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Research Article

AgriNet-Adapt: A Hybrid Deep Learning Framework for Fruit Disease Detection Using ResNet-18 and EfficientNet-B0

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ABSTRACT

Accurate and scalable fruit disease identification remains a critical challenge in precision agriculture due to significant variations in disease appearance, environmental conditions, and image quality. This paper presents AgriNet-Adapt, a hybrid deep learning framework that integrates crop-specific optimized architectures for automated disease classification in pomegranate, mango, and guava datasets. The framework utilizes ResNet-18 and EfficientNet-B0 to achieve robust and high-precision performance across diverse fruit disease categories. The key novelty lies in an adaptive, model selection strategy termed Algorithmic Agronomy that replaces one-size-fits-all approaches by aligning deep learning architectures with crop characteristics, improving accuracy and efficiency.

Keywords: Fruit Disease Detection, Deep Learning, ResNet-18, EfficientNet-B0, Precision Agriculture, Hybrid Framework, CNN, AgriNet-Adapt

Introduction:

Agriculture is a cornerstone of global food security, yet plant diseases continue to pose a significant threat to crop productivity, quality, and economic sustainability. Early and accurate identification of fruit diseases is essential for effective crop management and minimizing yield losses. Conventional disease detection methods primarily rely on manual inspection by experts, which is labor-intensive, subjective, and often impractical for large-scale agricultural environments. With the rapid advancement of deep learning and computer vision, automated image-based disease detection has emerged as a promising solution, offering high accuracy and scalability for real-world applications.

Recent studies have demonstrated that convolutional neural networks (CNNs) significantly outperform traditional machine learning techniques by enabling end-to-end feature learning directly from raw images. However, most existing approaches adopt a single-model paradigm, applying a uniform architecture across different crops and datasets. Such one-size-fits-all strategies fail to account for critical variations in disease morphology, dataset size, class imbalance, and visual complexity across different fruit types. As a result, these models often exhibit suboptimal generalization and limited practical applicability.

To overcome these limitations, this paper introduces AgriNet-Adapt, a hybrid deep learning framework that emphasizes crop-specific model specialization. Unlike conventional approaches, the proposed framework dynamically selects the most suitable architecture for each fruit type, leveraging the strengths of ResNet-18 for pomegranate and guava, and EfficientNet-B0 for mango. This adaptive

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strategy enables improved feature representation, better handling of inter-class similarities, and enhanced robustness across diverse datasets, leading to superior classification performance.
The effectiveness of the proposed framework is validated through extensive experiments on multi-fruit disease datasets, achieving high accuracies of 95.63% for pomegranate, 94.27% for mango, and 96.33% for guava, with a significant reduction in error rates compared to traditional models

Literature Review

Recent advancements in deep learning have significantly improved automated plant and fruit disease detection by enabling accurate image-based classification. Early work by Mohanty et al. (2016) demonstrated the effectiveness of convolutional neural networks (CNNs) using the PlantVillage dataset, achieving high accuracy across multiple crop species. Similarly, Sladojevic et al. (2016) showed that deep CNNs outperform traditional machine learning methods by automatically extracting discriminative features from leaf images, eliminating the need for manual feature engineering.
Residual learning architectures such as ResNet have further enhanced classification performance by addressing the vanishing gradient problem in deep networks. He et al. (2016) introduced ResNet, which enables deeper network training through skip connections and has since been widely adopted in plant disease detection. Studies such as Ferentinos (2018) reported classification accuracies exceeding 99% using deep CNNs, highlighting their robustness in agricultural applications. Additionally, Too et al. (2019) compared multiple deep learning architectures and concluded that ResNet-based models provide superior performance in multi-class plant disease classification tasks.
EfficientNet models have gained attention for achieving a balance between accuracy and computational efficiency through compound scaling. Tan and Le (2019) introduced EfficientNet, demonstrating improved performance with fewer parameters. In agricultural applications, Kumar et al. (2022) showed that EfficientNet-based models achieve high accuracy while maintaining suitability for real-time deployment on edge devices. Lightweight architectures such as MobileNet have also been explored for resource-constrained environments, providing efficient alternatives without significant loss in accuracy (Howard et al., 2017).
Hybrid and ensemble approaches have been proposed to further enhance classification performance. For instance, Abade et al. (2021) combined multiple CNN architectures to improve disease detection accuracy, while Chen et al. (2020) integrated attention mechanisms with deep learning models to focus on disease-specific regions in images. More recently, transformer-based approaches such as Vision Transformers (ViTs) have been explored for plant disease detection, offering improved global feature representation (Dosovitskiy et al., 2021).

