VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"Jnana Sangama", Belagavi-590018

Project Report

on

Automated Detection of Mango Diseases and Pesticide Residue using Hybrid Deep Learning Approaches

Submitted in partial fulfillment of the requirements of the degree of

BACHELOR OF ENGINEERING

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INFORMATION SCIENCE & ENGINEERING

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DEPARTMENT OF INFORMATION SCIENCE & ENGINEERING

GLOBAL ACADEMY OF TECHNOLOGY

(An Autonomous Institute Affiliated to VTU, Belagavi)

Ideal Homes, Rajarajeshwari Nagar, Bengaluru-560098.

(Approved by AICTE, New Delhi, NAAC Accredited with 'A' Grade, NBA Accredited 2022-2026)

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CERTIFICATE

Certified that the project work entitled **'Automated Detection of Mango Diseases and Pesticide Residue using Hybrid Deep Learning Approaches'** is a work carried out by **Rakesh J(1GA22IS119), Darshan DH(1GA23IS403), Deepak K (1GA23IS404)** and **Manoj Kumar BM(1GA23IS408)** bonafide students of **Global Academy of Technology, Bengaluru** in partial fulfillment for the award of the degree of Bachelor of Engineering in **Information Science & Engineering** of the **Visvesvaraya Technological University, Belagavi** during the year **2025-2026**. It is certified that all corrections/suggestions indicated for the Internal Assessment have been incorporated in the report deposited in the departmental library. The Project Work (22ISEP76) report has been approved as it satisfies the academic requirements in respect of project work prescribed for the said degree.

Signature of the Guide	Signature of the HOD	Signature of the Principal
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Professor, Department of ISE	Head of the Dept of ISE	Principal
GAT, Bengaluru.	GAT, Bengaluru.	GAT, Bengaluru.

Name of the Examiners: **Signature with date**

1. ____________________________ --

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DECLARATION

We, **Rakesh J(1GA22IS119), Darshan DH(1GA23IS403), Deepak K (1GA23IS404)** and **Manoj Kumar BM(1GA23IS408)** students of 7th semester BE in Information Science and Engineering, **Global Academy of Technology** , Bengaluru, hereby declare that the project work entitled **"Automated Detection of Mango Diseases and Pesticide Residue using Hybrid Deep Learning Approaches"** submitted to **Visvesvaraya Technological University** during the academic year **2025-26** is a record of an original work done by us under the guidance of **Dr. Deepak G, Professor**, Department of Information Science & Engineering, Global Academy of Technology, Bengaluru. This project work is submitted in partial fulfilment of the requirements for the award of the degree of Bachelor of Engineering in Information Science & Engineering. The results embodied in this report have not been submitted to any other University or Institute for the award of any degree.

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ABSTRACT

In recent years, ensuring food quality and safety has become a critical challenge due to the increasing demand for agricultural products and the growing risks associated with plant diseases and pesticide contamination. Traditional methods of mango quality inspection rely heavily on manual observation and laboratory testing, which are time-consuming, subjective, and prone to human error. This project presents an intelligent, AI-driven mango analysis system that automates disease identification and pesticide detection using deep learning and machine learning techniques.

The proposed system performs dual-task analysis by classifying mango images into multiple disease categories and determining the presence of pesticide residues. A hybrid artificial intelligence framework combining Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) is employed to achieve high accuracy and robustness. CNN models extract deep visual features from mango images, while SVM classifiers utilize these features to enhance classification performance. An intelligent model selection mechanism automatically chooses the best-performing model for each task, ensuring optimal prediction accuracy.

The system is implemented as a full-stack web application using a React-based frontend and a Flask-powered backend, enabling real-time image uploads, fast inference, and clear visualization of prediction confidence and class probabilities. Experimental results demonstrate an accuracy of 81.5% for multi-class disease detection and 97.1% for binary pesticide detection, highlighting the effectiveness of the hybrid approach.

Overall, this project demonstrates that integrating advanced AI models with modern web technologies provides a scalable, efficient, and reliable solution for automated fruit quality assessment. The proposed system has significant potential applications in agriculture, food safety monitoring, supply chain quality control, and smart farming systems.

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We earnestly thank **Dr. H. B. Balakrishna, Principal, Global Academy of Technology** for facilitating academic excellence in the college and providing us with the congenial environment to work in, that helped us in completing this project.

We wish to extend our profound thanks to our internal guide **Dr. Deepak G, Professor, Department of Information Science & Engineering, GAT,** for giving us the consent to carry out this project and valuable advice at every stage, which helped us in the successful completion of the project.

We owe our sincere thanks to our project coordinator, **Prof. Sharmila Chidaravalli, Assistant Professor, Department of Information Science & Engineering, GAT**, for her immense help during the project and also for his valuable suggestions on the project report preparations.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Agriculture plays a vital role in ensuring food security and economic stability, particularly in countries where fruits like mangoes are a major agricultural commodity. However, mango production and distribution face significant challenges due to plant diseases and excessive pesticide usage. Traditional methods of quality assessment rely on manual inspection and laboratory testing, which are time-consuming, costly, and often inconsistent due to human subjectivity. These limitations highlight the need for an automated, accurate, and scalable solution for mango quality analysis.

Advancements in Artificial Intelligence, particularly in computer vision and machine learning, have enabled the development of intelligent systems capable of analysing agricultural produce with high precision. Deep learning models such as Convolutional Neural Networks (CNNs) can automatically extract complex visual features from images, making them highly effective for disease detection. In this project, mango images are analysed to identify common diseases such as Alternaria, Anthracnose, Black Mould Rot, Stem End Rot, and Healthy conditions. By learning patterns from large datasets, the system can detect subtle visual symptoms that are often difficult to identify through manual observation.

