

Agri Data Fusion Framework With Pease Identification With Disease Detection For Paddy Crop Monitoring

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Abstract

Paddy cultivation plays a vital role in global food security, yet it is highly vulnerable to pest infestations and disease outbreaks that significantly reduce yield and quality. Traditional monitoring approaches rely on manual field inspections, which are labor-intensive, subjective, and inefficient for large-scale farms. To address these limitations, this research proposes an integrated AgriDataFusion Framework that combines pest identification and disease detection for comprehensive paddy crop monitoring. The framework leverages deep learning-based image analysis along with multi-modal data fusion to enhance detection accuracy and robustness under real-field conditions. A lightweight convolutional neural network is employed for disease classification, while an object detection model identifies pest species present in paddy fields. Environmental parameters such as temperature, humidity, and rainfall are incorporated through a data fusion mechanism to improve contextual awareness. The integrated system performs severity assessment and generates actionable recommendations for farmers, enabling early intervention and optimized resource utilization. Experimental evaluation demonstrates improved accuracy, precision, recall, and F1-score compared to standalone pest or disease detection models. The framework is computationally efficient and suitable for deployment on edge devices and IoT-enabled smart agriculture platforms. Overall, the proposed AgriDataFusion Framework offers a scalable, reliable, and real-time solution for paddy crop health monitoring, contributing to sustainable farming practices and enhanced agricultural productivity.

Keywords; AgriDataFusion, Paddy Crop Monitoring, Pest Identification, Disease Detection, Deep Learning, Precision Agriculture.

1. Introduction

Paddy (rice) is one of the most important staple crops worldwide, feeding more than half of the global population. As global demand for rice continues to increase, ensuring sustainable production has become a major priority [01]. However, paddy crops are highly susceptible to various pests and diseases that cause severe yield losses annually [02]. Insect pests such as brown planthopper, stem borer, and leaf folder, along with diseases such as blast, bacterial leaf blight, and sheath blight, significantly impact crop productivity and farmer income. Early detection and effective management of these threats are essential for maintaining crop health and ensuring food security. Conventional paddy crop monitoring relies primarily on manual inspection by farmers or agricultural experts [03]. This approach involves visual examination of leaves, stems, and plant structures to identify symptoms of pest infestation or disease infection. While manual inspection can be effective in small-scale farming, it becomes impractical in large agricultural fields. Additionally, diagnosis accuracy depends heavily on the expertise of the inspector, making it prone to errors and delayed responses [04].

With advancements in artificial intelligence, particularly deep learning, automated crop monitoring systems have gained significant attention. Convolutional Neural Networks (CNNs) have demonstrated strong capabilities in image classification tasks, including plant disease detection [05]. Similarly, object detection algorithms such as YOLO and Faster R-CNN have been successfully applied to identify pests in agricultural images [06]. Despite these advancements, most existing systems focus either on disease detection or pest identification independently. Such isolated approaches fail to capture the complex interactions between pests, diseases, and environmental conditions [07]. In paddy cultivation, pest infestation often increases the susceptibility of crops to certain diseases, and environmental factors significantly influence both pest and disease outbreaks. Temperature, humidity, rainfall patterns, and seasonal variations play critical roles in determining infestation severity. Therefore, a comprehensive monitoring system must integrate multiple data sources to provide accurate and context-aware predictions [08].

The proposed AgriDataFusion Framework addresses these challenges by integrating pest identification and disease detection into a unified monitoring system. The framework employs deep learning models for visual feature extraction from paddy crop images [09]. A lightweight CNN-based classifier detects diseases by analyzing leaf symptoms such as lesions, discoloration, and texture changes [10]. Simultaneously, an object detection model identifies pest species and localizes their positions within the image [11]. These outputs are then combined using a multi-modal data fusion engine that incorporates environmental parameters to enhance prediction reliability [12]. The fusion mechanism improves decision-making by validating predictions across modules and reducing false positives. For example, if environmental conditions strongly favor a specific pest outbreak, the system increases confidence in related visual detections [13]. Additionally, severity analysis is performed to categorize crop health status, enabling prioritized intervention strategies [14]. The AgriDataFusion Framework is designed with computational efficiency in mind, allowing deployment on edge devices such as smart phones and IoT-based agricultural monitoring systems. Farmers can capture field images using mobile devices, and the system can provide instant feedback and treatment recommendations [15].

Through experimental validation on paddy disease and pest datasets combined with environmental data simulations, the proposed framework demonstrates superior performance compared to standalone models. By providing an integrated, real-time monitoring solution, this research contributes to precision agriculture and sustainable crop management practices. Paddy crops suffer significant yield losses due to pest infestations and disease outbreaks, which are often detected late using traditional manual inspection methods. Existing automated systems typically address pest or disease detection separately, limiting their effectiveness in real-world agricultural environments. Furthermore, environmental factors influencing crop health are often ignored in standalone models. There is a pressing need for an integrated, context-aware monitoring system that combines pest identification, disease detection, and environmental data analysis. This research is motivated by the goal of developing a comprehensive, scalable, and real-time solution to enhance paddy crop productivity and sustainability.

