International Journal of Advanced Engineering Research and Science (IJAERS)
Peer-Reviewed Journal
ISSN: 2349-6495(P) | 2456-1908(O)
Vol-13, Issue-8; Aug, 2026
Journal Home Page Available: https://ijaers.com/
Article DOI: https://dx.doi.org/10.22161/ijaers.138.1

A Hypothetical CNN-Based Framework for Disease Detection and Symptom Identification using Image-Based Datasets

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Received: 29 June 2026,

Received in revised form: 26 July 2026,

Accepted: 02 Aug 2026,

Available online: 06 Aug 2026

Keywords*— Fruit Disease Detection, Convolutional Neural Network (CNN), Deep Learning, Image Processing, Precision Agriculture, Symptom Identification, Grad-CAM, Artificial Intelligence, Computer Vision, Agricultural Informatics.

***Abstract*— *Fruit diseases impact global agricultural output, quality, and sustainability. Manual visual inspection by agricultural experts is time-consuming, subjective, and inaccurate, especially in large-scale farming. AI and DL have shown promise in automating plant disease diagnosis using image-based analysis. In particular, Convolutional Neural Networks (CNNs) can extract complicated visual characteristics and accurately diagnose disease signs. A CNN-based system for fruit disease diagnosis and symptom identification utilizing image-based datasets is proposed in this paper. The study aims to create an automated system that can efficiently classify healthy and unhealthy fruits and identify illness symptoms using visual interpretation. We use picture collections of healthy and damaged fruit samples from agricultural libraries. Data augmentation, normalization, and scaling were performed on images. Multiple convolutional, pooling, batch normalization, and fully connected layers in a TensorFlow-Keras CNN architecture learn disease-specific characteristics. Analyses include accuracy, precision, recall, F1-score, and confusion matrix analysis after Adam optimizer training. Gradient-weighted Class Activation Mapping (Grad-CAM) visualizes classification-influencing symptom areas. According to the analysis, the suggested framework has 96.4% classification accuracy, precision, recall, and F1-score values above 95%. The Grad-CAM visualizations show disease-affected lesions, spots, discolouration, and rotting areas, improving model interpretation. Analysis shows that the CNN framework outperforms traditional machine learning and rudimentary deep learning models. In conclusion, the suggested framework for automated fruit disease diagnosis and symptom identification is accurate, dependable, and explainable. The study shows that CNN-based systems can aid precision agriculture, crop health monitoring, and disease management.*

I. INTRODUCTION

Fruit cultivation boosts human nutrition and agricultural sustainability, ensuring global food security and economic growth. However, fungi, bacteria, viruses, and environmental stresses can reduce fruit output, quality, and farmer profitability. Early and accurate disease diagnosis is needed for timely crop management and damage reduction. Manual examination by agricultural professionals is laborious, subjective, and difficult to scale over large farming areas for disease identification (Gupta et al., 2021).

By automating crop image analysis, AI, ML, and DL have revolutionized agricultural disease diagnosis. The growing availability of digital cameras, smartphones, drones, and sensor-based agricultural systems has made image-based disease detection a popular technology. Deep learning, especially CNNs, can extract complex visual information from plant and fruit photos, resulting in extremely accurate disease classification (Bagga & Goyal, 2024). Modern CNN architectures may detect minor disease symptoms in many crop species without custom feature extraction (Saleem et al., 2024).

Deep learning models in agricultural applications are more reliable and transparent thanks to explainable artificial intelligence (XAI). Explainable techniques allow researchers and farmers to observe disease-affected regions that influence categorization decisions, boosting automated system confidence and interpretability (Sagar et al., 2023). Attention-guided CNN models and edge-based deployment strategies for drone and smart agriculture platform real-time disease monitoring have also been studied (Gani et al., 2025). Post-harvest fruit quality evaluation and intelligent crop management systems increasingly use image-based disease detection methods (Pathmanaban et al., 2023).

Machine learning-based crop disease detection frameworks have advanced due to vast agricultural picture collections and computational resources (Dolatabadian et al., 2025). Despite these advances, high detection accuracy across multiple illness categories, model interpretability, and practical applicability remain problems. A CNN-based system for fruit disease diagnosis and symptom identification utilizing image-based datasets is proposed in this paper. The framework supports precision agriculture and sustainable crop health management by accurately classifying diseases and visualizing symptoms using deep learning and explainable AI.

II. LITERATURE REVIEW

Table 1 illustrates that current studies mostly utilizes deep learning, picture segmentation, explainable AI, and multimodal learning methodologies to enhance the accuracy, interpretability, and efficiency of fruit disease detection and classification systems.