Despite the availability of AI models, standalone approaches often suffer from limitations such as overfitting, slow inference, or poor generalization. To address these challenges, the proposed system integrates an intelligent hybrid model selection mechanism that automatically chooses the best-performing model based on validation accuracy. This ensures reliable predictions while maintaining low inference time. The system also provides confidence scores and per-class probabilities, enhancing transparency and user trust in the predictions.

The complete solution is implemented as a full-stack web application using a React-based frontend and a Flask-powered backend. Users can upload mango images through an intuitive interface, and the system processes the images in real time to deliver accurate results. By automating mango disease detection and pesticide analysis, the proposed system improves efficiency, reduces dependency on manual inspection, and supports better decision-making across agriculture supply chains.

1.2 Motivation of the Project

The core motivation behind this project is to address the persistent challenges associated with manual mango quality inspection and food safety assessment. In traditional agricultural and supply chain practices, disease identification and pesticide residue detection are largely dependent on visual inspection and laboratory testing. These methods are often inconsistent, time-consuming, expensive, and prone to human error, leading to misclassification of produce and potential health risks for consumers.

The lack of intelligent and automated systems in current fruit quality assessment processes creates opportunities for diseased or pesticide-contaminated mangoes to enter the market. This not only affects consumer health but also results in economic losses for farmers, exporters, and retailers. Manual inspection methods are unable to scale effectively with increasing production volumes and fail to provide real-time analysis, creating a significant gap between quality standards and actual market practices.

By incorporating Artificial Intelligence and automation, this project aims to provide a reliable, fast, and accurate mechanism for mango quality analysis. The use of deep learning models for disease detection and machine learning techniques for pesticide classification ensures objective decision-making based on data rather than human judgment. The hybrid CNN–SVM approach enhances prediction accuracy while reducing inference time, making the system suitable for real-world deployment.

The motivation is to create a transparent, scalable, and intelligent solution that supports farmers, quality inspectors, and food safety authorities in making informed decisions. By automating disease detection and pesticide identification through a user-friendly web interface, the system minimizes manual intervention, reduces inspection errors, and promotes safer agricultural practices. Ultimately, the proposed system contributes to improved food safety, better market trust, and the advancement of smart agriculture technologies.

1.3 Existing System

The existing mango quality assessment system predominantly relies on manual inspection and traditional laboratory-based testing methods. In most agricultural markets and supply chains, mangoes are visually examined by farmers, traders, or quality inspectors to identify surface-level defects and diseases. Pesticide residue detection is typically carried out through chemical analysis in specialized laboratories. While these methods are widely used, they are time-consuming, costly, and not suitable for large-scale or real-time assessment.

A major limitation of the current system is its dependence on human judgment, which is inherently subjective and prone to inconsistency. Visual inspection often fails to detect early-stage diseases or subtle symptoms that are not easily noticeable to the naked eye. Similarly, laboratory testing for pesticide residues requires advanced equipment, trained personnel, and significant processing time, making it impractical for routine screening at farms, markets, or distribution centers.

Another drawback of the existing system is the lack of automation and centralized data management. Inspection results are rarely stored digitally or shared across different stakeholders, making it difficult to track disease patterns, quality trends, or contamination history. The absence of real-time monitoring increases the risk of diseased or pesticide-contaminated mangoes entering the consumer market, potentially leading to health hazards and economic losses.

Furthermore, traditional quality assessment methods do not scale effectively with increasing agricultural production. Manual processes slow down supply chain operations and provide limited transparency in quality control. These shortcomings highlight the need for an intelligent, automated, and data-driven solution that reduces human dependency, improves detection accuracy, and ensures consistent quality assessment throughout the mango supply chain.

1.4 Limitations of Existing System

The traditional mango quality assessment methods currently in use face several limitations due to their reliance on manual inspection and laboratory-based analysis. These approaches lack automation, real-time processing, and intelligent decision-making capabilities. As a result, they are often inefficient, inconsistent, and unsuitable for large-scale agricultural operations. The absence of advanced image processing and machine learning techniques restricts the ability to detect diseases accurately and assess pesticide contamination effectively.

One of the major drawbacks of the existing system is the dependence on human observation for disease detection. Manual inspection is subjective and prone to error, especially when identifying early-stage diseases or visually similar symptoms. Laboratory testing for pesticide residues, although accurate, is time-consuming, expensive, and not feasible for on-site or real-time analysis. This delay can allow contaminated or diseased mangoes to enter the market, posing risks to consumer health and food safety.

Additionally, current systems lack centralized data storage and real-time monitoring capabilities. Inspection results are often recorded manually or not documented at all, making it difficult to analyze historical trends, track quality issues, or take preventive measures. There is minimal transparency for farmers, vendors, and quality inspectors, as the system does not provide confidence scores, prediction explanations, or automated reporting.

Furthermore, traditional quality assessment methods do not scale efficiently with increasing production volumes and expanding supply chains. The absence of intelligent automation limits throughput and increases operational costs. These limitations highlight the need for an AI-powered solution that offers accurate detection, real-time analysis, scalability, and improved transparency.

Key Limitations of the existing system are:

- No automated disease detection or intelligent classification mechanisms.
- Heavy reliance on manual inspection leading to subjective and inconsistent results.
- Time-consuming and costly laboratory testing for pesticide residue detection.
- Lack of real-time monitoring, centralized data storage, and analytics.
- Inability to detect early-stage diseases or subtle visual symptoms.
- Limited scalability and inefficiency in handling large volumes of produce.

