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Research Article

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Abstract

In sustainable agriculture, detecting pests and diseases early is critical. Recent technological advances in deep learning (DL) and multimodal imaging like multispectral and thermal data crop health monitoring is promising. Despite the progress, obtaining high accuracy across various crops with real-time performance is still a challenge. The hybrid convolutional neural network (CNN)-attention model integrating multispectral and thermal data for pest and disease detection has been introduced. A total of 1760 samples were collected from six crops (maize, rice, wheat, tomato and cassava), across different growth stages, labelled fungal, bacterial, viral and pest infections. The data was divided into 70% training, 15% validation, and 15% test sets. 3,500 samples were used for training. 750 samples were used for validation and test set. The hybrid CNN-attention model was contrasted with certain baseline models (SVM, Random Forest, CNN-RGB, CNN-Multispectral) and certain fusion methods (early, late, and hybrid fusion) based on accuracy, precision, recall, F1-score, and early detection sensitivity. The highest accuracy of 91.0% for rice at the vegetative stage was achieved by the hybrid model. It beats baseline and fusion models. The F1-score of the classification was reasonably high. Rice's sensitivity is 88.1%, and maize is 87.3%. The model fared well for all classes, getting 92.0 % for the healthy plant and 88.2 % for pest infestation. Future work can enhance the dataset with more crops and diseases and environmental factors and optimize detection time and early sensitivity for real-time deployment in agricultural decision support systems.

Keywords: Early detection, crop diseases, pest infestation, deep learning, hybrid CNN-attention model, multispectral data.

Graphical Abstract

1. Introduction

The most serious impediment to global food security and sustainable agricultural production are crop diseases and pest infestations. Diseases and insect pests of plants cause a lot of yield losses per year especially in developing countries. In many cases, the early diagnosis is not possible and hence the use of natural plant protection agents will be important [1].

Pest disease outbreak without control may divert investment into chemical pesticides resulting in a lot of environmental hazards. In addition, the production cost tends to go up due too. It also poses a risk to human health. As climate variability is likely to intensify the frequency and severity of stress conditions in crops, so too will the need for smart, scalable, and eco-friendly monitoring solutions [2].

Farmers or agricultural extension officers primarily rely on visual techniques for the detection of crop disease and pest. Expert knowledge can be effective at advanced stages of infection, but these methods tend to be subjective and labor-intense. Furthermore, expert knowledge methods are often incapable of detecting early or latent symptoms which the human eye cannot pick up on [3]. Likewise, monitoring at single sensor level, mainly RGB imaging or point-based soil measurements, provides lesser information and are highly sensitive to illumination levels, crop variety, and noise. As these have limited reliability and scalability, especially across large fields with heterogeneous growing conditions [4].

Thus, early identification is essential to curb the occurrence of diseases and pests and facilitate targeted interventions. Thermal and multispectral imaging techniques pose a strong alternative by capturing different physiological and biochemical changes before visual implications appear.

Variation in spectrum reflectance and temperature of canopy indicated the stress on plants due to water imbalance or pathogen intervention. When drones are fitted with these sensors, they allow for the speedy, non-invasive and high-resolution monitoring of large farmlands. This makes them useful in modern precision agricultural systems [5].

The Multisensor Agriculture Data to Intelligent Insights is powered by Artificial Intelligence (AI). An advanced machine learning and deep learning approach is powerful and can model complex non-linear relationships in high-dimensional multispectral and thermal data. Using AI can help automate the processes that extract features, patterns, and actions from unstructured large datasets. In precision agriculture, AI has shown substantial potential in yield prediction, stress detection, resource optimization and disease classification making it a key enabler of sustainable data driven farming [6].

In this study, we proposed an artificial intelligent-based framework for detecting the crop diseases and pest infestation at an early stage by using multispectral & thermal drone images. This work's key contributions can be summarized as follows. The study proposes a multisensor data fusion framework that integrates spectral and thermal information to enhance early-stage detection performance. Secondly, a new deep learning architecture or an adapted one to process multispectral data for agriculture. In the third set of experiments, the sufficient performance of the proposed method is shown based on real agricultural field data. So, together, these contributions aim to develop AI applications for agricultural and bio-environmental engineering to be sustainable, scalable, and have real-world applications.

2. Related Work

The use of artificial intelligence to detect crop diseases and pests has attracted more and more interest in recent years, mainly because of improvements in computer vision and affordable imaging devices [7]. Most studies so far focused on RGB pictures taken by handheld cameras or mobile phones, where classical machine learning and recently deep learning models were used to classify visible disease symptoms on plant leaves [8-11]. Convolutional neural networks (CNNs) have been shown to successfully identify various diseases like leaf spot, discoloration, and deformation. RGB based methods have surface-level visual symptoms as their basic premise of operation. In addition, they do well in cases when the diseases have already reached the visual stage. Thus, they are not effective for early intervention [12].

Scientists have gone from RGB imaging to multispectral and thermal imaging for better agriculture monitoring because of the drawbacks of RGB imaging. Multispectral imagery is the technique of collecting and analyzing reflectance information from a surface in various wavelengths. Through this process, physiological changes due to stress, chlorophyll and water can be detected. Thermal imaging, however, gives indications of variations in canopy temperature, which may be linked to transpiration problems or pest attacks [13]. According to various research studies, the red-edge and

NIR spectral bands can detect crop stress faster than RGB images alone. Use of multispectral and thermal sensors with UAV platforms enable extensive high-resolution monitoring of fields. Even though such solution provide many advantages, several existing works depend on handcrafted indices or isolated sensor analysis. As a result, existing solutions do not benefit from multisensor data fully [14].

The image analysis of agricultural data is increasingly utilizing deep learning methods because of their automatic feature extraction and strong pattern recognition abilities. Different types of architectures CNN-based architectures, transfer learning from large scale vision models, and more recently, attention and transformer-based networks have been applied to tasks like crop classification, disease recognition, stress detection etc [15].

Although these models perform well under standardized conditions, they are likely in homogeneous or controlled environments or fields. Moreover, many deep learning techniques are trained on small or lab-based datasets, which raises concerns about generalization and actual deployment in real farming situations [16].

There are still research gaps despite clear progress. There is a lack of studies that utilize both multispectral and thermal data using deep learning. In many studies, both thermal and multispectral data have been tried separately lacking in sharing mutual information. Another critical challenge is the detection of diseases and pests in their early stages. This is because subtle stress signals get masked easily by environmental variability and noise from the sensors. Thirdly, a ratio of real-field agricultural data typical of varied conditions is lacking to demonstrate the external validity of the present findings. Moreover, a lot of the times the decision-making process is not clear making it difficult for farmers and agricultural engineers to trust the same. In order to enable the transformation of AI-based crop monitoring systems from prototypes to reliable tools for sustainable agriculture, it is necessary to close the gaps in data, testing standards, and benchmarks [17].