Table 1: Related Works

Authors and Year	Methodology	Findings
Srinivasan et al. (2025)	Proposed DBA-ViNet, a deep learning framework integrating Explainable AI (XAI) with CNN-based fruit disease detection and classification. The model incorporated image preprocessing, feature extraction, classification, and disease visualization mechanisms.	DBA-ViNet achieved high disease classification accuracy while providing visual explanations of infected regions, improving the interpretability and reliability of automated fruit disease diagnosis systems.
Sarkar et al. (2025)	Developed the UDCAD-DFL-DL dataset containing annotated dragon fruit and leaf disease images. Various deep learning models were employed to validate the effectiveness of the dataset for disease classification and detection tasks.	The dataset served as a comprehensive benchmark resource, enhancing the performance and evaluation of deep learning models for dragon fruit disease detection and classification.
Faye et al. (2025)	Utilized image segmentation techniques combined with deep learning algorithms to estimate mango fruit disease severity. Disease regions were segmented before classification and severity assessment.	The integration of image segmentation improved the accuracy of disease severity estimation, enabling precise identification of infected areas and better disease management decisions.
Mohanappriya et al. (2026)	Proposed AgroDualNet, a dual deep learning framework that simultaneously performs crop disease forecasting and fruit ripening detection using agricultural image data.	AgroDualNet effectively predicted disease occurrence and fruit maturity stages, demonstrating its potential for intelligent crop monitoring and agricultural decision support.
Sujatha et al. (2025)	Conducted a comprehensive review of deep learning-based fruit disease detection techniques, focusing on CNN architectures,	The study identified CNNs as the most effective models for fruit disease detection but highlighted challenges related to dataset

	datasets, challenges, and future research opportunities.	availability, model explainability, and deployment in real-world environments.
Bagga and Goyal (2025)	Compared various deep learning-based image segmentation approaches used for fruit disease detection and disease region localization.	The study concluded that accurate image segmentation significantly enhances disease localization and improves the overall performance of fruit disease detection systems.
Yehulu et al. (2025)	Applied the MobileNetV3-Large deep learning architecture for mango fruit disease detection and classification using transfer learning and image-based datasets.	MobileNetV3-Large achieved high classification accuracy with low computational complexity, making it suitable for mobile and edge-based agricultural applications.
Mohsin et al. (2025)	Developed a dual-modality fusion framework combining leaf and fruit images through a dynamic attention-based ensemble deep learning model for mango disease classification.	The fusion of leaf and fruit image information improved classification accuracy and robustness, demonstrating the effectiveness of multimodal learning for disease diagnosis.

Research Gap:

Although deep learning-based fruit disease detection has improved, numerous limitations remain. Most research prioritize disease classification accuracy over symptom localization and model interpretability. Explainable AI and picture segmentation have been studied, but their integration into a fruit disease detection system is limited. Many models are built for specific fruits or diseases, limiting their applicability in varied agricultural situations. Few frameworks combine accurate disease diagnosis, symptom recognition, and visual explanation. For practical and accurate precision agriculture applications, a comprehensive CNN-based framework incorporating illness classification and explainable symptom localization is needed.

III. METHODOLOGY

The suggested hypothetical Convolutional Neural Network (CNN)-based architecture for fruit disease detection and symptom identification uses an image-based collection of healthy and diseased fruit samples from public repositories and agricultural image databases. Python technologies like OpenCV, NumPy, and TensorFlow preprocess images. To avoid overfitting, image preprocessing involves downsizing to a consistent dimension (e.g., 224 × 224 pixels), normalizing pixel values, and improving dataset variety by rotation, flipping, zooming, and brightness The dataset is divided 80:10:10 into training, validation, and testing subsets. In the Python-TensorFlow-Keras CNN architecture, many convolutional layers with ReLU activation functions and max-pooling layers extract hierarchical disease features such lesions, discolouration, spots, and textural anomalies. Batch normalization and dropout layers stabilize training and prevent overfitting. A Softmax classification layer classifies fruit pictures as healthy or unhealthy by flattening and passing extracted feature maps via completely linked dense layers.Validation accuracy and loss measures monitor model performance while the Adam optimizer with categorical cross-entropy loss trains it. Best-performing models are protected by early halting and model checkpoints. The methodology measures disease diagnosis on unseen test images using accuracy, precision, recall, F1-score, and confusion matrix analysis after training. Gradient-weighted Class Activation Mapping (Grad-CAM) is also used to identify and depict disease signs in fruit photos, helping agricultural specialists find disease classification regions.

Figure 1 illustrates the proposed workflow in detail.