1.5 Problem Statement

The current mango quality assessment process faces several challenges due to the reliance on manual inspection methods, inconsistent disease identification, and limited accessibility to pesticide residue testing. These limitations often lead to inaccurate classification of mango quality, allowing diseased or pesticide-contaminated fruits to reach consumers. The lack of automation, real-time analysis, and centralized monitoring reduces the effectiveness of quality control mechanisms across agricultural supply chains.

This project addresses these challenges by leveraging Artificial Intelligence and Machine Learning techniques to automate mango disease detection and pesticide residue identification. By integrating deep learning-based image analysis, hybrid classification models, and real-time data processing, the system aims to provide accurate, transparent, and scalable quality assessment. The proposed solution enhances decision-making, improves food safety, and supports efficient monitoring of mango quality, thereby promoting safer consumption and smarter agricultural practices.

1.6 Proposed System Overview

The proposed system introduces an intelligent, AI-driven framework designed to automate and enhance mango quality assessment through disease detection and pesticide residue analysis. It integrates advanced image processing with deep learning and machine learning techniques to ensure accurate, consistent, and real-time evaluation of mango quality.

The system employs Convolutional Neural Networks (CNN) for automated feature extraction from mango images, enabling precise identification of multiple disease categories such as Alternaria, Anthracnose, Black Mould Rot, Stem End Rot, and healthy conditions. For pesticide residue detection, a hybrid classification approach combining CNN-based feature extraction with Support Vector Machine (SVM) classification is utilized. This dual-model strategy enhances robustness and accuracy, particularly for binary classification between organic and pesticide-treated mangoes.

Users interact with the system through a web-based interface that allows image uploads and displays prediction results in real time. Once an image is submitted, the backend processes the input, selects the best-performing model based on validation metrics, and generates predictions along with confidence scores and class probabilities. All analysis results are stored in a centralized database, enabling traceability, historical analysis, and quality trend monitoring.

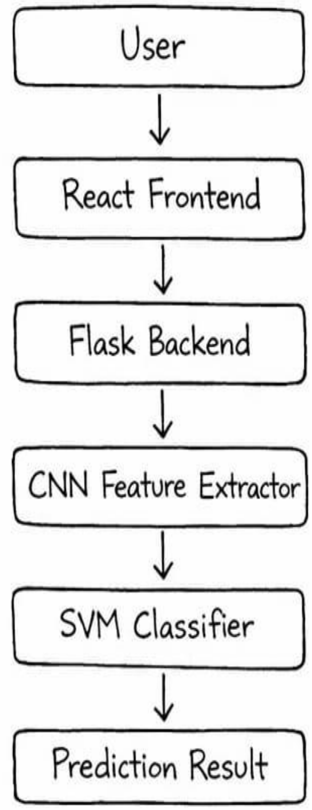

Figure 1.3: Block Diagram

1.7 Objectives of the Project

The objectives of this project are:

- To develop an AI-driven system for automated mango disease detection using deep learning techniques, ensuring accurate and consistent identification of multiple disease categories.
- To design and implement a machine learning-based pesticide residue detection mechanism that differentiates between organic and pesticide-treated mangoes with high reliability.
- To provide a real-time, user-friendly web-based interface for image upload,

analysis, and visualization of prediction results.

- To create a centralized data management system that enables traceability, performance monitoring, and quality trend analysis for improved agricultural decision-making.

1.8 Scope of the Project

This project focuses on designing and developing a full-stack web application for automated mango quality analysis, combining deep learning and machine learning techniques for disease and pesticide detection. The scope covers end-to-end functionality, starting from image upload to real-time prediction, while providing detailed confidence scores and per-class probabilities for each analysis task.

From a technological perspective, the system integrates advanced AI components such as Convolutional Neural Networks (CNN) for feature extraction and Support Vector Machines (SVM) for hybrid classification, along with web development technologies including React for the frontend and Flask for the backend. A centralized database stores model artifacts, training histories, and prediction records to enable traceability and performance monitoring.

While the initial application targets mangoes, the system architecture is scalable and can be adapted for quality inspection in other fruits, vegetables, or agricultural products. The project also supports real-time analysis, hybrid AI model selection, and a responsive web interface suitable for desktop and mobile devices, making it versatile for agricultural monitoring, research, and commercial quality control applications.

1.9 Significance of the Project

The significance of this project lies in its ability to enhance agricultural quality assessment through intelligent automation and precise detection of diseases and pesticide residues. Traditional manual inspection of mangoes is time-consuming, error-prone, and highly dependent on expert availability, which can lead to inconsistent results. By leveraging artificial intelligence, this system provides rapid, accurate, and standardized analysis, ensuring high-quality produce reaches consumers while minimizing the risk of contamination.

The system improves reliability by integrating a hybrid AI model that combines CNN-based feature extraction with SVM classification for optimal accuracy. Real-time predictions with confidence scores and per-class probabilities enable growers, traders, and quality control authorities to make informed decisions, enhancing transparency and traceability throughout the supply chain.

Moreover, the project offers strong potential for scalability and adaptability. Although primarily designed for mangoes, the modular architecture can be extended to other fruits and vegetables, supporting broader applications in agriculture and food safety. By providing an easy-to-use web interface with real-time monitoring, the system empowers users with varying technical backgrounds, promoting inclusivity and adoption of AI-driven agricultural practices. This contributes directly to reducing post-harvest losses, improving consumer safety, and fostering intelligent, technology-driven agricultural governance.

CHAPTER 2

LITERATURE SURVEY

S S, Kumar [1] examined an in-depth analysis using DL techniques to interpret data related to fruits through comprehensive research methodologies. The current focus on this field has garnered substantial interest because it holds promise for dramatically transforming agriculture by greatly improving our ability to monitor crops effectively. This document thoroughly examines current studies on these topics: distinguishing fruits based on their characteristics and identifying them visually in images. Different types of deep learning architecture designs are examined; notable examples include convolutional neural networks (CNNs), along with specific applications such as object detection using methods like You Only Look Once (YOLO). This comprehensive study emphasizes significant avenues for further investigation into automated, visual assessment of fruits through rigorous research and innovation.