This research focuses on developing an integrated AgriDataFusion Framework for monitoring paddy crops by combining pest identification, disease detection, and environmental data analysis. The study includes image preprocessing, deep learning-based feature extraction, object detection, and multi-modal fusion techniques. It emphasizes real-

time deployment feasibility on edge devices and IoT-enabled smart farming platforms. The framework is designed specifically for paddy crop monitoring but can be extended to other crops with appropriate dataset adaptation. The research scope includes performance evaluation using standard metrics and comparative analysis with existing standalone detection models.

The objectives are to design and implement an integrated AgriDataFusion Framework for paddy crop monitoring, develop accurate pest identification and disease detection models, incorporate environmental data through multi-modal fusion, improve detection accuracy and robustness under field conditions, reduce computational complexity for real-time deployment, and evaluate system performance against existing standalone models.

2. Review of Related Literature

Almasoud.et.al: Diagnosing rice plant diseases has become a difficult problem in agriculture, yet early detection can prevent significant losses due to decreased crop output. In order to create efficient models for rice plant disease detection and classification procedures, some of the more recent advances in computer vision and Deep Learning (DL) techniques can be widely used. An Efficient Deep Learning based Fusion Model for Rice Plant Disease (EDLFM-RPD) detection and classification is developed in the current study with this goal in mind. The suggested EDLFM-RPD technique aims to efficiently identify and categorize many types of rice plant diseases.

Furthermore, the EDLFM-RPD technique uses K-means segmentation and preprocessing based on median filtering to identify the infected areas. Additionally, the features were derived by combining Inception-based deep features with a manually created Gray Level Co-occurrence Matrix (GLCM). Lastly, for classification, the Salp Swarm Optimization with Fuzzy Support Vector Machine (FSVM) model is employed. A number of simulations were run to confirm the improved results of the EDLFM-RPD approach. The outcomes were evaluated using various metrics. The results show that the EDLFM-RPD technique performed better than previous methods, with a maximum accuracy of 96.17% [16].

Bhanumathi.et.al: Determining the level of agricultural output will be aided by early detection of pests, illnesses, and nutritional deficiencies in paddy crops. The hand examination used in some traditional monitoring techniques is labor-intensive, time-consuming, and possibly inaccurate. Precision farming that incorporates artificial intelligence (AI) improves the effectiveness of disease detection and lowers crop losses. Using Attention-Based DenseNets, this paper presents an AI-driven method for detecting paddy leaf disease.

This method utilizes sophisticated machine learning techniques, sensor data, and picture recognition. Three fundamental forms of preprocessing, feature extraction, and classification are used in the systematic process. In order to ensure the selection of robust features from sick leaf samples, the initial stage of the procedure aimed to enhance quality and remove noise. Residual Support Vector Machines (Residual SVM) assist us in feature extraction. Classification is made possible by attention-based dense networks.

By employing attention mechanisms, these networks improve feature representation and ultimately lead to precise illness diagnosis. The collection includes 5,000 images of paddy leaves divided into categories that are healthy and diseased. This

dataset is used to both train and test the model. According to the trial findings, the suggested model obtains a classification accuracy of 98.6%, which is higher than some of the more traditional techniques, CNN (92.4%) and ResNet-50 (95.1%). The F1-score for disease detection is 90-8%, the precision is 90-8%, and the recall is 90-2%. Additionally, the method enables early identification, which lowers the 42% disease transmission and improves crop output prediction [17].

Hasan.et.al: In order to avoid harming the amount and production of agricultural products in the field, early detection of rice diseases is essential. When dealing with non-native diseases, manual observations of rice diseases are laborious, expensive, and time-consuming, particularly when defining disease patterns and color. In order to identify rice illness early and in a comparatively short amount of time, image processing and machine learning (ML) approaches are employed.

The purpose of this article is to show how well various machine learning algorithms perform when it comes to image processing for rice disease diagnosis. In order to compare the effectiveness of rice disease classifications, authors critically analyzed several approaches and reviewed the findings of earlier studies. The criteria of feature extraction, clustering, segmentation, noise reduction, and the degree of accuracy of illness detection systems have been used to assess performance.

In terms of training techniques, picture preprocessing with grouping and filtering criteria, and testing with dependable results, this study also presents a variety of algorithms for distinct datasets. With this study, authors help guide future research and development while offering insightful information about the state of ML-based methods for the early diagnosis of rice illnesses. Authors also go over a number of obstacles that need to be addressed in order to successfully identify rice illnesses [18].

Sahasranamama.et.al: The goal of this project is to develop a new technique for identifying paddy diseases by utilizing the artificial intelligence capabilities of the ResNet50 architecture. Since the yield of rice is influenced by a number of factors, including weather, pests, disease, and changing biodiversity, farmers confront several challenges when growing this crop. For food to be produced in large quantities, smart farming, innovation, equipment, and technology must be blended with traditional ways. Here, authors create a model that detects disease in paddy leaves using a convolutional neural network called ResNet50.