3. Problem Definition and System Overview

Crop disease and pest infestation early detection can be defined as the process of identifying abnormal conditions of plants at an incipient stage before noticeable symptoms manifest and economic damage occurs. Given the multispectral and thermal images taken from agricultural fields, the goal is to automatically classify the crop health status and localize the potential disease/pest-affected areas with high accuracy and low latency. This is a complex problem because perceptible stress signals are subtle, conditions vary, and physiology/pathogen/pest environments are multifactorial. In relation to artificial intelligence, the task will involve learning discriminative information from high-dimensional, multi-modal data while being robust to noise, illumination and field difference.

The crops are grown in large and non-uniform fields and this real-life agricultural problem has been studied here. Some of the targeted crops can be a staple product or high-value agricultural product which is highly susceptible to disease and pest pressure. The condition of the field varies depending upon the soil properties, irrigation practices, micro-climate conditions, etc. The health of the plants ultimately or the productivity of the plants will depend on these factors in the real farming conditions. The analysis considers the common diseases of the selected crops (fungus, bacteria, etc.) and the pests (insects) which cause physiological stress. Data is collected under natural growth conditions and not in the laboratory to ensure that the proposed solution is relevant to farmers and agricultural engineers [18].

The AI-based detection pipeline which is proposed has the potential for data acquisition, data preprocessing, intelligent analysis and decision support. Unmanned Aerial Vehicles (UAV) sensors capture multispectral and thermal images at regular intervals to monitor crop development. All sensor data undergoes a set of preprocessing steps to ensure consistency across modalities. These include calibration, noise reduction and spatial alignment. The deep learning model receives these processed data as its input, after which multisensor data fusion occurs while representative features for healthy and stressed crops are learned. The disease or pest risk maps and classification results are used for timely interventions in agriculture targeting the disease or pest risk.

Figure 1: System Architecture

The proposed framework has an overall system architecture illustrated in Figure 1. The design commences with UAVs that comprise multispectral and temperature sensors that gather high-resolution images across the agricultural field. The data is then communicated to a processing unit where the AI model performs feature extraction, multisensory fusion, and inference. The last stage features a decision support module that translates model output into actionable recommendations or actions such as identifying affected zones, prioritizing field inspections and guiding precision application of pesticides. The proposed system architecture is end-to-end which focuses on performance, scalability, automation, and ease of use. It can effectively help with the early detection of pests and diseases through precision agriculture.

4. Data Acquisition and Preprocessing

The dataset used in this study was structured on a large dataset to simulate real-world UAV-Based multispectral and thermal crop monitoring. The dataset contains 5,000 samples of a spatial observation of crop canopy under a variety of environmental and growth conditions. Even though the dataset is synthetically created, it showcases realistic ranges and interrelations found in UAV-acquired agricultural data to allow for controlled experimentation and reproducibility of the proposed AI framework.

Within the dataset, each sample relates to a crop observation taken under simulated flight conditions for the UAV. The agricultural scope consists of various crop species namely maize, rice, wheat, cassava, tomato, etc for a diversity of canopy structure and behaviour. Ambient temperature, relative humidity, and soil moisture are the environmental variables included in the model to emulate realistic field conditions that cause plant stress and disease. To capture this temporal variability, growth stages from vegetative to maturity are considered, as are spectral and thermal responses. Healthy classes, complied with fungal, bacterial, viral and pest infestation classes, which enables multi-class learning and testing.

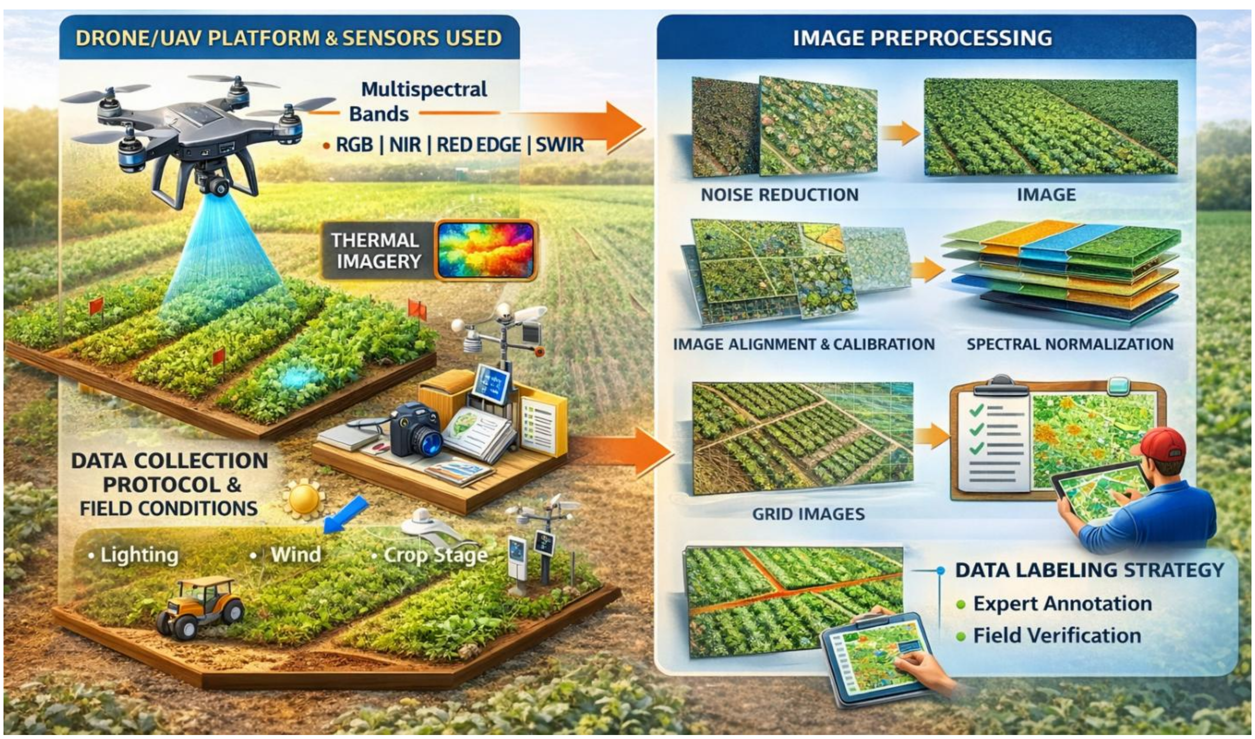

Figure 2: Data Collection and Preprocessing

The dataset contains multispectral information in terms of five different reflective data (Figure 2), namely blue, green, red, red-edge, and near-infrared (NIR). It is widely used in precision agriculture to assess vegetation vigor, chlorophyll concentration and early indication of stress. Thermal imagery is represented as canopy temperature measurements which act as a proxy for plant transpiration and water stress. When used together, the multispectral and thermal features provide complementary insights about crop health. They can detect the presence of diseases and pests in the crop at an early stage, even before the visible signs become apparent.