Lu et al. [2] proposed a new lightweight deep learning solution for automated crop management in the study titled "Improved MobileNetV2 Crop Disease Identification Model for Intelligent Agriculture." The paper addresses the critical challenge of accurately identifying plant diseases on mobile and edge devices, which typically operate with limited computing resources. The core of the proposal is an advanced MobileNetV2 model that includes several architectural improvements to balance accuracy and efficiency. The main modification involves reducing the number of model parameters by shrinking the operation channels using point-by-point convolution. Tested on the PlantVillage dataset, the improved model achieved a high recognition rate of 99.53% accuracy. Importantly, the model reduced the number of parameters by 59% and improved inference speed by 8.5% compared to the original MobileNetV2.

Suryawanshi [3] presented the CSXAI model, a lightweight hybrid 2D CNN–SVM system designed for highly accurate identification and classification of various crop diseases in intelligent agriculture. The model successfully classifies 10 categories, including diseased and healthy states in crops such as strawberry, peach, cherry, and soybean, achieving an impressive average accuracy of 99.09%. A key innovation of this work is the integration of Explainable AI (XAI), specifically using Grad-CAM to generate visual heatmaps. This approach allows farmers to clearly visualize the exact diseased areas on leaves, providing an interpretable and practical solution that combines high performance with resource efficiency suitable for real-time field applications.

M. Kumar et al. [4] present a hybrid deep learning framework for plant disease detection that combines the efficient MobileNetV2 architecture with a lightweight compact CNN to optimize both accuracy and computational speed. The study achieved an impressive 95% accuracy using MobileNetV2 for disease classification, while the compact CNN demonstrated high efficiency with a minimum training time of 420 seconds. A key innovation of this work is the integration of LIME (Local Interpretable Model-agnostic Explainability), which provides transparent and visual insight into the model's decision-making process, effectively addressing the "black box" problem in AI adoption. This robust system establishes a practical benchmark for agricultural applications by balancing high disease detection rates for conditions such as apple scab and black rot with computational efficiency and meaningful result interpretation.

Thorata et al. [5] review recent advances in techniques for identifying pesticide residues on fruits and vegetables, a serious public health concern due to the risks associated with overconsumption. The study critiques traditional laboratory-based methods, such as liquid chromatography, for being time-consuming and expensive. It highlights a shift toward integrated systems that combine embedded technologies, sensors, and machine learning to automate detection. These modern approaches enable rapid and cost-effective identification of both the types and concentrations of pesticide residues, making them highly suitable for real-world agricultural and food safety applications.

Duhan et al. [6] address the challenge of deploying complex deep learning models for plant disease identification on resource-constrained edge devices by proposing RTR_Lite_MobileNetV2, an efficient and lightweight model derived from the standard MobileNetV2 architecture. The model incorporates several enhancements, including residual connections to improve feature flow, a trimmed channel attention mechanism for effective feature recalibration, and a hard-switch activation function to boost overall performance. This architecture is specifically designed to balance high classification accuracy with the computational efficiency required for deployment on edge devices.

Mohammad Manzurul Islam. [7] present a two-step model for improved detection of mango leaf diseases, addressing the strong dependence of many countries on the quality and yield of this economically important crop. The first stage employs an innovative handcrafted spatial feature extraction method to isolate critical disease-related features, while the second stage uses a knowledge distillation process to train a compact and efficient student network from a large, high-capacity teacher network. This combined approach results in a highly accurate system for rapid and reliable disease detection. The efficiency and targeted design of the model make it a valuable and practical tool for precision agriculture, supporting the economic sustainability of mango production.

Islam et al. [8] present a two-level model for improved detection of mango leaf diseases, addressing the strong reliance of many nations on the quality and yield of this crop. The first level employs an innovative handcrafted spatial feature extraction method to isolate critical disease characteristics, while the second level uses a knowledge distillation process to train a compact and efficient student network from a large, high-capacity teacher network. This combined approach results in a highly accurate system for early and reliable disease identification. The performance and specialized focus of the model make it a valuable and practical tool for precision agriculture, contributing to the economic stability of mango production.

Yamaçli et al. [9] explore the enhancement of plant disease detection by first applying essential image filtering and enhancement techniques—such as adjustments to brightness, contrast, sharpness, and blur—on raw leaf images. These preprocessed images are then used to train and evaluate two state-of-the-art deep learning models, MobileNetV2 and Xception. The core focus of the research is to assess how image enhancement impacts model performance in classifying and detecting plant health issues. The results demonstrate that filtering and enhancement significantly improve classification accuracy, offering valuable insights for strengthening the reliability and foundational stages of intelligent agriculture systems.

Gaikwad [10] provides a comprehensive review of image processing techniques specifically applied to the detection of defects in fruits. The study emphasizes that automation is crucial in agriculture to accelerate processing and ensure high product quality. It details various image processing methods used to identify different types of fruit defects, including bruises, rot, and physical damage. This research serves as a valuable reference for developers aiming to implement advanced computer vision solutions in post-harvest handling and food-sorting machinery.

Jhansi et al. [11] propose an IoT and Machine Learning (ML) system for real-time detection of pesticide residues on fruits and vegetables, addressing growing concerns about food safety. The system employs a hardware setup with pH and gas sensors for chemical data collection, along with an ESP32 camera to capture images of produce. This integrated, cost-effective, and non-destructive approach provides a practical and user-friendly solution to enhance monitoring and support informed decision-making in both agricultural and consumer contexts.

