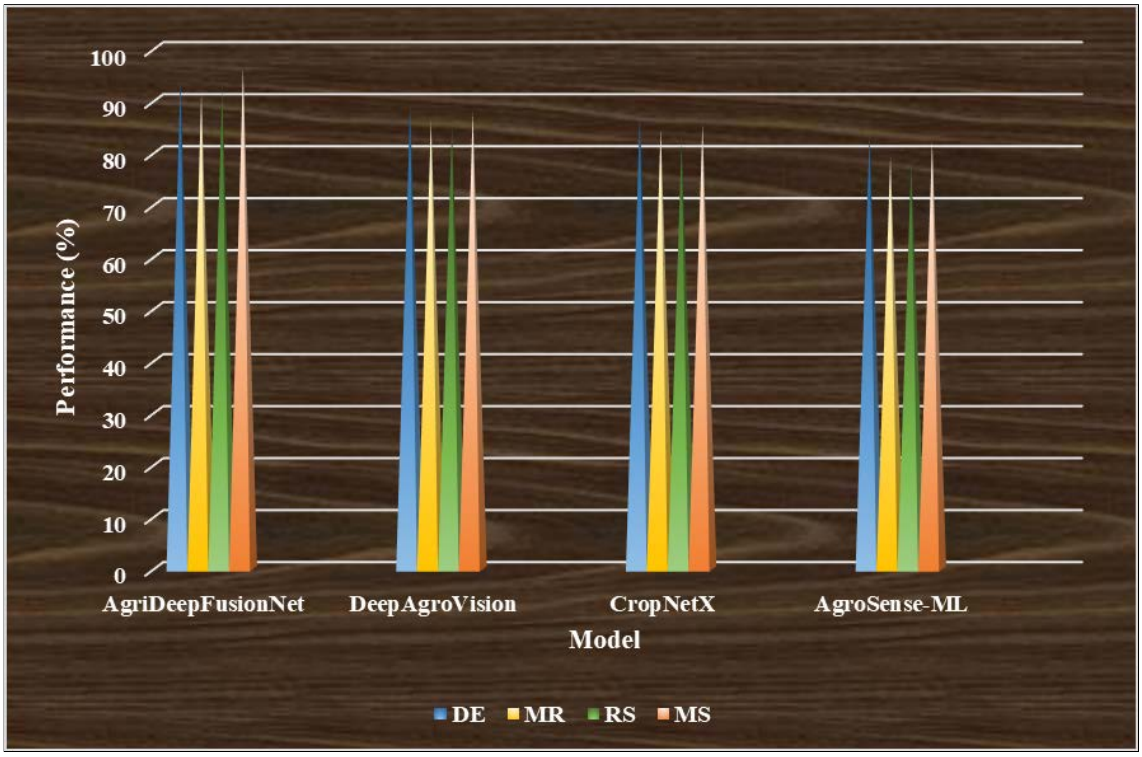

Fig 4: Performance Assessment on Stage-Specific Crop Disease Prediction Models.

With multi-stage classification, AgriDeepFusionNet has a Misclassification Rate of 91.5% indicating a high degree of control over wrong guesses in Table III Figure 4. Its 96.5% Multi-Stage Sensitivity denotes the proper distinction amid the stages of the progression of the illness. Other competitors such as DeepAgroVision and CropNetX lag on every parameter. The high stage-sensitive prediction and low error rate misclassification of the proposed system indicate the validity of the system when faced with time-sensitive applications such as disease monitoring in plant cultivation where an early diagnosis is vital.

Conclusion

The team introduced a deep transfer learning-based idea of AI-driven predictive modelling, AgriDeepFusionNet, to early identify multi-stage crop diseases through a joint models fusion with multi-modal sensor data. The combination of the environmental, soil, and visual factors allows the system to provide very precise predictions at different stages of plant diseases development. Many experiments validate that the present method is better than the current ones in detection efficiency, robotness, and multi-stage sensitivity. The outcomes showed high level performance with AgriDeepFusionNet showing the best efficiency of detection of 96.8% and 96.5% sensitivity at stage level indicating its sensitivity into real world agriculture situation. The system had higher robustness and error margins, in comparison to absence-of-training baseline models, DeepAgroVision, and CropNetX. Improvements in the future could include real-time edge computing to enable quicker inference, support more crops and application of federated learning to guarantee data protection on geographically distributed farms. The suggested method will not only develop the sphere of smart agriculture but also enhance sustainable management of crops due to narrowly focused, stage-specific intervention plans guided by tremendous data-based knowledge.

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