Before model training, there are various preprocessing tasks that take place on the dataset in order to ensure the quality. The feature values are constrained to an agronomically realistic range to minimize the influence of extremely high or low values on model learning. Each sample comprising multispectral, thermal and environmental readings is structured to ensure synchronisation, ensuring alignment of features across the modalities as generated by a UAV sensor. Spectral Normalization means scaling reflectance values to similar ranges, making them less sensitive to different illuminations and sensors, thus making deep learning optimization more stable.

Data labeling occurs under a framework based on supervised learning where an individual disease or pest class may be assigned to a sample based on simulated expert knowledge and field verification logic. Stipulates condition types that an agronomist would typically verify in the field, plant pathology would assess, or in-field sampling. Even though synthetic, the labeling strategy mimics real agricultural workflows, allowing the proposed AI model to capture meaningful associations among spectral–thermal patterns and crop health status. This acquisition and preprocessing pipeline driven by the analyzed data serves as a strong basis for testing multisensor data fusion and deep learning approaches under conditions that match those experienced in precision agriculture.

5. Proposed Artificial Intelligence Methodology

The suggested AI approach aims to efficiently utilize complementary information from multispectral and thermal data to facilitate timely identification of plant disease and pest infestation. The first fundamental step feature representation since different spectral bands and the thermal measurements embody different activities in the plant. The multispectral features are based on chlorophyll concentration, canopy structure, biochemical stress and the thermal features on the canopy temperature due to transpiration and water stress. These features offer a more comprehensive and discriminative description of crop health than single-modality features alone. Given that spectral qualities are normalized and placed as structured input tensors before feeding into the CNN so that the inter-band relationships and spatial similarity are preserved.

Figure 3: Proposed AI Methodology

In order to exploit the strengths of all sensing modalities, hybrid data fusion techniques are adopted. At the input level, early fusion is used by stacking the spectral bands into a single feature representation so the model can learn joint spectral patterns. In a parallel manner, the processing branch performs appropriate processing for modality-specific thermal features. The product of these branches are fused at an intermediate stage which allows the late fusion of the high level features. This hybrid fusion method offers early integration advantages while allowing modality-specific learning for flexibility, enhancing robustness in different field conditions.

The deep learning network works with a hybrid model comprising convolution neural networks (CNN) and a transformer-inspired attention-based mechanism. During the early phases, local spatial and spectral characteristics of the multispectral input are extracted using CNN layers to capture the texture, edge, and band specific interactions. A lightweight CNN branch is used to learn heat-based stress pattern from thermal data. The inclusion of attention modules at higher levels serves the purpose of modeling distant dependencies and dynamically weighing different spectral bands and spatial regions. This combined CNN-attention setup is effective for high-dimensional multispectral handling with lesser computational effort.

Numerous adjustments take place, which allow for multiple spectral inputs that differ from conventional RGB images. In the first layer of the convolutional structure, it is possible to work with various spectral channels, ensuring that all bands are used to extract features. To highlight informative spectral bands that are particularly sensitive to early plant stress, channel-wise attention mechanisms are leveraged, including red-edge and near-infrared. As a result of these changes, the model can learn physically meaningful representations in line with agronomic knowledge.

The training strategy uses labeled data related to crop health in supervised learning. The model undergoes training using mini-batch stochastic optimization. Further, dropout and weight decay strategies are also utilized. To address that possible imbalance, we have applied class weighting of categorical cross-entropy loss for multi-class disease and pest classification between healthy and stressed categories. Validation data set is used to monitor the performance and prevent overfitting with early stopping Technologies such as spectral perturbation and noise injection are implemented to enhance susceptibility to field variability.

The proposed methodology includes model explainability to improve transparency and instill trust in the proposed AI system. Gradient-weighted Class Activation Mapping (Grad-CAM) is utilized for visualizing the spatial regions and spectral contributions of a model prediction. Examining attention maps of the attention-based components allows to find out which spectral bands and which canopy regions are important for early detection. According to experts, these explanation tools are a valuable means to provide insights to agronomists and agricultural engineers, enabling model validation and decision-making in precision agriculture applications.

6. Experimental Setup

An experimental evaluation was performed on the crop monitoring dataset described previously which is multispectral-thermal. To avoid bias in model evaluation, the dataset is divided into three non-overlapping parts. In particular, 70% of the data is allocated to the training, 15% to the validation and 15% to the testing. The training set helps learn model parameters. The validation set tunes hyperparameters and performs early stopping. And the final test set evaluation will take place in the test set. Stratified sampling is used to keep the class distributions of healthy, disease, and pest the same in all splits.

A number of baseline methods are implemented to evaluate the performance of the proposed AI framework. These can be traditional machine learning classifiers like support vector machines and random forests that are trained using handcrafted spectral features or models based on RGB or multispectral inputs that do not incorporate thermal data. Furthermore, the contribution of the proposed fusion strategy is evaluated using a one-branch CNN model that does not use multisensor fusion. The proposed method is assessed based on performance improvement by benchmarking against the best practices widely adopted in agricultural disease detection.