Boppana et al. [12] introduce a hybrid deep learning framework for plant disease detection that combines the efficient MobileNetV2 architecture with a lightweight Compact CNN to optimize both accuracy and computational speed. The study achieved 95% accuracy using MobileNetV2 for disease classification, while the Compact CNN demonstrated high efficiency with a minimal training time of 420 seconds. A key innovation of this work is the integration of LIME (Local Interpretable Model-agnostic Explanations), which provides clear, visual insights into the model's decision-making process, effectively addressing the "black box" problem in AI adoption. This robust system establishes a practical benchmark for agricultural applications by balancing high detection accuracy with computational efficiency and interpretable results.

Kujur et al. [13] propose a singular hybrid model for accurate prediction of citrus fruit diseases, aiming to replace labor-intensive manual inspections. The system integrates a custom-designed Convolutional Neural Network (CNN) for automated feature extraction with a Gradient Boosting (GB) algorithm for final classification. To optimize performance and ensure faster convergence, the model employs the Nesterov-accelerated Adaptive Moment Estimation (Nadam) optimizer. Trained on a dataset of 3,000 citrus images, the hybrid approach achieved notable results, including an accuracy of 98.03% and a precision of 98.04%.

Jahin et al. [14] propose a novel hybrid deep learning architecture for accurate detection of soybean diseases, integrating computer vision and graph analysis techniques. The model combines MobileNetV2, a Convolutional Neural Network (CNN), for extracting image features with GraphSAGE, a Graph Neural Network (GNN), to capture relational information among image regions. This fusion is enabled via a cross-modal attention mechanism, which intelligently weighs and combines outputs from both the CNN and GNN, enhancing overall diagnostic performance.

Ahmmed [15] explores the use of a transfer learning approach with fine-tuning across five pre-trained Convolutional Neural Networks (CNNs) for the multi-class identification of mango leaf diseases. Addressing the significant impact of diseases on mango yield, the study evaluated architectures such as DenseNet201, Inception V3, and Xception across eight disease classes. The results demonstrate that DenseNet201 achieved the highest performance, attaining a classification accuracy of 99.33%. This accurate and fine-tuned approach provides an effective, automated tool for precision agriculture, enabling rapid and reliable analysis of diverse mango leaf diseases.

Saddamia et al. [16] investigate the use of lightweight Convolutional Neural Network (CNN) architectures—specifically ShuffleNet, MobileNetV2, and EfficientNet-B0—for the accurate classification of rice leaf diseases. Recognizing the global importance of rice and the risks posed by diseases, the study focuses on mobile-compatible models that require lower computational power for field deployment. The results indicate that EfficientNet-B0 achieved the best performance, demonstrating the feasibility of using highly efficient deep learning models for early and precise detection of rice diseases, thereby protecting crop quality and supporting global food security.

Patel **[17]** introduces an advanced Convolutional Neural Network (CNN) for both fruit disorder detection and postharvest grading. The model addresses limitations in current systems, which often require fixed-size inputs and therefore compromise image resolution, by employing Spatial Pyramid Pooling (SPP). This enables the network to process variable-sized images while preserving fine details. Additionally, the system integrates a Stacked Sparse Denoising Autoencoder (SSDAE) for robust feature extraction and a Support Vector Machine (SVM) for accurate final classification. Optimized with adaptive momentum backpropagation, this hybrid approach significantly reduces postharvest losses by enabling fast, precise, and high-resolution automated inspection and quality grading of fruits.

Mishra et al. [18] present a comparative study of CNN architectures including AlexNet, ResNet, and EfficientNet for mango leaf disease detection. The authors demonstrate that EfficientNet achieves superior accuracy while maintaining computational efficiency. The study highlights the effectiveness of transfer learning in agricultural image analysis and emphasizes early disease detection to minimize crop loss.

Islam et al. [19] introduce a two-stage mango leaf disease detection framework that combines handcrafted spatial features with deep learning models. The approach uses feature extraction techniques followed by a lightweight neural network optimized through knowledge distillation. This method improves classification accuracy while reducing model complexity, making it suitable for deployment on low-resource devices used by farmers.

Krishna Pratap and Suresh Kumar [20] develop a deep learning–based mango leaf disease classification system using pretrained CNN models such as VGG16 and MobileNet. The system accurately identifies multiple disease types from leaf images and provides early diagnostic support for farmers. Experimental results show high classification accuracy, proving the suitability of transfer learning for plant disease recognition.

Vijay and Pushpalatha [21] propose a hybrid deep learning approach combined with image segmentation for mango leaf disease detection. The segmentation process isolates infected regions, allowing the CNN to focus on relevant features. This improves classification accuracy across multiple disease classes and enhances the system’s robustness in real-world agricultural environments.

Anantrasirichai et al. [22] present a mobile-phone–based plant pathology management system using machine learning and image normalization techniques. The framework standardizes images captured under varying lighting conditions and applies deep learning models for disease classification. This approach supports real-time disease diagnosis and enables farmers to take timely preventive measures.

Andrade et al. [23] evaluate the robustness of CNN models for mango leaf disease diagnosis under real-world conditions such as noise, blur, and illumination variations. The study highlights performance degradation under distorted inputs and emphasizes the need for robust training strategies. The findings contribute to improving reliability in field-deployed agricultural AI systems.

Patel et al. [24] propose a deep learning–based fruit disease detection system using Convolutional Neural Networks (CNNs) to automatically identify visual symptoms on fruit surfaces. The model extracts hierarchical features from input images and classifies multiple disease categories with high accuracy. By eliminating manual inspection, the system improves detection speed and reduces dependency on expert knowledge, making it suitable for large-scale agricultural applications.