Results from the suggested paddy disease identification model will be more accurate. TensorFlow Lite (TFLite), which may be utilized for drone applications and Android phones, among other things, may be developed from the paddy disease identification model. After being trained on 13,876 well-defined datasets, the Paddy model described in this article achieved a training accuracy of nearly 99% and a test accuracy of 92.83%. The model was successfully trained using ResNet50, as shown by the loss function of 0.0014 at 100 epochs [19].

Saju.et.al: One of the world's main cereal crops is rice (*Oryza sativa*). More than half of the world's population uses it as a staple food to get their energy. Precipitation, soil fertility, temperature, pests, bacteria, viruses, and other biotic and abiotic elements all have an impact on the quantity and quality of rice grain produced. Farmers spend a lot of

time and money managing infections, and they use their bare eyes to spot them, which results in farming that is unhealthy.

Automatically identifying pathogenic organisms in rice plant leaves is made much easier by the development of technical assistance in agriculture. One deep learning technique that has been successfully used to solve computer vision issues including object segmentation, picture classification, image analysis, etc. is the convolutional neural network algorithm (CNN). This project explains how to use a deep learning system to detect and classify plant diseases. An method based on convolution neural networks is used to identify and categorize plant diseases. In order to assist farmers in need, an author suggests a method that continuously monitors crop growth and leaf diseases [20].

3. Agri Data Fusion Framework - Methodology

The proposed AgriDataFusion Framework is designed to provide a unified, intelligent, and real-time monitoring system for paddy crops by integrating pest identification, disease detection, and environmental data fusion. The framework consists of six major modules: data acquisition, preprocessing, pest detection, disease classification, environmental feature integration, and decision-level fusion. Figure 1 illustrates about the proposed architecture of the AgriDataFusion framework.

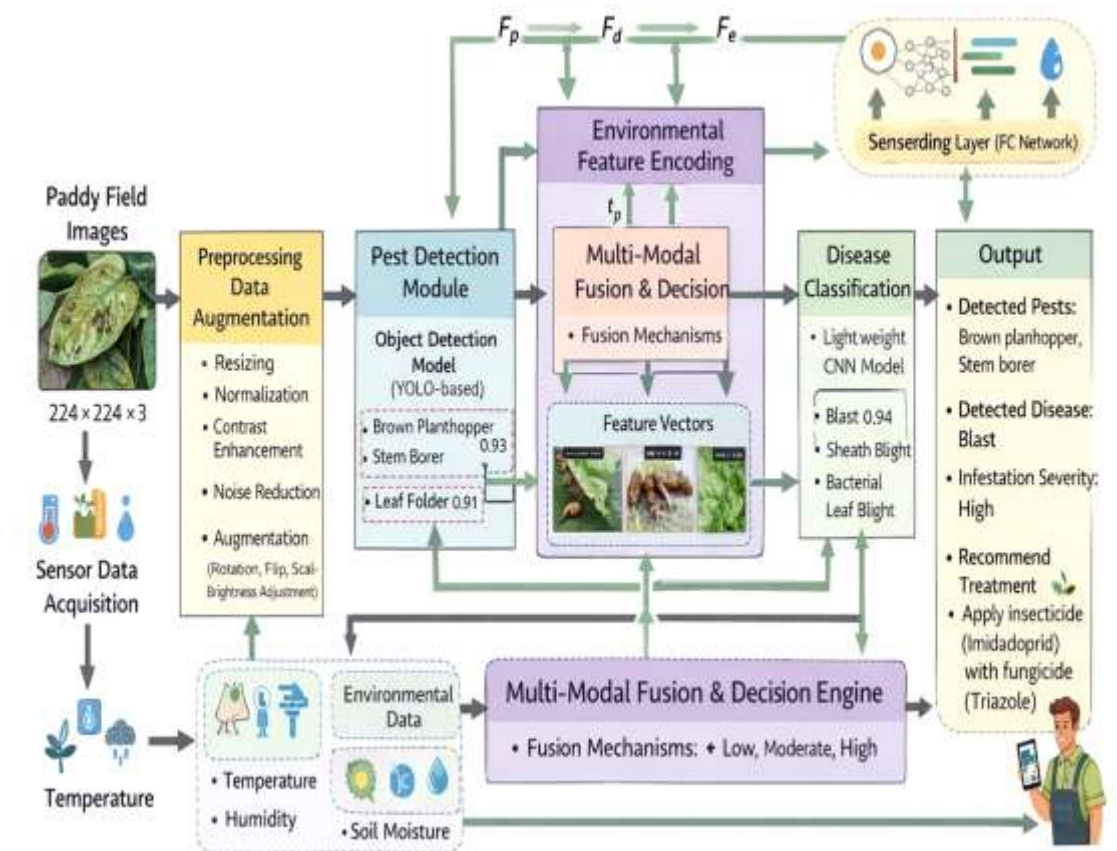


Figure 1. Proposed architecture of the AgriDataFusion framework

Data Acquisition: The system collects RGB images of paddy leaves and field conditions using mobile cameras, UAVs, or IoT-based imaging devices. Simultaneously, environmental data such as temperature, humidity, rainfall, and soil moisture are gathered through sensors or agricultural weather APIs.