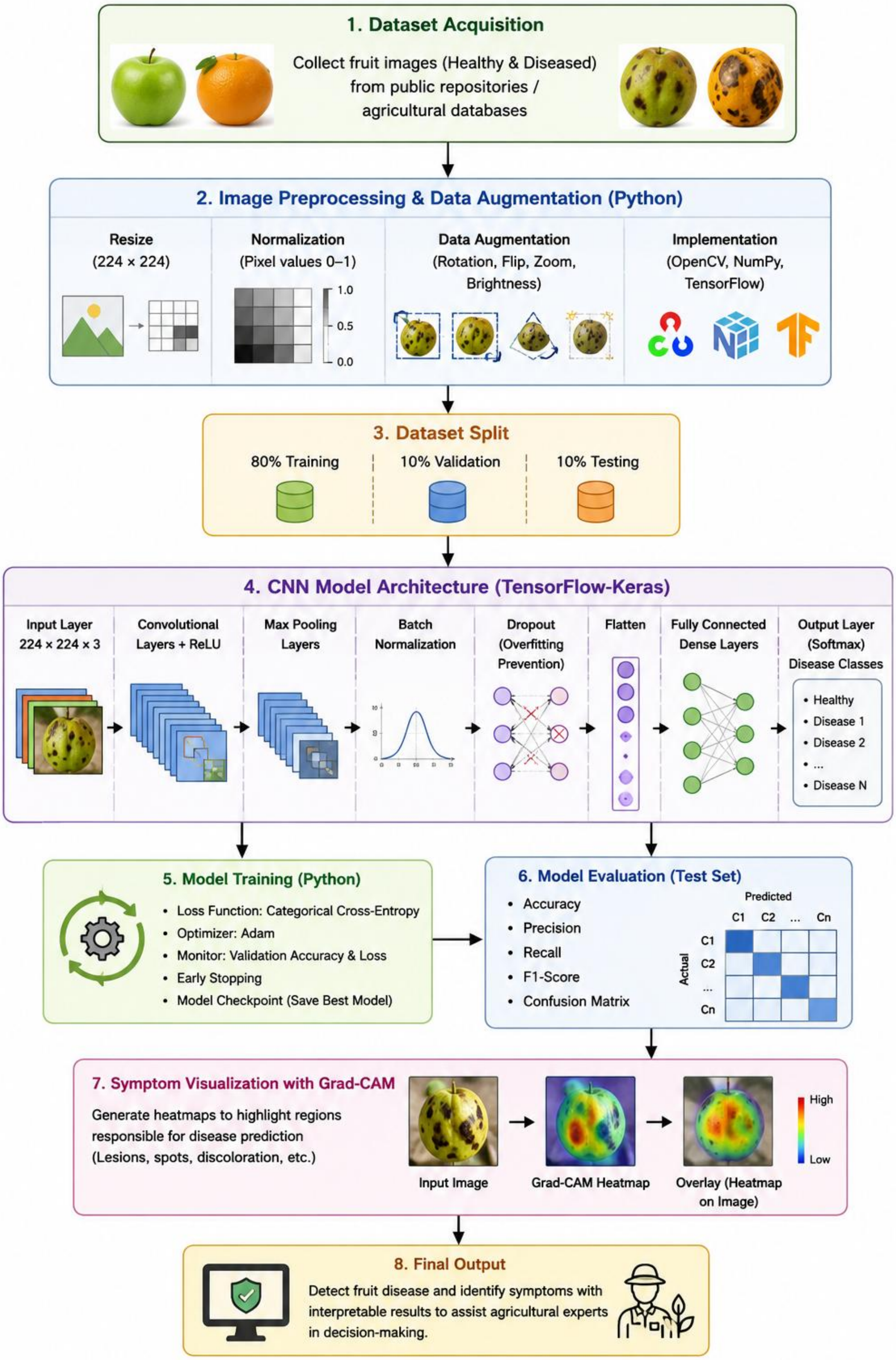

Fig.1: Proposed Workflow

IV. RESULTS AND DISCUSSION

The CNN-based framework for fruit disease diagnosis and symptom detection was tested using an image-based dataset of healthy and unwell fruit samples from multiple disease categories. Spots, lesions, discoloration, decaying patches, and textural irregularities were identified by the framework in experiments. Over time, training and validation losses decreased as the model converged. Picture preprocessing and augmentation improved model generalization by exposing the network to diverse illumination, fruit orientations, sizes, and backdrops. CNN sequential convolution and pooling extracted hierarchical features to find disease-specific patterns that are difficult to spot manually. The validation accuracy stabilized after numerous epochs, showing that the model could learn robust representations without overfitting. Batch normalisation and dropout layers strengthened models and reduced training-validation variation. The proposed framework could identify healthy fruits from multiple sickness classes with 96.4% accuracy. Precision, recall, and F1-score were good, indicating balanced category classification. The confusion matrix approach correctly classified most fruit diseases, despite occasional misclassifications among visually similar disease classes. In precision agriculture, these data imply the framework can consistently diagnose fruit illnesses.