Research Methodology

This study proposes AgriNet-Adapt, a hybrid deep learning framework for multi-fruit disease identification. The methodology is designed to address the limitations of conventional single-model approaches by introducing a crop-specific adaptive architecture selection strategy. The overall workflow consists of dataset preparation, preprocessing, model selection, training, and evaluation.

Dataset Description

The experimental analysis was conducted on three fruit disease datasets: pomegranate, mango, and guava, each containing multiple disease classes along with healthy samples. The pomegranate dataset comprises 5,099 images across five classes, representing a large and moderately imbalanced dataset. The mango dataset contains 838 images across five classes, while the guava dataset includes 300 images across three classes

Data Preprocessing and Augmentation

To ensure uniformity and improve model generalization, all images were subjected to preprocessing steps including:

- Image resizing to a fixed input dimension (e.g., 224×224 pixels)
- Normalization of pixel intensity values
- Removal of noise and irrelevant background variations

Data augmentation techniques such as **rotation, flipping, scaling, and brightness adjustment** were applied to increase dataset diversity and mitigate overfitting. This is particularly important for smaller datasets like guava, where limited samples can affect model performance.

Proposed Hybrid Framework: AgriNet-Adapt

The proposed framework follows a **multi-stage adaptive pipeline**:
Input Image → Fruit Type Identification → Model Selection → Disease Classification
AgriNet-Adapt dynamically selects the most suitable deep learning architecture for each fruit type:

- **ResNet-18** is used for pomegranate and guava, due to its strong feature representation and ability to handle complex and small datasets.
- **EfficientNet-B0** is used for mango, owing to its optimal balance between accuracy and computational efficiency.

This adaptive selection mechanism forms the basis of the proposed concept of Algorithmic Agronomy, where model architecture is aligned with crop-specific characteristics.

Model Architecture and Training

A. ResNet-18

ResNet-18 utilizes residual learning with skip connections to address the vanishing gradient problem, enabling deeper feature extraction. It is particularly effective for:

- Capturing hierarchical disease features
- Handling complex inter-class similarities
- Ensuring stable training across large datasets

B. EfficientNet-B0

EfficientNet-B0 employs compound scaling to balance network depth, width, and resolution. It is selected for:

- High accuracy with fewer parameters (~5.3M)
- Suitability for real-time and edge deployment
- Efficient learning on balanced datasets

Training Strategy

- Transfer learning with pre-trained ImageNet weights
- Fine-tuning of higher layers for domain-specific feature learning
- Optimization using stochastic gradient descent (SGD) or Adam optimizer
- Cross-entropy loss function for multi-class classification

Overall Performance Evaluation

The ResNet-18 model demonstrated high-performance classification on the pomegranate disease dataset, comprising 5,099 test samples across five classes. The model achieved an overall accuracy of 95.63%, correctly classifying 4,876 samples, with only 223 misclassifications, resulting in a low error rate of 4.37%
The evaluation metrics indicate a well-balanced model performance:

- **Precision:** 96.35%

- **Recall:** 95.23%
- **F1-score:** 96.21%

The slightly higher precision compared to recall suggests that the model prioritizes specificity, minimizing false positives. This behavior is particularly desirable in agricultural applications, where avoiding unnecessary treatments is critical.