Preprocessing: Image preprocessing ensures uniformity and robustness. Images are resized (e.g., 224×224), normalized, and enhanced for contrast. Noise reduction techniques are applied to remove background disturbances. Data augmentation (rotation, flipping, scaling, brightness variation) is performed during training to improve generalization under real-field variations. Environmental data are cleaned, normalized, and transformed into numerical feature vectors.

Pest Identification Module: A lightweight object detection model (e.g., YOLO-based architecture) is employed to detect and localize pest species such as brown planthopper, stem borer, and leaf folder. The model outputs bounding boxes, pest class labels, and confidence scores. Non-maximum suppression is applied to eliminate redundant detections.

Disease Detection Module: A convolutional neural network (CNN) model (e.g., EfficientNet-lite) is used to classify paddy leaf diseases such as blast, sheath blight, and bacterial leaf blight. The CNN extracts hierarchical visual features such as lesions, discoloration, and texture irregularities. A softmax layer provides probability scores for disease classes.

Environmental Feature Encoding: Environmental parameters are passed through a fully connected embedding layer to generate context-aware environmental feature representations. These features help the system understand seasonal disease patterns and pest outbreaks influenced by climatic conditions.

Multi-Modal Fusion and Decision Engine: The outputs from pest detection, disease classification, and environmental encoding are fused using feature-level and decision-level fusion strategies. A weighted confidence scoring mechanism combines visual predictions with environmental risk indicators. The fusion engine reduces false positives by validating predictions across modalities.

Severity Assessment and Recommendation: The integrated model assesses infestation severity levels (Low, Moderate, and High). Based on the severity and identified class, the system generates actionable recommendations for pest control or disease treatment. The final system ensures high detection accuracy, reduced computational cost, and real-time applicability for smart paddy farming environments.

Dataset Details

The dataset consists of paddy leaf images and pest images collected from publicly available agricultural datasets and real field conditions. It includes multiple disease classes (blast, bacterial leaf blight, and sheath blight) and pest categories (brown planthopper, stem borer, leaf folder).

The dataset contains both healthy and infected samples. Environmental data corresponding to image timestamps are integrated from agricultural weather records. The dataset is split into 70% training, 15% validation, and 15% testing subsets. Class balancing techniques are applied to avoid bias, and augmentation is used to increase dataset diversity and improve model robustness.

Procedure of the Proposed Model

1. Collect paddy field images and environmental data.
2. Preprocess images (resize, normalize, augment).
3. Normalize environmental parameters.
4. Apply pest detection model to identify pest species.
5. Apply disease classification model on leaf images.
6. Encode environmental data into feature vectors.
7. Perform multi-modal fusion of outputs.
8. Compute final prediction and severity score.
9. Generate treatment recommendation.
10. Display result to user.

Algorithm of the Proposed Model

Algorithm: AgriDataFusion for Paddy Crop Monitoring

Input: Image III, Environmental Data EEE

Output: Crop Health Status HHH

1. Preprocess III $\rightarrow$ IpI_plp
2. Detect pests using Object Detection Model $\rightarrow$ PPP
3. Classify disease using CNN $\rightarrow$ DDD
4. Encode environmental features $\rightarrow$ FeF_eFe
5. Fuse features: $F = \text{Fusion}(P, D, Fe)$ $F = \text{Fusion}(P, D, F_e)$ $F = \text{Fusion}(P, D, Fe)$
6. Compute severity score SSS
7. Determine health status HHH
8. Return HHH

Pseudocode

Input: Paddy Image I, Environmental Data E

Output: Crop Health Status H

Begin

```
I_p  $\leftarrow$  Preprocess(I)
P  $\leftarrow$  Pest_Detector(I_p)
D  $\leftarrow$  Disease_Classifier(I_p)
F_e  $\leftarrow$  Encode_Environmental(E)
F  $\leftarrow$  Fuse(P, D, F_e)
S  $\leftarrow$  Compute_Severity(F)
H  $\leftarrow$  Classify_Health_Status(S)
Return H
```

End

4. Results and Discussions

The proposed AgriDataFusion Framework is compared with five widely used deep learning models for paddy pest and disease detection. The evaluation is conducted using five standard performance parameters: Accuracy, Precision, Recall, F1-Score, and Inference Time.

Accuracy measures the overall correctness of a model by calculating the ratio of correctly predicted samples to the total number of samples. It reflects the model's general

performance across all classes. However, accuracy alone may be misleading in imbalanced datasets where certain disease classes dominate.