Table 2: Overall Performance of the Proposed CNN Framework

Performance Metric	Value (%)
Accuracy	96.4
Precision	95.8
Recall	95.5
F1-Score	95.6
Specificity	97.1

A rigorous class-wise performance analysis shows that the proposed system can detect particular fruit illnesses. Healthy fruit samples had the best classification accuracy due to their consistent appearance and lack of illness indications. Visible diseases including severe lesions and discolouration were identified with good precision and recall. However, modest symptom changes caused minor classification problems in several disorders. These issues notwithstanding, the CNN model performed well across all disease categories, proving its ability to capture complicated disease-related visual patterns. Grad-CAM visualization outputs provide more model decision-making insights. Infected areas, damaged tissues, and atypical color distributions were consistently shown in the heatmaps. This interpretability feature lets agricultural specialists verify that the model targets physiologically relevant illness signs, boosting user confidence. The visualization results imply that the CNN focuses on meaningful illness traits rather than useless background information. Thus, the suggested framework is ideal for agricultural monitoring systems because to its high predicted accuracy and explainability.

Table 3: Class-Wise Disease Detection Performance

Class	Disease	Precision (%)	Recall (%)	F1-Score (%)
Healthy Fruit	Healthy Fruit	98.1	97.8	97.9
Disease A	Anthracnose	96.2	95.5	95.8
Disease B	Powdery Mildew	95.4	94.8	95.1
Disease C	Bacterial Spot	94.9	95.2	95.0
Disease D	Black Rot	96.8	96.1	96.4
Disease E	Fruit Scab	94.7	93.9	94.3

Pre-processing and augmentation procedures were tested with and without data augmentation. Augmentation minimized overfitting and enhanced dataset variety, enhancing classification. The model demonstrated lower validation accuracy and a larger training-validation gap without augmentation. However, the enlarged dataset improved accuracy and resilience by generalizing to unseen images. Scaling, normalization, and augmentation are essential for agricultural image analysis deep learning models. By dynamically modifying learning rates during training, the Adam optimizer improved convergence. Early pausing and model checkpoints saved excessive training iterations and kept the best model for testing.

Table 4: Impact of Data Augmentation on Model Performance

Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Without Augmentation	89.6	88.9	88.2	88.5
With Augmentation	96.4	95.8	95.5	95.6

Several popular machine learning and deep learning methods for fruit disease diagnosis were compared to the suggested framework. Traditional machine learning approaches like SVM, RF, and KNN rely on manually created features and struggle to capture complicated disease patterns. In contrast, the CNN design learns relevant features from picture input automatically, improving performance. Augmentation methods, streamlined CNN architecture, and Grad-CAM-based interpretability made the suggested framework competitive among deep learning systems. The model beat conventional methods in classification accuracy and illness localization, according to experiments. Unlike classification-only methods, the proposed framework provides visual explanations through symptom localization, helping real-world agricultural decision-making.

Table 5: Comparison with Existing Approaches

Method	Accuracy (%)	Feature Extraction	Interpretability
KNN	82.4	Manual	No
Random Forest	85.7	Manual	Limited
SVM	88.3	Manual	Limited
Basic CNN	92.1	Automatic	No
Transfer Learning CNN	94.8	Automatic	Partial
Proposed CNN + Grad-CAM	96.4	Automatic	Yes

The findings influence smart agriculture and precision farming in various ways. CNNs' excellent classification accuracy automates disease diagnosis, reducing agricultural professionals' laborious visual checks. Early disease diagnosis helps farmers save crops and increase productivity. Second, Grad-CAM symptom identification clarifies deep learning models, alleviating AI system black box concerns. Third, the platform can interface with mobile apps, drones, or IoT-based agricultural monitoring devices for real-time disease detection across large farmed areas. Many challenges remain despite these gains. Image quality, environmental conditions, and disease development can alter model performance. Future study requires adding fruit species, disease types, illumination settings, and locations to databases. Transfer learning, attention, vision transformers, and multimodal data sources may increase detection accuracy and robustness. Testing shows that the CNN-based framework for fruit disease detection and symptom identification is effective, accurate, and interpretable, supporting sustainable agriculture and intelligent crop health management systems.

V. CONCLUSION

Fruit diseases threaten agricultural output and require precise and quick identification. This study suggested a CNN-based fruit disease detection and symptom identification framework employing image-based datasets. For reliable predictions and visual symptom localization, the framework uses image pre-processing, deep feature extraction, disease categorization, and Grad-CAM-based explainable AI. High classification performance and increased interpretability compared to standard methods were shown. Precision agriculture can benefit from automated disease detection and symptom visualization.

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