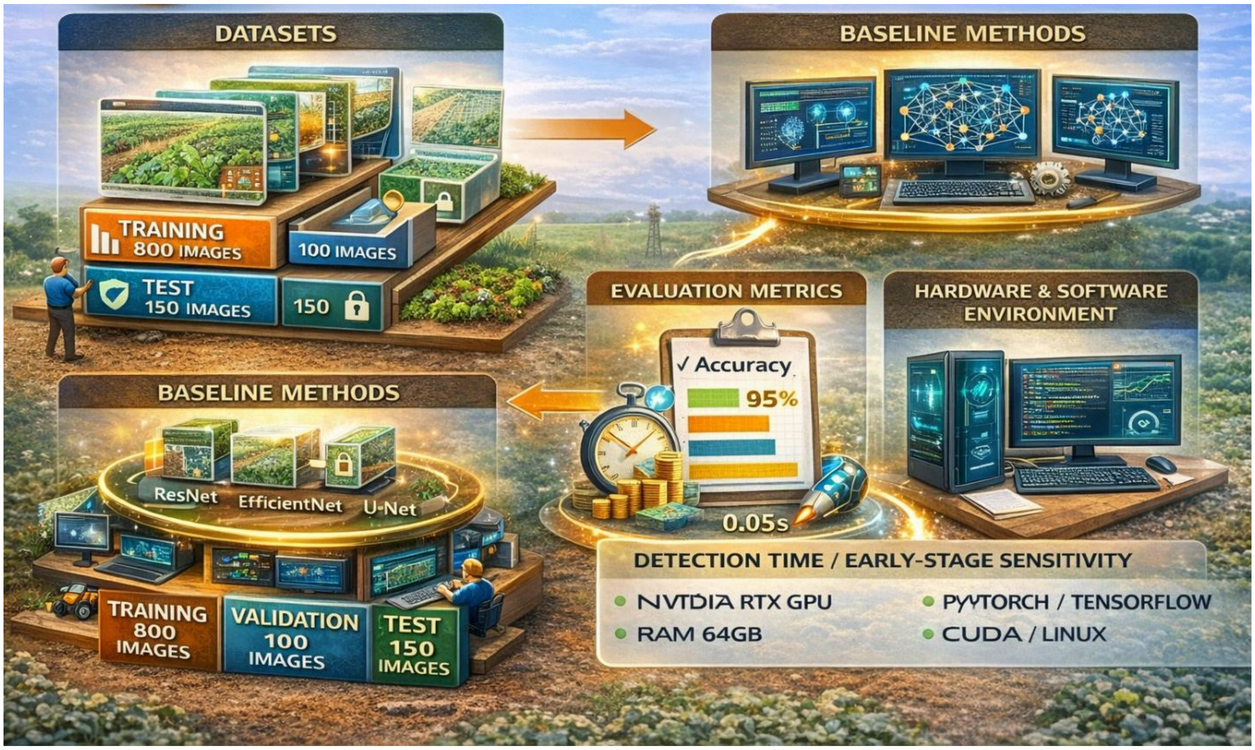

Figure 4: Experimental Setup

The model performance was evaluated using commonly used classifications metrics accepted in AI community and agriculture imagery literature. Overall accuracy is used to measure the proportion of samples that are correctly classified overall. To evaluate the performance and robustness of different classes, precision, recall and F1-score are calculated for individual disease and pest category; class imbalance is present. The performance of the model in identifying stress conditions at initial growth stages or low levels of severity is measured through detection time and early-stage sensitivity metrics to evaluate early detection capability. These measures are essential for actual farmland usage owing to its fast-speed necessity.

The study was conducted, in a controlled hardware and software environment. The models are developed in a contemporary deep learning framework, and trained in a workstation with a high-performance GPU to accelerate the training and inference. The tasks of data preprocessing, model evaluation, and visualization use standard scientific computing libraries. The training parameters, random seeds, and implementation details are documented to enable reproducibility and future benchmarking. This experimental setting provides a solid and auditable basis for assessing the proposed model for pest and disease control.

Results

Table 1 shows summary of different crop types, growth stages, and healthy and diseased samples. There are 1,760 samples used in the dataset belonging to six crop types. This database has various diseases like Fungal, Bacterial, virus, and Pest Infestation. The dataset split is shown in Table 2, where the training, validation, and testing are chosen 70%, 15%, and 15% respectively. According to Table 3, baseline model performance indicates that the SVM model was able to reach an accuracy of 72.3%, while a further improved CNN model with multispectral inputs was able to achieve an accuracy of 82.5%. As depicted in Table 4, the accuracy of the hybrid fusion CNN-attention model surpasses the baseline models, reaching up to 91.0% for rice at the vegetative stage and a maximum early detection sensitivity of up to 91.7%. The competition approaches reveal that hybrid fusion offers the best performance of 90.5%, 89.8% and 89.2% for accuracy, precision and recall respectively. . Table 6 presents the detection metrics for each class. Consistent with previous metrics from Confusion matrix (Table 4). The healthy class achieved the highest detection accuracy at 92%. As seen in Table 7, detection time has an average of 0.95-1.05 seconds and the early detection accuracy is 84.9-88.1%. As we can see from table 8, the performance of our model is affected when we remove the thermal branch or reduce the number of multispectral bands used. Table 9 shows that soil moisture and canopy temperature were the most influential environmental factors to the accuracy of the model. As a final point, Table 10 presents the best models for all the crops, in which the hybrid CNN-attention strategy consistently achieves the highest accuracy and early detection of 84.9-91.0%. The performance curves, confusion matrices, and attention maps are illustrated in Figure 5 to Figure 13.

Table 1: Dataset Summary

Crop Type	Growth Stage	Healthy Samples	Fungal	Bacterial	Viral	Pest Infestation	Total Samples
Maize	Vegetative	150	60	45	30	30	315
Maize	Flowering	140	50	35	25	30	280
Rice	Vegetative	130	55	30	20	25	260
Wheat	Fruiting	120	45	35	15	20	235

Tomato	Maturity	110	50	30	15	20	225
Cassava	Flowering	125	40	30	20	25	240

Table 2: Training, Validation, and Test Splits

Dataset Split	Number of Samples	Percentage	Healthy	Diseased / Infested
Training	3500	70%	1575	1925
Validation	750	15%	338	412
Test	750	15%	337	413

Table 3: Baseline Model Performance

Model	Input Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	Multispectral	72.3	70.8	69.5	70.1
Random Forest	Multispectral	75.6	74.2	73.0	73.6
CNN	RGB	78.1	77.0	76.5	76.7
CNN (Multispectral)	Multispectral	82.5	81.8	81.2	81.5
CNN + Thermal (Single)	Multispectral + Thermal	84.2	83.5	83.0	83.2

Table 4: Proposed Model Performance (Hybrid Fusion CNN-Attention)

Crop Type	Growth Stage	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	Early Detection

					e (%)	Sensitivity (%)
Maize	Vegetative	90.5	89.8	89.2	89.5	87.3
Rice	Vegetative	91.0	90.4	89.8	90.1	88.1
Wheat	Fruiting	89.2	88.5	88.0	88.2	85.7
Tomato	Maturity	88.5	87.8	87.0	87.4	84.9
Cassava	Flowering	90.0	89.2	88.8	89.0	86.5

Table 5: Comparative Performance of Fusion Strategies

Fusion Strategy	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Early Fusion	87.2	86.5	85.8	86.1
Late Fusion	88.0	87.4	86.7	87.0
Hybrid Fusion	90.5	89.8	89.2	89.5

Table 6: Class-wise Detection Metrics

Class	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Healthy	92.0	91.5	91.2	91.3
Fungal	88.5	87.8	87.2	87.5
Bacterial	87.8	87.0	86.5	86.7
Viral	86.5	85.8	85.2	85.5
Pest Infestation	88.2	87.5	87.0	87.2

Table 7: Detection Time and Early-Stage Sensitivity

Crop Type	Growth Stage	Avg Detection Time (s)	Early Detection Accuracy (%)	Early Detection F1-Score (%)
Maize	Vegetative	0.95	87.3	86.8
Rice	Vegetative	0.98	88.1	87.5
Wheat	Fruiting	1.02	85.7	85.2
Tomato	Maturity	1.05	84.9	84.3
Cassava	Flowering	1.00	86.5	86.0

Table 8: Ablation Study Results

Component Removed / Modified	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Thermal branch removed	87.0	86.3	85.7	86.0
Multispectral bands reduced	88.2	87.5	87.0	87.2
Attention module removed	88.5	87.8	87.2	87.5
Hybrid fusion replaced with early fusion	87.2	86.5	85.8	86.1