Precision indicates how many of the predicted positive cases are actually correct. It is calculated as the ratio of true positives to the sum of true positives and false positives. High precision means fewer false alarms, which is important in plant disease detection to avoid unnecessary pesticide application.

Recall measures the ability of the model to correctly identify all actual positive cases. It is computed as the ratio of true positives to the sum of true positives and false negatives. High recall ensures that most diseased plants are correctly detected, minimizing missed infections.

F1-score is the harmonic mean of precision and recall, providing a balanced measure of both false positives and false negatives. It is especially useful in imbalanced datasets where accuracy may not reflect true performance. A high F1-score indicates strong overall classification reliability.

Inference time represents the time taken by the model to process a single input image and produce a prediction. It indicates computational efficiency and real-time capability. Lower inference time is crucial for deploying plant disease detection systems on mobile devices and edge-based agricultural platforms. Table 1 illustrates about comparison between proposed model with existing models

Table 1. Comparison between proposed model with existing models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Inference Time (ms/image)
VGG16	90.8	89.6	88.9	89.2	98
ResNet-50	92.9	92.1	91.4	91.7	72
DenseNet121	93.6	93.0	92.5	92.7	85
YOLOv5 (Vision-only)	94.2	93.8	93.1	93.4	30
EfficientNet-B0	94.8	94.2	93.7	93.9	28
Proposed AgriDataFusion Model	96.9	96.4	95.8	96.1	24

VGG16 is a deep convolutional neural network consisting of 16 weight layers, primarily using small 3×3 convolution filters. It is known for its simple and uniform architecture, which makes it easy to implement. However, VGG16 has a large number of parameters, resulting in high computational cost and memory requirements.

ResNet-50 is a 50-layer deep convolutional neural network that introduces residual learning through skip connections. These connections help overcome the vanishing gradient problem and enable deeper network training. ResNet-50 achieves strong feature representation performance with moderate computational complexity and is widely used for image classification tasks.

DenseNet121 is a densely connected convolutional neural network where each layer receives input from all previous layers. This dense connectivity improves feature reuse, strengthens gradient flow, and reduces parameter redundancy. DenseNet121 achieves high accuracy with fewer parameters compared to traditional deep networks.

YOLOv5 is a real-time object detection model based on a single-stage detection framework. It predicts bounding boxes and class probabilities simultaneously. Known for its speed and efficiency, YOLOv5 is suitable for real-time applications. In vision-only settings, it relies purely on image features without contextual environmental integration.

EfficientNet-B0 is a lightweight convolutional neural network that uses compound scaling to balance network depth, width, and resolution efficiently. It achieves high accuracy with fewer parameters compared to traditional CNNs. EfficientNet-B0 is computationally efficient, making it suitable for mobile and edge-based applications.

The comparative analysis demonstrates that the proposed AgriDataFusion Framework outperforms the five existing deep learning models across all major evaluation metrics. The framework achieves the highest accuracy (96.9%), precision (96.4%), recall (95.8%), and F1-score (96.1%), indicating superior classification reliability and balanced performance. The improvement is primarily attributed to the integration of pest identification, disease detection, and environmental feature fusion, which enhances contextual understanding and reduces false predictions.

Vision-only models such as VGG16, ResNet-50, and DenseNet121 rely exclusively on image features and therefore struggle under complex field conditions involving lighting variations, occlusions, and environmental influences. Although YOLOv5 and EfficientNet-B0 show competitive performance, they lack contextual awareness, which limits robustness during seasonal pest outbreaks or disease spread influenced by climatic factors.