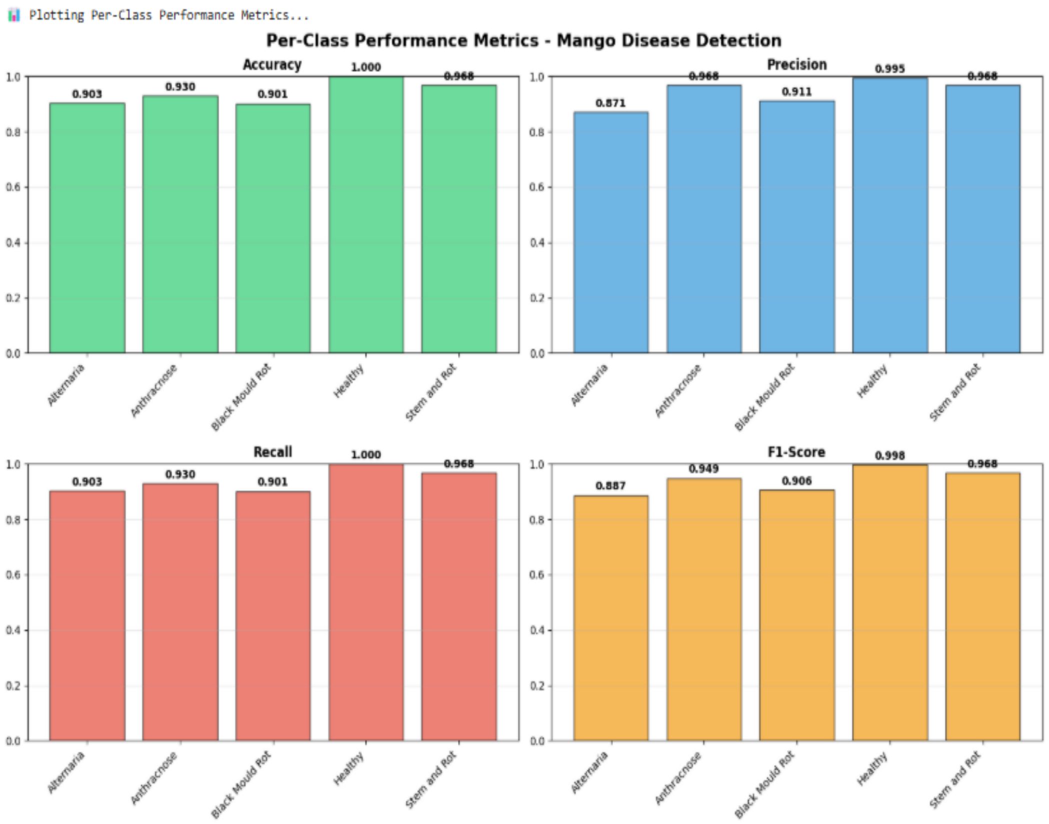
Class-Wise Performance Analysis

The class-wise evaluation reveals consistent and robust performance across all disease categories.

- **Healthy Pomegranate** achieved the highest performance with **100% recall** and **99.86% accuracy**, ensuring reliable identification of healthy samples and preventing unnecessary interventions.
- **Anthracnose** exhibited excellent classification with an F1-score of **96%**, indicating strong discrimination capability.
- **Cercospora Fruit Spot** demonstrated high recall (**96%**) and balanced performance.
- **Alternaria Fruit Spot** and **Bacterial Blight** showed slightly lower performance (F1-score ~93%), primarily due to visual similarity between disease symptoms.

The narrow performance range (**92.55%–99.86%**) across classes indicates **high consistency**, despite moderate dataset imbalance.

Figure 1 :Per-Class Performance Metrics for Mango Disease Detection Using EfficientNet-B0.



Confusion Matrix and Error Analysis:

Figure 2: Confusion Matrix for Mango Disease Classification Using EfficientNet-B0