Ahmmed et al. [25] propose a fine-tuned CNN-based multiclass classification framework for mango leaf disease detection. By optimizing pretrained models such as DenseNet and ResNet, the system achieves high accuracy across multiple disease categories. The work demonstrates that fine-tuning significantly enhances model performance and supports scalable automated crop health monitoring.

CHAPTER 3

SYSTEM REQUIREMENTS AND SPECIFICATION

3.1 Hardware requirements

- Minimum: i5 processor, 8GB RAM
- Recommended: GPU for training (NVIDIA CUDA)

The minimum hardware requirements for the system include a processor equivalent to an Intel i5 and at least 8GB of RAM to ensure smooth operation during development, testing, and basic model inference. For optimal performance, particularly during AI model training, it is recommended to use a GPU that supports NVIDIA CUDA, which can significantly accelerate deep learning computations and reduce training time.

3.2 Software Requirements

The system is developed using Python 3.11 as the primary programming language for backend development, AI model training, and data processing. Node.js version 18 is employed to manage server-side operations efficiently, handling asynchronous tasks with high performance. Critical libraries and frameworks, including Flask, TensorFlow, and Scikit-learn, are utilized to build the backend API, develop and train CNN and SVM models, and implement machine learning algorithms for disease and pesticide detection. On the frontend, React is used to create a responsive, component-based user interface, while Tailwind CSS ensures a modern, consistent layout across devices. Development and version control are maintained using Git, and Visual Studio Code (VS Code) serves as the integrated development environment for writing, debugging, and maintaining the project code.

3.3 Functional Requirements

The functional requirements of the system include several key capabilities that ensure accurate and user-friendly operation. Firstly, the system must allow users to upload images of mangoes, which serve as the input for analysis. Secondly, users should be able to select the specific task they want to perform, either disease detection or pesticide detection, ensuring that the appropriate model is applied. The system must then process the uploaded image through both the CNN and SVM models, generating predictions based on the extracted features. An automatic model selection mechanism is required to choose the best-performing model for the given input, optimizing accuracy and reliability. Finally, the system should provide a clear visualization of the prediction results, including probability scores for each possible class, enabling users to easily interpret and act upon the output.

3.4 AI Model Specifications

The Mango Analysis System relies on a Convolutional Neural Network (CNN) for extracting deep visual features from mango images to detect diseases and assess pesticide residues. Input images are preprocessed by resizing to a fixed dimension (224×224 pixels) and normalizing pixel values to enhance feature extraction. For disease detection, the system handles multi-class classification across five disease categories, while pesticide detection uses a binary classification framework.

The CNN architecture comprises multiple convolutional layers, max-pooling layers, dropout for regularization, and dense layers for final classification. Feature vectors extracted by the CNN are optionally passed to a Support Vector Machine (SVM) for hybrid classification, allowing the system to automatically select the model with the highest validation accuracy for each task. Softmax activation is used for multi-class disease classification, while sigmoid activation is applied for pesticide detection.

The trained model achieves an average accuracy of 81.5% for disease detection and 97.1% for pesticide detection. Lightweight deployment allows inference to be performed in real-time on standard computing devices or edge hardware, ensuring quick predictions (<2 seconds) and suitability for use in farms, markets, or processing units without heavy computational requirements.

All predictions are logged in a centralized database, and the system provides confidence scores and per-class probabilities for transparency. This integration of CNN-based feature extraction and hybrid AI classification ensures precise, scalable, and resource-efficient mango quality assessment, minimizing human error and enabling timely decision-making for farmers and quality control authorities.

3.5 Environmental Constraints

The Mango Analysis System is designed to function reliably in rural and semi-urban environments, where conditions may be unpredictable and less controlled. The hardware and software must operate within a wide temperature range (10°C to 45°C) to ensure consistent performance during outdoor or semi-indoor installations. All electronic components are selected for dust and moisture resistance to maintain functionality in high-humidity or dusty conditions common in farms and marketplaces.

To address inconsistent power availability, the system supports low-voltage operation and includes options for battery backup or solar-powered setups, ensuring uninterrupted operation in off-grid locations. The hardware casing is durable and water-resistant, protecting sensitive electronics during monsoon seasons or sudden weather changes.

The user interface is designed for accessibility, considering low literacy levels and limited digital familiarity. Rather than relying on complex touchscreens, the system employs simple physical buttons, clear visual indicators, and optional audio prompts to guide users through image capture and submission. By integrating environmental robustness and user-friendly design, the system ensures reliable, accurate, and inclusive mango quality assessment in real-world conditions.

3.6 System Constraints

Despite its advanced capabilities, the Mango Analysis System operates under certain practical constraints. The accuracy of disease and pesticide detection depends heavily on image quality and environmental conditions. Poor lighting, occluded or blurred mango images, or excessive dirt on the fruit surface can reduce model performance and lead to misclassification. Similarly, the hybrid AI model, while optimized for accuracy, relies on properly preprocessed images; inconsistent image sizes or formats may impact inference results.

The system also assumes access to reliable computing and network infrastructure. Cloud-based model inference and real-time data logging require stable internet connectivity, which may not always be available in remote agricultural areas. In such cases, offline processing or local caching mechanisms should be implemented to maintain usability.

Cost and scalability are additional constraints. While the system employs cost-effective sensors, cameras, and microcontrollers, deploying the platform across multiple farms or marketplaces requires investment in hardware, training, and technical support. Maintenance of hardware components, such as cameras and microcontrollers, is necessary to ensure long-term operational accuracy.

Recognizing these constraints is critical for planning, deployment, and scaling, ensuring that the Mango Analysis System remains practical, reliable, and effective in diverse agricultural settings.