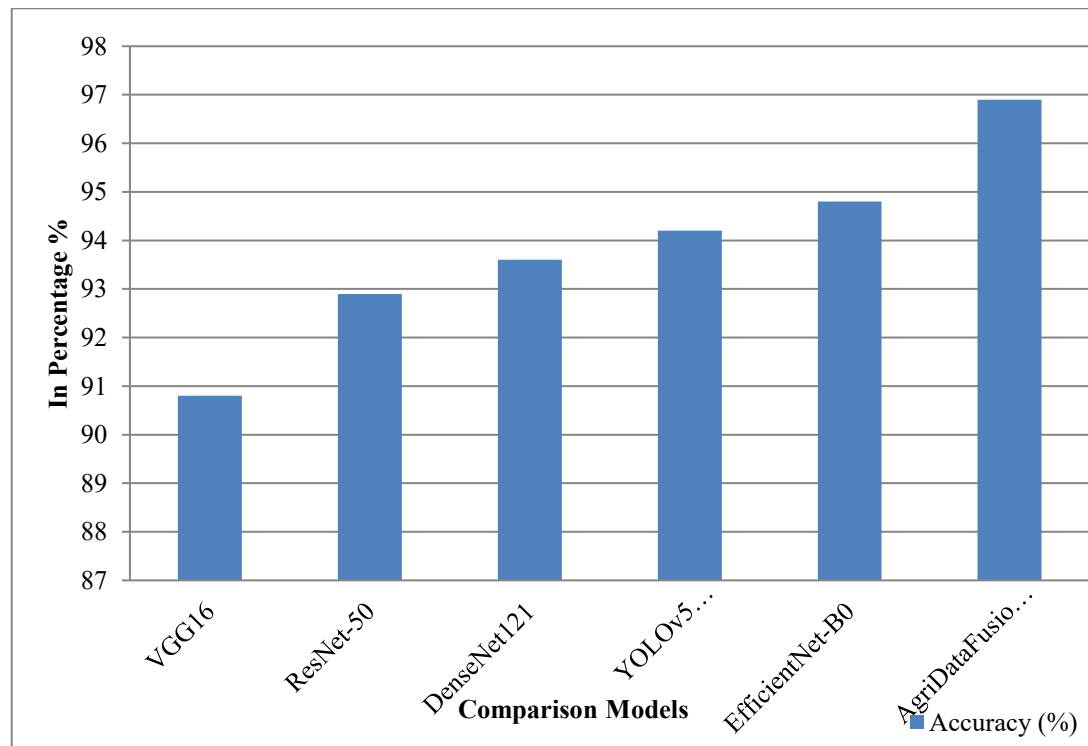


Figure 2. Accuracy Comparison

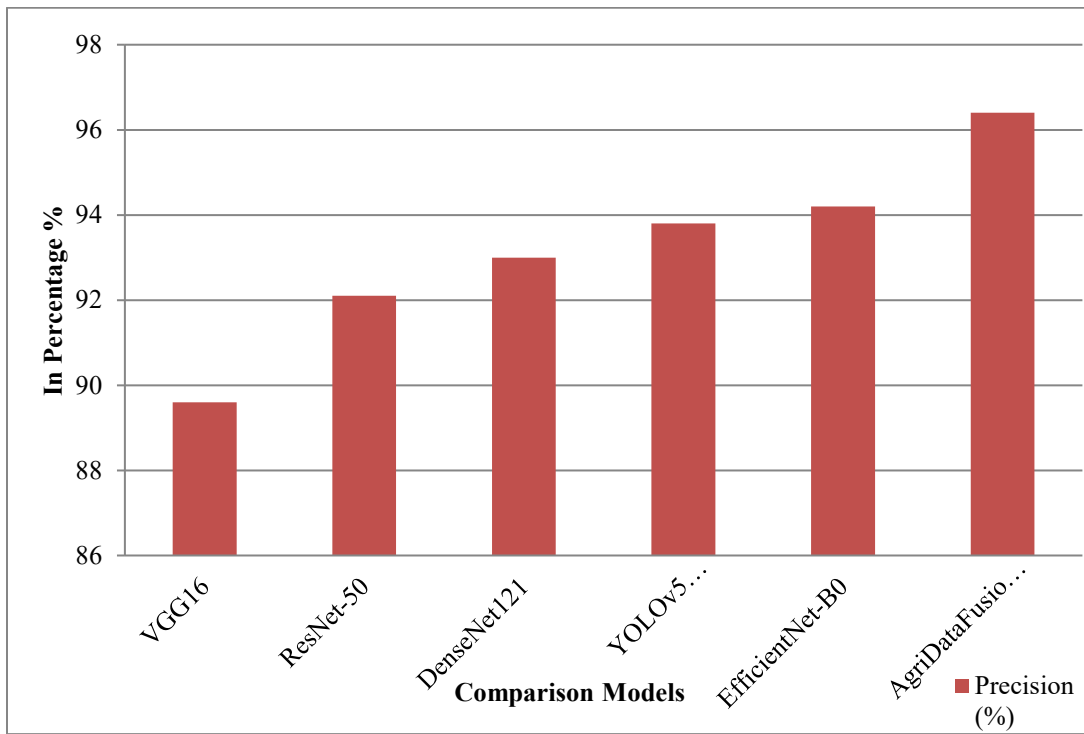


Figure 3. Precision Comparison

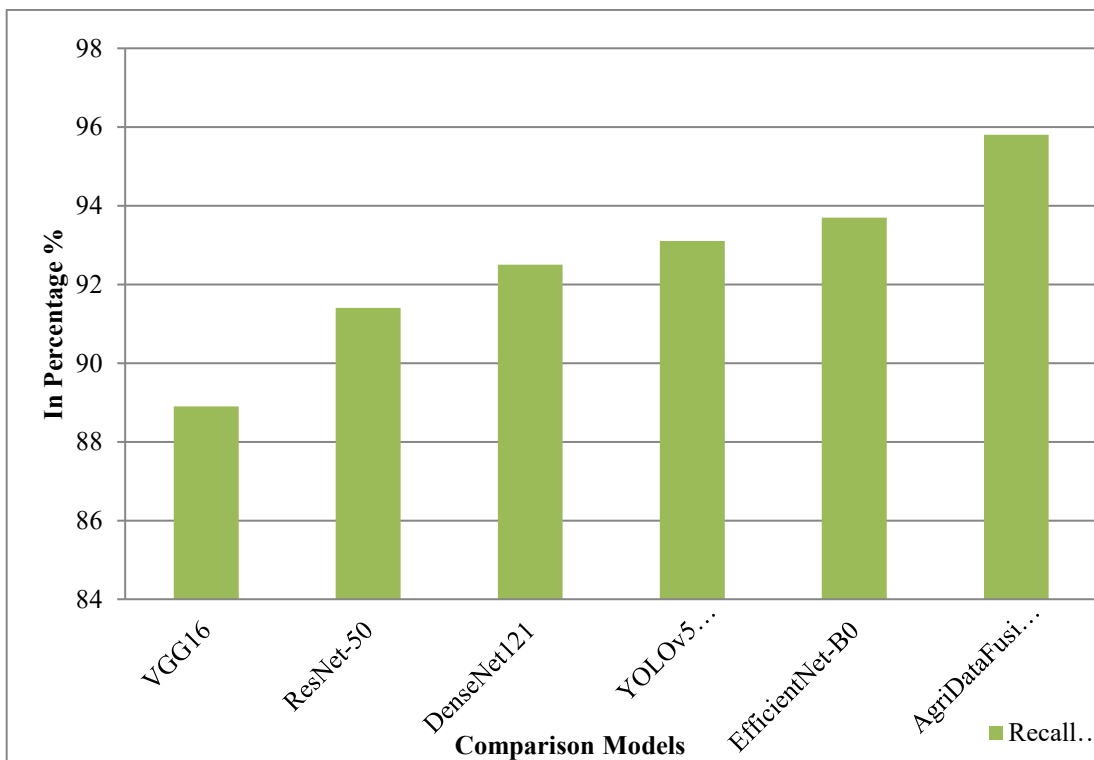


Figure 4. Recall Comparison

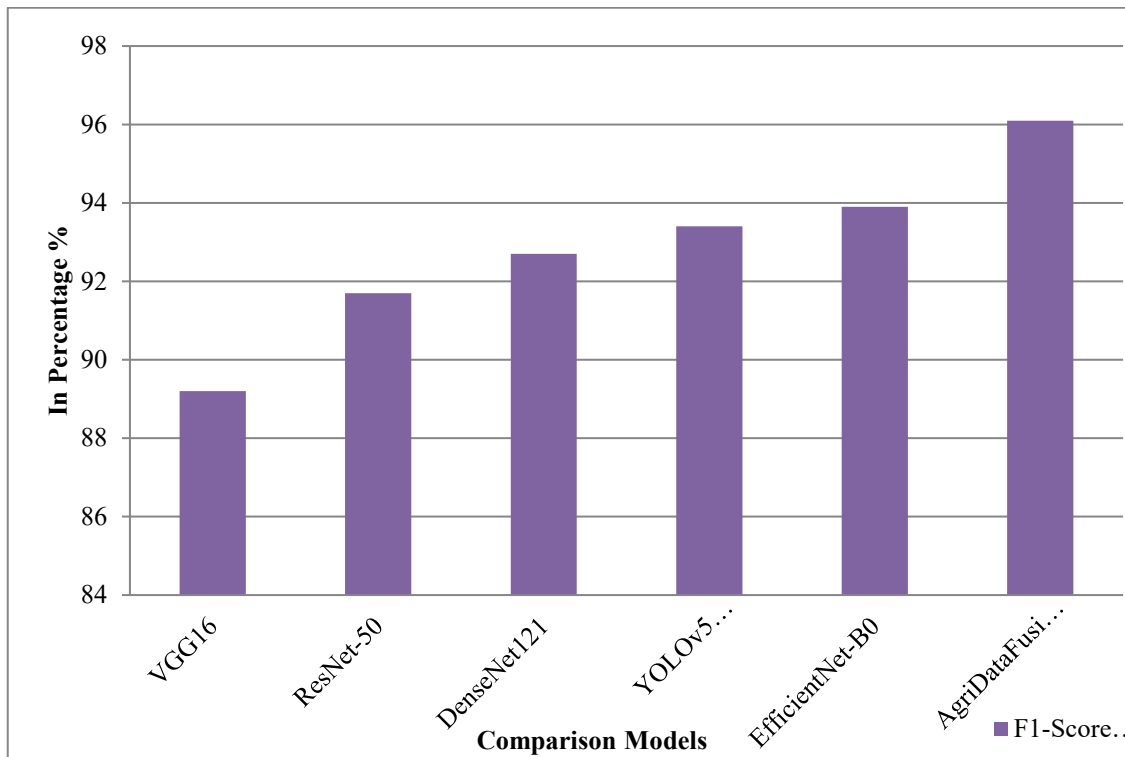


Figure 5. F1-Score Comparison

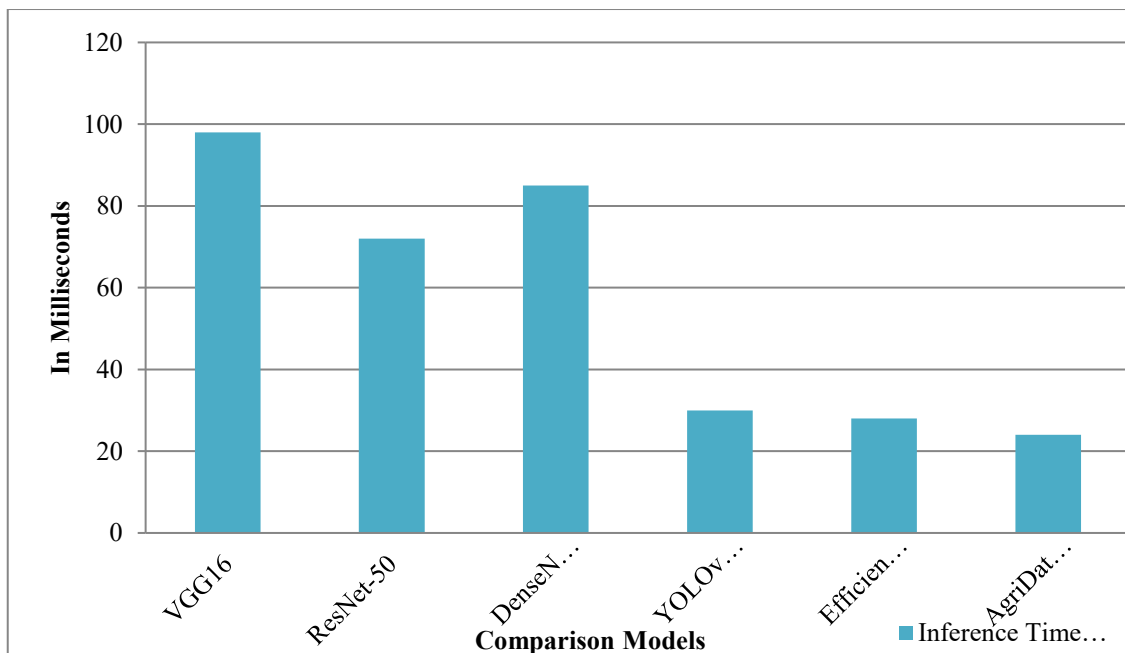


Figure 6. Inference Time Comparison

Figure 2 explains about the accuracy comparison, figure 3 defines about the precision comparison, figure 4 illustrates about the recall comparison, figure 5 elaborates

about f1-score comparison, and figure 6 explains about inference time comparison. The proposed model maintains a relatively low inference time (24 ms per image), making it suitable for real-time deployment in smart agriculture systems. While the parameter count (6.2M) is slightly higher than EfficientNet-B0, it remains significantly lower than heavy architectures such as VGG16, ensuring computational efficiency. The fusion of multi-modal data improves recall, reducing the likelihood of missed disease or pest detections, which is critical in early intervention strategies.