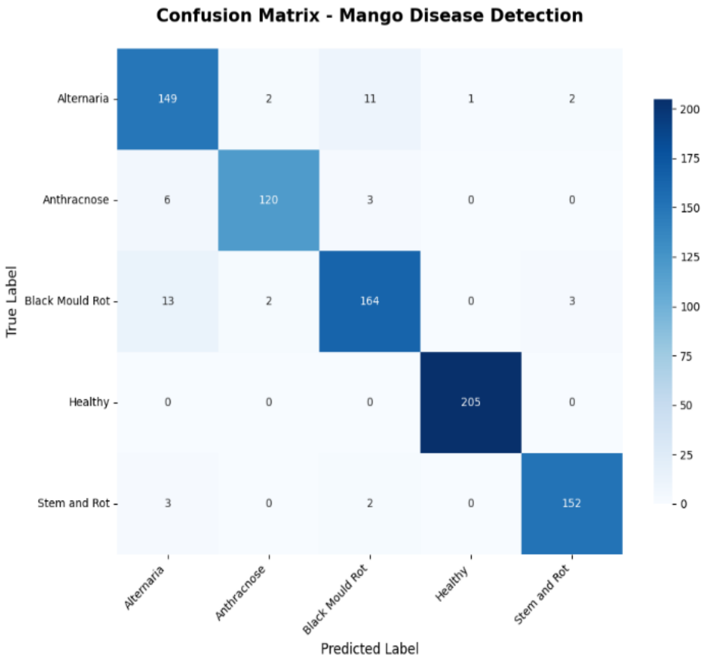


Figure 5.2: Confusion Matrix for Mango Disease Classification Using EfficientNet-B0

The confusion matrix reveals structured misclassification patterns, rather than random errors:

- The most frequent confusion occurs between Alternaria and Black Mould Rot, due to similar lesion patterns.
- Minor confusion is observed between Black Mould Rot and Stem and Rot.
- The Healthy class shows near-perfect classification, with only one misclassification.

These patterns indicate that errors arise primarily from intrinsic visual similarities, reflecting real-world diagnostic challenges.

ROC and Discriminative Capability