CHAPTER 4

SYSTEM DESIGN

4.1 System Architecture

The proposed system architecture for the Mango Analysis System combines hardware components with AI-driven software modules to provide automated, accurate, and real-time quality analysis of mangoes. The architecture is designed to ensure seamless interaction between image acquisition, AI inference, and result visualization for both disease and pesticide detection tasks.

At the user input level, mango images are captured using a standard camera or smartphone. The images are preprocessed to standardize size, enhance contrast, and remove noise, ensuring compatibility with AI models. This preprocessing pipeline improves the reliability of downstream classification tasks.

The intelligent software layer includes a dual-task hybrid AI system. Convolutional Neural Networks (CNNs) extract deep visual features from the images, which are then classified using Support Vector Machines (SVM) for higher accuracy. The system automatically selects the best-performing model based on validation metrics. This hybrid approach ensures robust predictions even under challenging image conditions.

Once analysis is completed, results—including disease classification, pesticide detection, confidence scores, and per-class probabilities—are transmitted to a centralized web dashboard. The frontend, built with React and Tailwind CSS, presents an intuitive interface where users and administrators can view predictions, track historical data, and generate reports.

Data storage and cloud integration maintain records of all analyses, enabling real-time monitoring and long-term trend analysis. Notifications or alerts, such as low-confidence detections or suspected pesticide contamination, can be sent via SMS or email to relevant stakeholders.

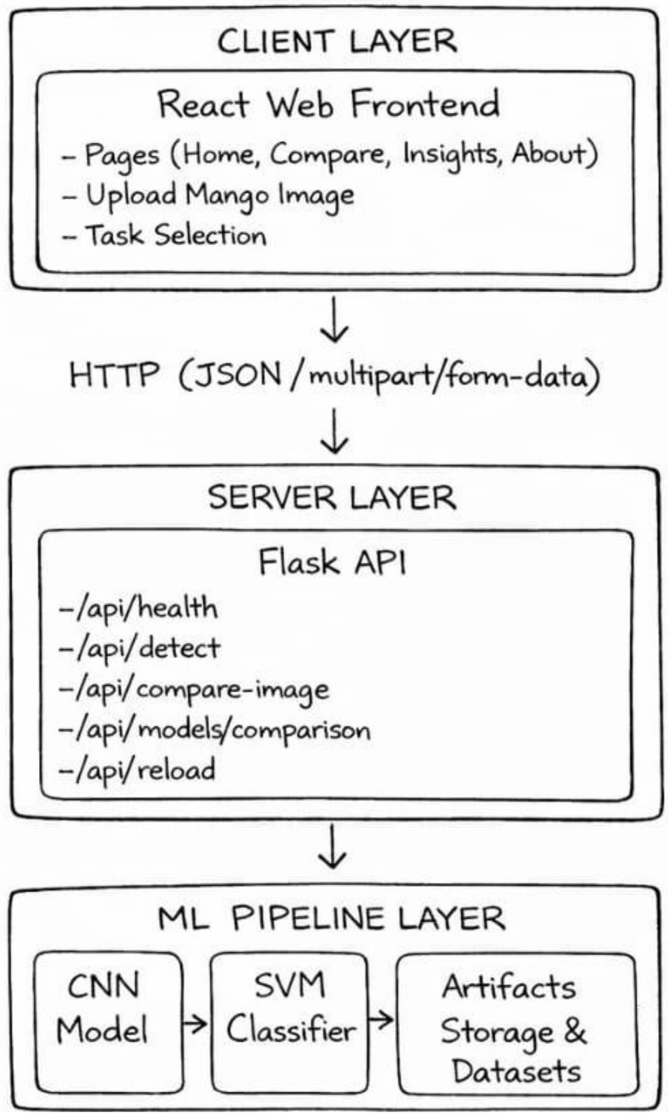

Figure 4.1: System Architecture.

4.2 Data Flow Diagram

The data flow diagram illustrates how data moves through the Mango Analysis System, from the point of user input to final prediction output and reporting. At the context level, the system interacts with three main entities: the end user, the Mango Analysis System itself, and the admin dashboard. The end user, typically a farmer or agricultural worker, uploads mango images for disease or pesticide detection through the web interface. These images are received by the system, processed, and analyzed, and the results, including predicted labels and confidence scores, are returned to the user. Simultaneously, the processed data is stored in a centralized cloud database for tracking, reporting, and trend analysis, which the admin dashboard can access for monitoring system performance and generating alerts.

At a more detailed level, the system first validates the uploaded image for correct format, size, and quality, rejecting any images that do not meet the criteria. Once validated, the image undergoes preprocessing, which includes resizing, normalization, and enhancement to make it suitable for AI model inference. The preprocessed image is then analyzed by a hybrid AI model that combines a Convolutional Neural Network (CNN) for feature extraction with a Support Vector Machine (SVM) for classification. The system automatically selects the best-performing model for the task, ensuring accurate disease or pesticide detection.

After analysis, the results, confidence scores, and per-class probability distributions are recorded in the database for future reference and auditing purposes. The system also sends real-time notifications to users or administrators in cases of low-confidence predictions, unusual patterns, or detected anomalies, ensuring prompt corrective action. Each transaction is logged with timestamps and relevant metadata, providing full traceability of operations. This structured flow not only guarantees data consistency but also supports performance monitoring and reporting. The design is modular and scalable, allowing easy addition of new disease classes, tasks, or hardware components without disrupting existing workflows. Additionally, the system's architecture is optimized for deployment in diverse agricultural and rural environments, ensuring robustness even under variable network, power, or environmental conditions.