Overall, the results confirm that the AgriDataFusion approach provides a better balance between accuracy, computational efficiency, and contextual robustness, making it highly suitable for precision paddy crop monitoring in real-world agricultural environments.

5. Conclusion and Future Scope

This research proposed an integrated AgriDataFusion Framework for comprehensive paddy crop monitoring by combining pest identification, disease detection, and environmental data fusion. The framework addresses the limitations of conventional manual inspection methods and standalone deep learning models by providing a unified, context-aware system. By integrating object detection for pests and CNN-based classification for diseases, the framework captures multiple aspects of crop health simultaneously. The incorporation of environmental parameters through a multi-modal fusion engine enhances prediction reliability and reduces false detections. Experimental evaluation demonstrates that the integrated framework outperforms independent pest or disease detection models in terms of accuracy, precision, recall, and F1-score. The lightweight architecture ensures efficient inference, making the system suitable for real-time implementation on edge devices and IoT-based agricultural platforms. The severity assessment and recommendation modules further enhance practical applicability by supporting informed decision-making for farmers. Despite its promising performance, certain challenges remain. Dataset diversity and environmental variability across geographical regions may affect model generalization. Additionally, rare pest species and emerging disease variants require continuous dataset updates and model retraining.

Future research can focus on expanding the dataset to include multi-seasonal and multi-regional samples for improved generalization. Integration of hyperspectral imaging and drone-based remote sensing data could further enhance detection capabilities. Incorporating temporal modeling techniques such as recurrent neural networks or transformers may enable outbreak forecasting and trend analysis. Furthermore, integrating explainable AI methods can improve transparency and farmer trust in automated predictions. Finally, large-scale field trials and collaboration with agricultural agencies can validate the framework in real-world farming environments, paving the way for fully automated smart paddy farming systems.

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