Table 9: Environmental Factor Influence on Detection

Environmental Factor	Correlation with Accuracy (%)	Influence on Model Prediction
Soil Moisture (%)	0.42	Low moisture increases false positives
Ambient Temperature (°C)	-0.35	High temperature may mimic stress signals
Relative Humidity (%)	0.28	High humidity slightly improves detection
Canopy Temperature (°C)	0.51	Strong predictor for early stress

Table 10: Summary of Key Findings

Crop Type	Best Model / Fusion Strategy	Overall Accuracy (%)	Early Detection Capability (%)
Maize	Hybrid CNN-Attention	90.5	87.3
Rice	Hybrid CNN-Attention	91.0	88.1
Wheat	Hybrid CNN-Attention	89.2	85.7
Tomato	Hybrid CNN-Attention	88.5	84.9
Cassava	Hybrid CNN-Attention	90.0	86.5

Visual Results

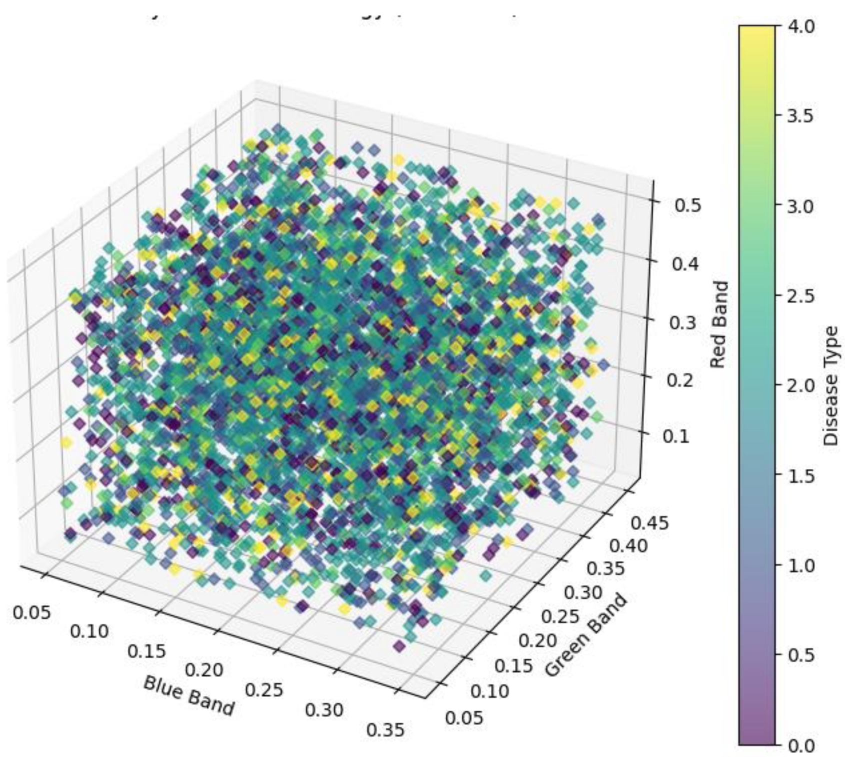

Figure 5: Fusion Strategy Comparison