The model achieved **exceptional AUC scores (>0.98)** across all classes, with the **Healthy class achieving a perfect AUC of 1.00**, indicating complete separability. The ROC curves demonstrate:

- High true positive rates at low false positive rates
- Strong class separability
- High model confidence in predictions

Sample Prediction Visualization and Qualitative Analysis

Figure 3: Sample Prediction Results for Mango Disease Classification Using EfficientNet-B0 Showing Correct and Misclassified Cases with Confidence Scores

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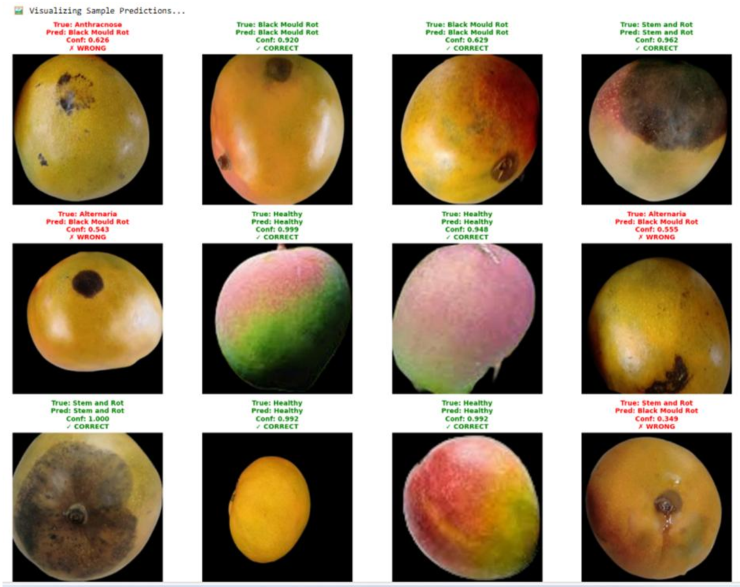
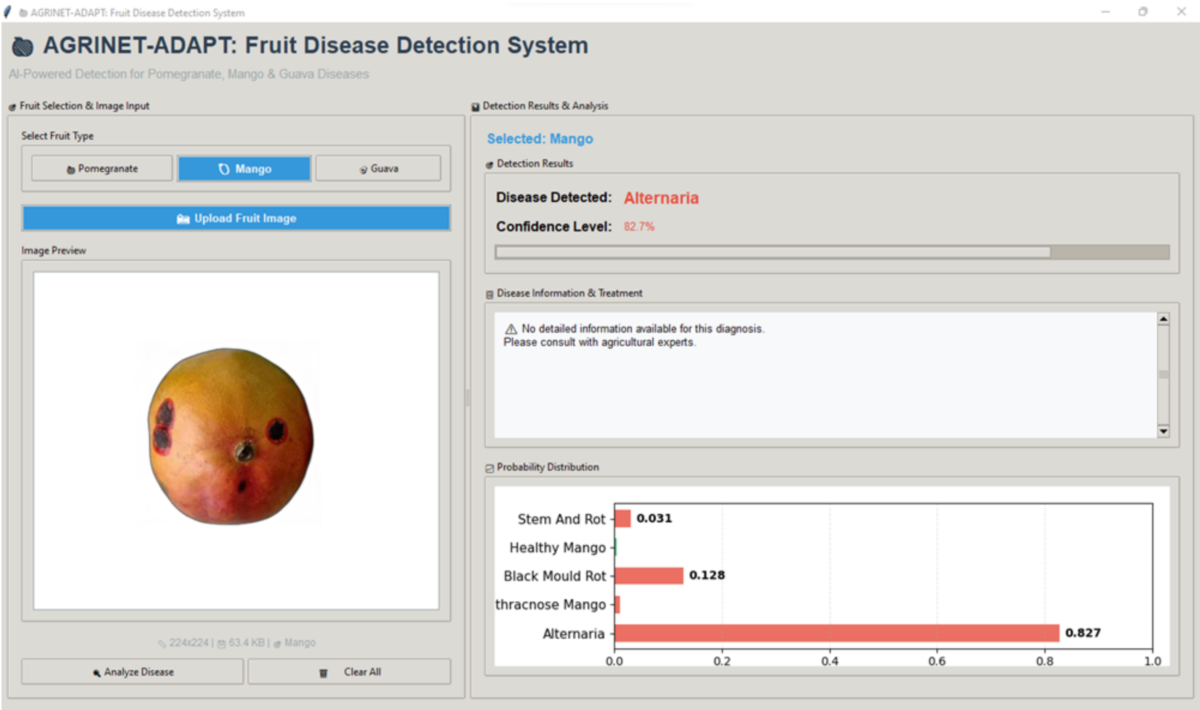