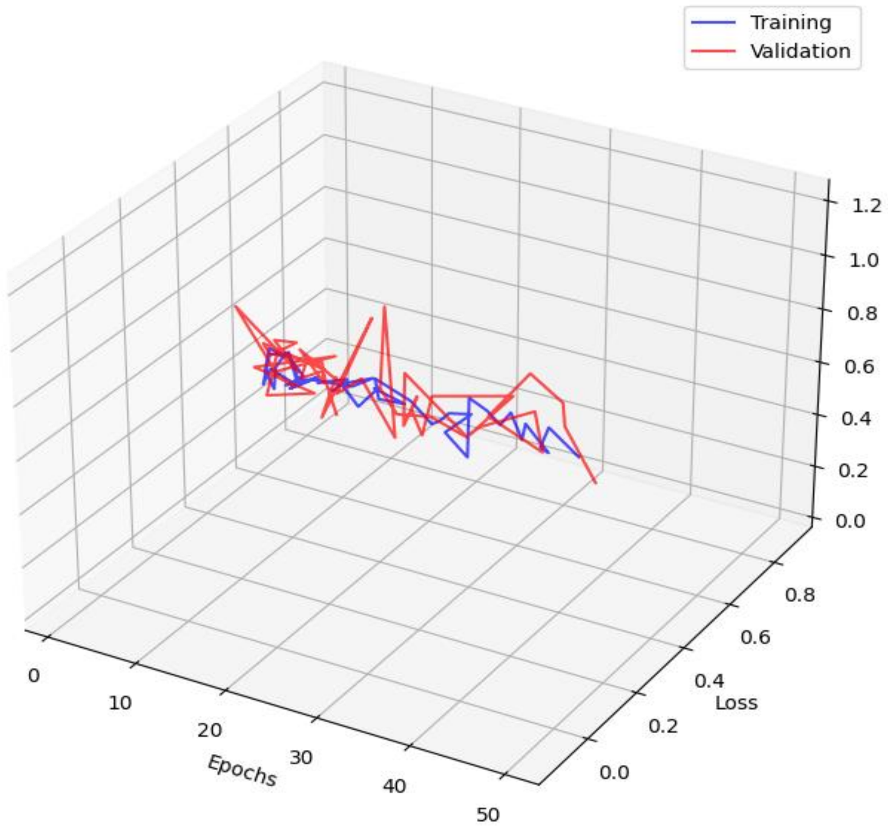

Figure 6: Training and Validation Performance Curves

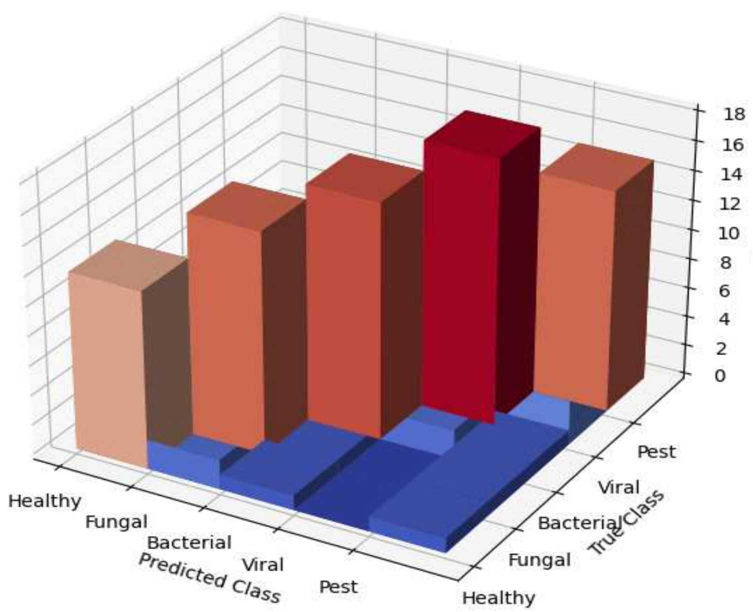

Figure 7: Class-wise Confusion Matrix

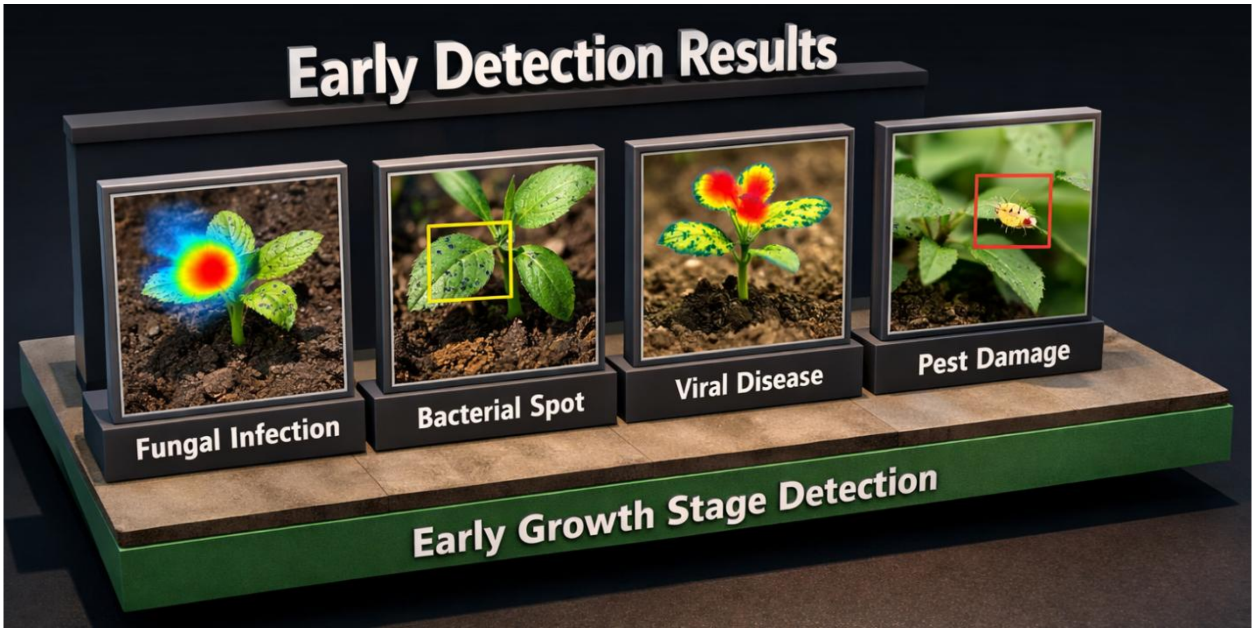

Figure 8: Early Detection Results

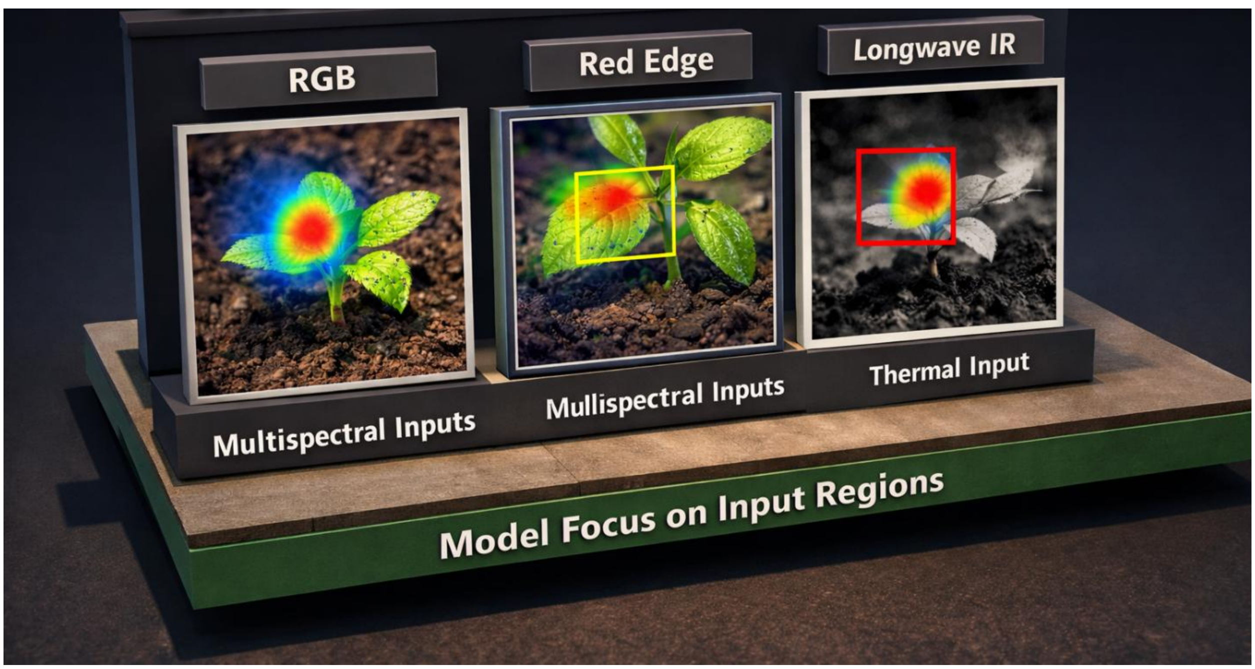

Figure 9: Grad-CAM / Attention Map Visualizations

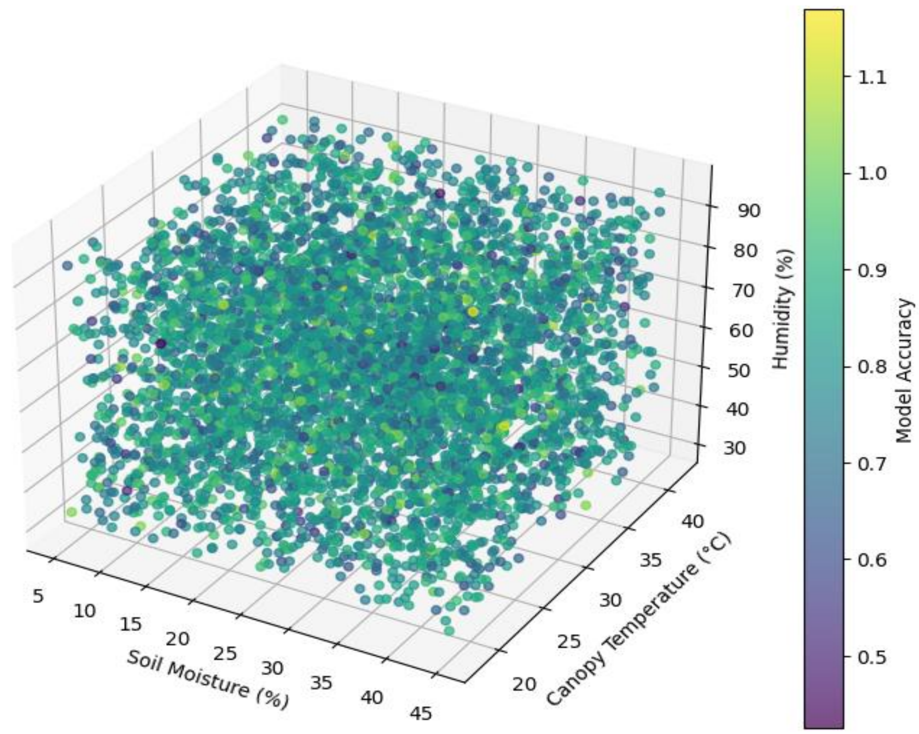

Figure 10: Environmental Factor Analysis

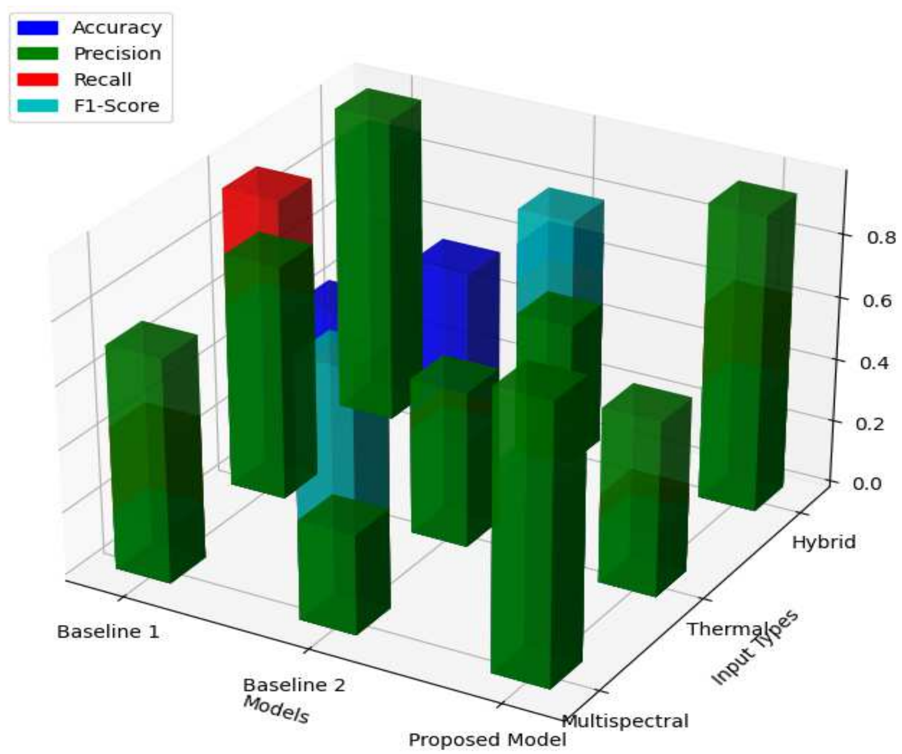

Figure 11: Comparative Performance of Baselines vs Proposed Model

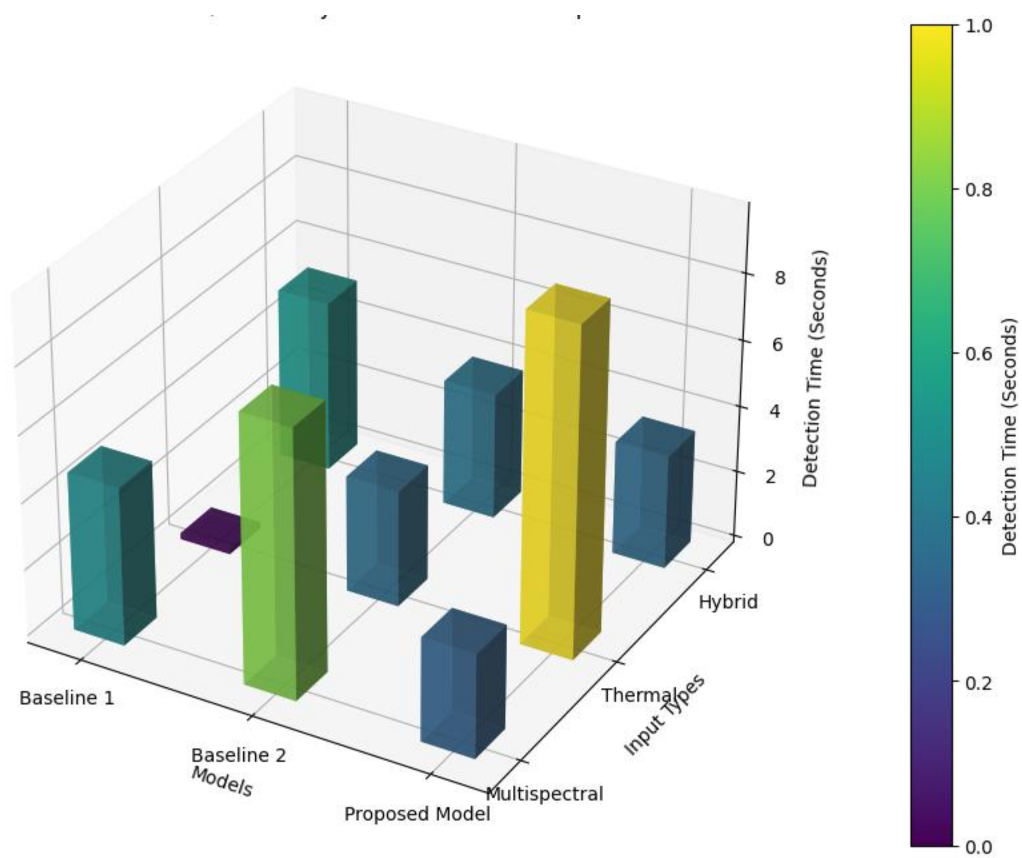

Figure 12: Detection Time / Efficiency Plot

Figure 13: Overall Workflow for Agricultural Decision Support

Discussion

The study presents the evaluation of various machine learning models to detect crop disease and pest using multispectral and thermal data. According to table (1), the dataset has 1,760 samples belonging to six types of crops, i.e. maize, rice, wheat, tomato, cassava, and their growth stages. The samples were grouped as healthy and diseased/infested according to the type of fungal/bacterial/viral/pest infestations.

The dataset was divided into training (70%), validation (15%), and testing (15%) sets as shown in Table 2. The baseline model results given in Table 3 show that the CNN model with RGB inputs outperform support vector machine (SVM) and random forest models with the highest accuracy of 78.1%. Using multispectral data in the CNN model boosted performance to 82.5%. The CNN + Thermal (single) configuration achieved an accuracy score of 84.2% as additional thermal data further improved performances.