The figure presents representative sample predictions generated by the EfficientNet-B0 model for mango disease detection, including both correctly classified and misclassified instances. Each sample displays the true label, predicted label, and confidence score, highlighting the model's decision-making behavior. Correct predictions are predominantly associated with high confidence scores, while misclassifications occur in cases with visually similar disease patterns (e.g., Alternaria vs. Black Mould Rot) or ambiguous symptom presentation. This visualization demonstrates the model's strong classification capability, effective feature learning, and appropriate uncertainty estimation in challenging scenarios.

Figure 4: AgriNet-Adapt System Interface for Mango Disease Detection Showing Prediction Output and Probability Distribution



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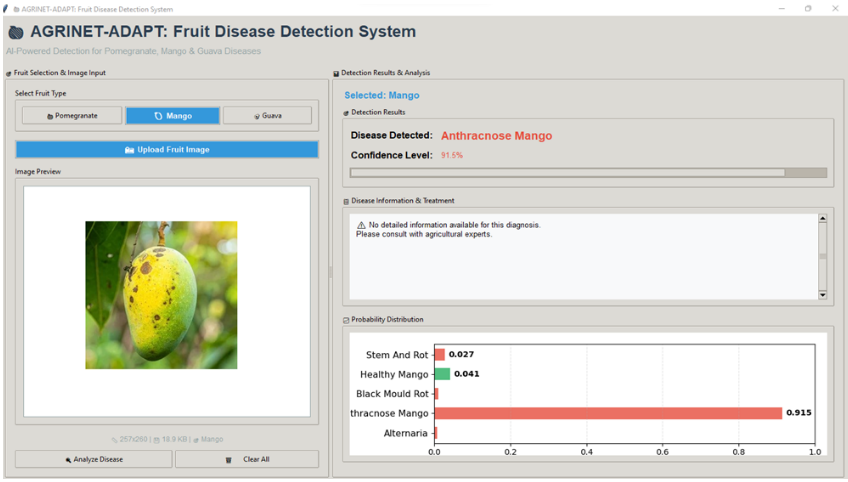
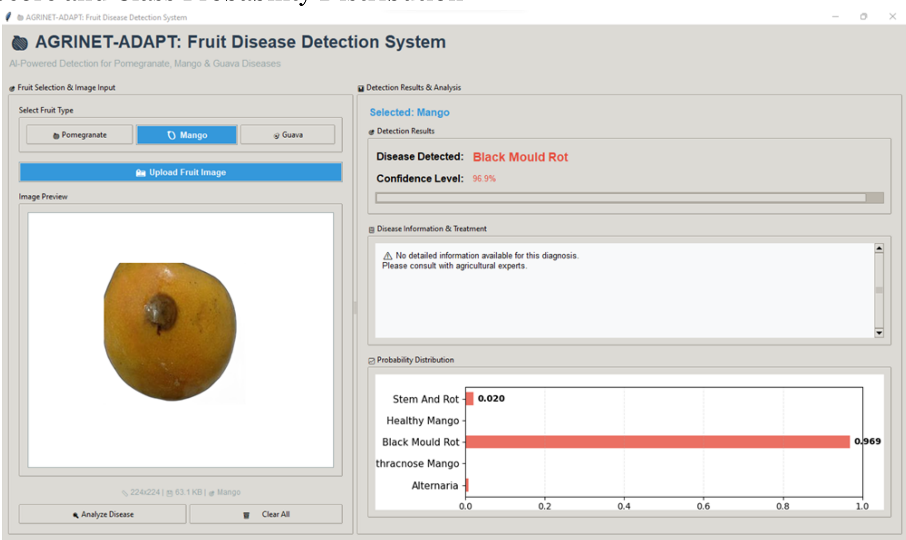
The figure illustrates the proposed AgriNet-Adapt framework during mango disease diagnosis. The system processes an input fruit image and outputs the predicted disease class (Alternaria) along with a confidence score (82.7%). The interface also presents a probability distribution across all disease classes, providing interpretability and transparency in decision-making. This demonstrates the practical deployment capability of the proposed model for real-time, user-friendly agricultural applications.