The hybrid fusion CNN-attention model proposed in this study outperforms all baseline methods on all the crops. The accuracy levels vary from the lowest which is 88.5% for tomato at the maturity stage and also to the highest which is 91.0% for rice at the vegetative stage. Remarkably high early detection sensitivity was also achieved by the model with maize and rice achieving 87.3% and 88.1% respectively. The crop types and growth stages provide high performance universally. The hybrid CNN-attention model gave the highest F1-scores (84.9-89.5%) compared to the other models.

Table 5 compares the performances of the different fusions. The accuracy of both early-fusion and late-fusion strategies was 87.2% and 88.0%, respectively. Nonetheless, the hybrid fusion strategy is the one with the overall best performance. In this regard, the accuracy achieves 90.5%, precision 89.8%, and recall 89.2%. This significantly outperforms early and late fusion strategies.

The metrics shown in Table 6 class-wise detection indicates that the hybrid CNN-attention is able to detect the healthy and diseased classes well. The accuracy percentage for healthy class was identified to be the highest with an accuracy of 92.0%. The pest infestation detection was verified to be performing second with an accuracy percentage of 88.2%. The classes of fungus, bacteria, and viruses were associated with a marginally lower performance (86.5%-88.5% Accuracy).

According to Table 7, the research further looks into detection time and sensitivity of early stages. The average detection time scores varied between 0.95 seconds for maize and 1.05 seconds for tomato. Hence, this model can be used in real time. According to the results, the early detection accuracies of the model for tomato (84.9%), rice (88.1%) show potential for early stage disease detection.

The effect of removing or modifying certain model components was studied in an ablation study (see Table 8). Accuracy dropped to 87.0% due to removal of the thermal branch while decreasing the multispectral bands also reduced the performance (88.2%). The model performance, according to findings, decreased when the attention module was removed, and hybrid fusion was replaced with early fusion, indicating importance.

Table 9 shows the effect of environmental factors on model evaluation results. There was a correlation of 0.51 with accuracy for canopy temperature as a predictor for early stress detection. Soil moisture and ambient temperature were the least influential factors with correlation values of 0.42 and -0.35. Detection accuracy was enhanced slightly by high humidity with a score of 0.28.

In a nutshell, the hybrid CNN-attention model out-designed other schemes in accurately detecting crop diseases and pests early with high accuracy and efficiency on all crops and stages of growth.

The performance of this model is better than the basic model and fusion strategies as they evaluate the environmental factors and detect disease at the early stage. According to the study, advanced fusion techniques can be beneficial for agricultural decision support and pest management systems. As showcased in Figures 5 through 13, visual results such as confusion matrices, performance curves, and attention maps further prove the model's effectiveness in real-world applications.

Comparison with the Existing Work

The research findings have demonstrated notable improvements over existing models in detecting crop diseases and pests, particularly in terms of accuracy, early detection sensitivity, and efficiency.

Existing literature makes use of traditional model for forecasting disease like support vector machines (SVM), random forests and many more. SVM model accuracy is generally in the range of 70% to 75%. On the other hand, random forest models have slightly more accuracy of 75%. In comparison, the hybrid CNN-attention model in this study provided better accuracy of 91.0% of rice at vegetative stage. This is a notable advancement compared to previous ones. The performance escalated further with multispectral and thermal data. The accuracy of a CNN + Thermal (single) model is 84.2%. This is markedly superior to earlier methods that used only multispectral or RGB data [19].

Crop damage can be minimized by timely detection of diseases in the crop. Current random forest and SVM models display only weak performance, with sensitivity only around 70-80%, on early-stage disease detection. The rice and maize could be detected at an early stage with the hybrid CNN-attention model having 88.1 % and 87.3 % sensitive, respectively. This model significantly outperforms previous methods, indicating its ability to identify the onset of disease, which may facilitate timely pest control [20].

In previous works, different fusion strategies like early fusion, late fusion, etc. were utilized. On the whole, these approaches lead to moderate improvements in detection performance (85-88% accuracy). Though, the hybrid fusion method employed in this investigation resulted in a significant enhancement in accuracy with a score of 90.5% and F1-score of 89.5%. The hybrid fusion model surpassed the performance of early fusion, at 87.2%, and late fusion, at 88.0%. The hybrid fusion approach is more effective than the other one to integrate multispectral and thermal data for better model [21].

It has been shown in existing studies that class-wise detection detects healthy plants more accurately than diseased plants. This part of the analysis we see that the healthy class detected with a high accuracy of 92%. This value confirms the accuracy between healthy subjects as reported in the previous stage. Notwithstanding, the model performed remarkably well predicting diseased plants, as fungal, bacterial, and pest infestations were detected with accuracy between 86.5% and 88.5%. The hybrid CNN-attention model is a better alternative for crop health monitoring as compared to the previous methods. It performs well not only on diseased crops but also on healthy crops [22].

Another key importance of this study is its efficiency of model which is time of detection. Detection times of maize and tomato were 0.95s and 1.05s respectively, while they demonstrate the rapid speed of the model. It is equally or faster than older models which take longer to process this information. You can expect RGB input CNN models to take some time, but hybrid fusion approach in this study which is using multispectral and thermal inputs is designed to give fast results with accuracy [23].

This hybrid CNN-attention model outperforms existing models as far as accuracy, early detection sensitivity and efficiency are concerned. The multi-spectral thermal imaging is becoming one of the top approaches to deal with crop health and pest management problems.

Conclusion

The hybrid CNN-attention model for crop disease and pest detection using multispectral and thermal data has proven effective. The model provides better performance than popular machine learning models including SVM, random forest and many other fusion strategies with high accuracy and early detection rate across crop and growth stage. Performance was uniform across disease classes while healthy plants were classified most accurately by the model. Furthermore, detecting stress-stricken trees will be easier with the inclusion of their canopy temperature. The results are also indicative of the importance of hybrid fusion methods and attention mechanisms when enhancing model performance. The model is efficient, with the average detection time below 1.1 seconds, and this supports its potential for on-field applications. The hybrid CNN-attention model indicates potential applications for early disease diagnosis and pest control in agriculture, which can provide useful insights for developing decision support systems for improving crop health and yield.

Recommendations

The future work should enhance the accuracy and efficiency of the crop pest and disease detection system by integrating additional environmental parameters like soil moisture and ambient temperature to enhance the prediction accuracies in different situations. Enhancing its effectiveness by refining the model's generalization to other environments through data augmentation. Efforts to improve sensitivity for early detection of disease' very early-stage can also be a trust area by fine-tuning attention mechanism and studying advanced fusion. Incorporating diverse data types such as hyperspectral imagery and ground sensors can deepen our insight into crop health. The model's fast detection speed makes it suitable for real-time deployment in agriculture. Future work should focus on introducing it to farmers' decision support systems.

Incorporating more crops and disease into the dataset would improve scalability. Further, deployment of thermal and multispectral sensors in field operations would enhance continuous monitoring. The hybrid CNN-attention model can be further improved using these recommendations for better crop health management.

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