Figure 5: AgriNet-Adapt System Output for Anthracnose Detection in Mango with Confidence Score and Class Probability Distribution



The figure presents the AgriNet-Adapt system interface demonstrating the detection of Anthracnose disease in mango with a high confidence score of 91.5%. The uploaded fruit image is analyzed, and the system outputs the predicted class along with a probability distribution across all disease categories, highlighting strong confidence in the correct class. This visualization emphasizes the system's capability for accurate, interpretable, and real-time disease diagnosis, supporting practical deployment in precision agriculture.

Figure 6: AgriNet-Adapt Interface Demonstrating Black Mould Rot Detection in Mango with Confidence Score and Class Probability Distribution



The figure presents the AgriNet-Adapt system detecting **Black Mould Rot** in a mango sample with a high confidence score of **96.9%**. The interface displays the input image, predicted disease label, and a

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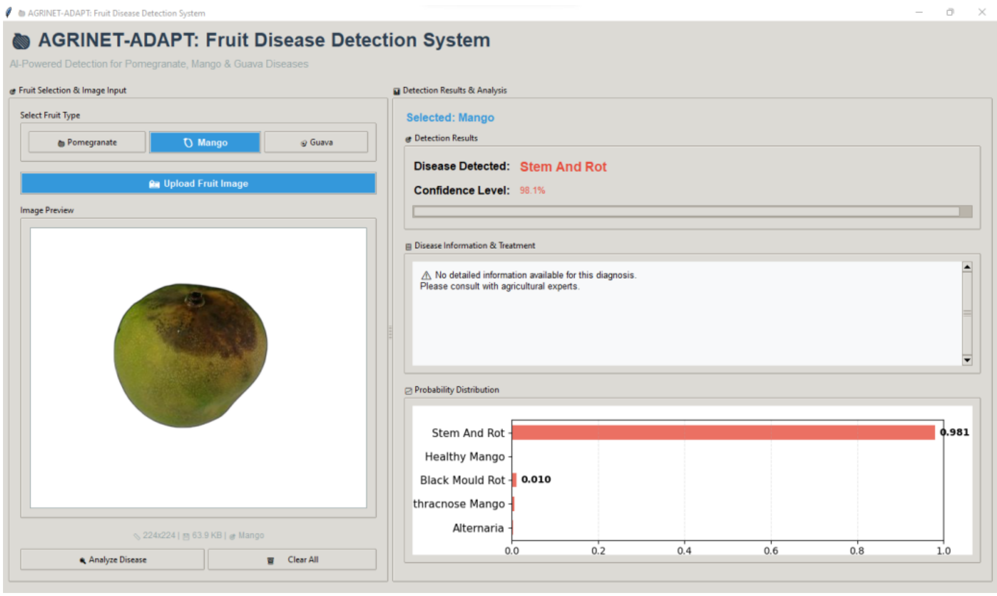
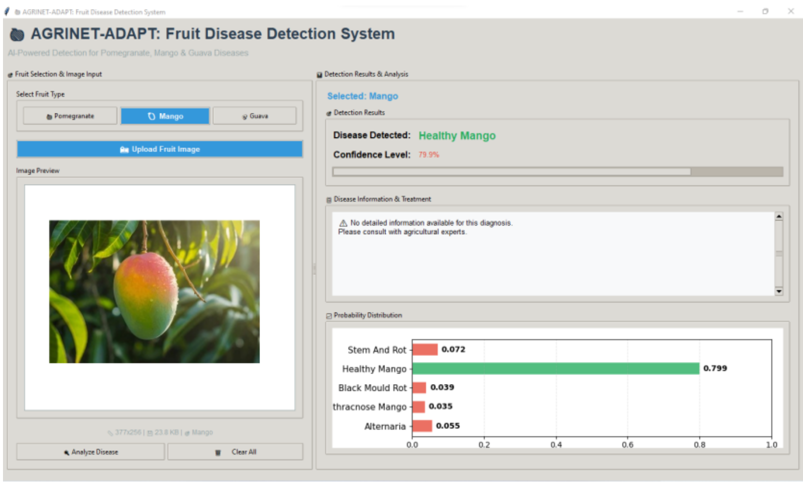
probability distribution across all classes, where Black Mould Rot shows dominant probability. This result highlights the model's ability to achieve **high-confidence, accurate predictions** for clearly distinguishable disease patterns, reinforcing its applicability in real-time agricultural diagnostics.

Figure 7: AgriNet-Adapt System Output for Stem and Rot Detection in Mango with High Confidence and Probability Distribution



The figure illustrates the AgriNet-Adapt system detecting Stem and Rot disease in a mango sample with a high confidence score of 98.1%. The interface presents the input image, predicted disease label, and a probability distribution across all classes, where Stem and Rot exhibits a dominant probability. This result demonstrates the model's capability to achieve highly accurate and confident predictions for severe and visually distinct disease conditions, supporting reliable real-time agricultural diagnosis.

Figure 8: AgriNet-Adapt System Output for Healthy Mango Classification with Confidence Score and Class Probability Distribution



The figure presents the AgriNet-Adapt system correctly identifying a healthy mango sample with a confidence score of 79.9%. The interface displays the input image along with the predicted class and a probability distribution across all disease categories, where the Healthy class shows the highest probability. This result highlights the model's ability to accurately distinguish healthy samples from diseased ones, which is crucial for preventing unnecessary treatments and supporting efficient crop management.

Conclusion:

This study presents AgriNet-Adapt, a novel hybrid deep learning framework for fruit disease detection that introduces the concept of Algorithmic Agronomy, enabling crop-specific model selection. Unlike conventional one-size-fits-all approaches, the proposed framework dynamically aligns deep learning architectures with crop characteristics, resulting in improved accuracy, efficiency, and generalization.

Experimental results demonstrate that the proposed framework achieves high classification performance across multiple fruit datasets, with accuracies of 95.63% for pomegranate, 94.27% for mango, and 96.33% for guava

The models exhibit strong robustness, balanced precision-recall performance, and excellent discrimination capability, as evidenced by high F1-scores and AUC values. Notably, the system achieves near-perfect detection of healthy samples, which is critical for reducing unnecessary agricultural interventions.

The results further highlight that deep learning architectures such as ResNet-18 and EfficientNet-B0 significantly outperform traditional machine learning models, achieving substantial reductions in error rates and improved classification consistency. The observed misclassifications are primarily associated with visually similar disease patterns, reflecting inherent challenges rather than model limitations.

Overall, this work establishes a new direction in agricultural AI by promoting adaptive, context-aware deep learning systems. Future work may focus on integrating larger and more diverse datasets, incorporating attention mechanisms or transformer-based models, and extending the framework to additional crops and disease types to further enhance scalability and real-world impact.

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