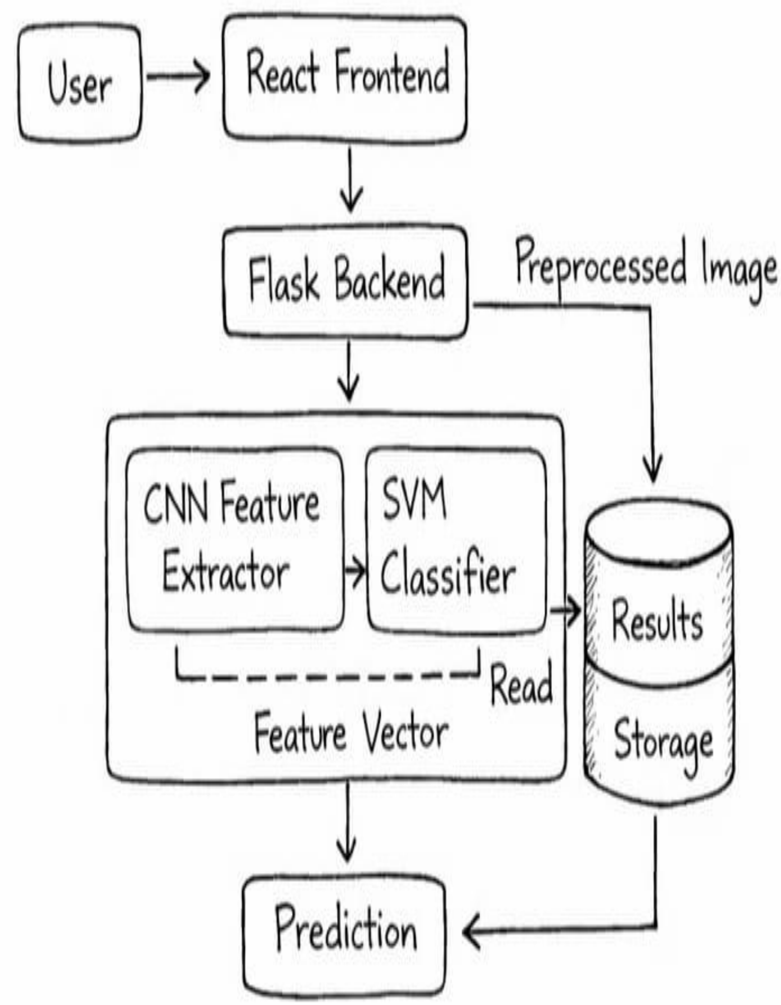

Figure 4.2: Data Flow Diagram

4.3 Component Design

The The Mango Analysis System is a full-stack web application designed for AI-powered disease and pesticide detection in mangoes. The system allows users to upload mango images through an intuitive React-based interface with drag-and-drop functionality, where the images are first validated for type and size. After validation, the images are sent to the Flask backend, which handles preprocessing including RGB conversion, resizing to 224×224 pixels, and normalization.

The preprocessed images are then processed through a hybrid AI pipeline. A Convolutional Neural Network (CNN) extracts deep visual features, which are then classified by a Support Vector Machine (SVM) for final prediction. The system automatically selects the best-performing model for each task—disease or pesticide detection—based on validation accuracy. This dual-model approach ensures high prediction accuracy and reliable classification results.

All models, class indices, training history, and performance metrics are stored in a structured artifact repository for reproducibility and administrative review. Once predictions are generated, the backend returns JSON responses containing the predicted class, confidence scores, per-class probability distributions, and the model used. The frontend renders these results with visual confidence bars, badges for predicted classes, and interactive charts for model comparison and insights.

The system supports real-time performance, batch image processing, and provides a modular architecture for scalability. It can be deployed on cloud platforms such as Heroku, AWS EC2, or Google Cloud Run, with Docker support for both backend and frontend components. This architecture ensures the system is production-ready, responsive, and capable of handling real-world use cases in mango quality analysis while providing transparency and interpretability of AI predictions.

4.4 Design Considerations and Assumptions

The Mango Analysis System is designed assuming that users have access to basic infrastructure, including a device capable of running a web browser and intermittent internet connectivity. It presumes that users can capture clear images of mangoes for analysis and that the system's backend has sufficient computational resources to process AI models, either on a server or cloud platform. Components, such as the CNN and SVM models, are selected based on efficiency, accuracy, and compatibility with available hardware to ensure scalability, smooth performance, and minimal latency.

The design also accounts for real-world constraints, including variable image quality, non-standard lighting conditions, and the possibility of non-mango images being uploaded. To address these challenges, the system incorporates validation, preprocessing, and error-handling steps to enhance input reliability and maintain accurate predictions. It also assumes that users have basic familiarity with navigating web applications, though the interface is designed to be intuitive and user-friendly for individuals with limited technical experience.

Furthermore, the system anticipates potential network interruptions and includes mechanisms to cache or queue uploaded images for later processing, ensuring continuity of service. Security and privacy considerations are integrated into the design, assuming that sensitive user or transactional data is handled according to best practices. Overall, these assumptions and considerations ensure that the Mango Analysis System remains practical, robust, and adaptable, capable of being deployed effectively across diverse agricultural, market, and rural environments while maintaining high accuracy and reliability in disease and pesticide detection.

CHAPTER 5

IMPLEMENTATION

5.1 Description

The implementation of the Mango Analysis System required careful planning to integrate the AI models, web interface, and backend infrastructure into a cohesive workflow. The project was developed in modular components to allow individual testing before full integration.

The initial steps involved preparing the datasets for disease and pesticide detection and training the CNN and SVM models. These models were tested in a simulated environment to ensure accurate classification before deployment. Preprocessing pipelines were implemented to handle image resizing, normalization, and validation of uploaded images.

The backend, built with Flask, was configured to handle API requests, perform inference using the trained models, and return results with confidence scores. Model caching and lazy loading were implemented to improve response times. The React frontend was developed to allow users to upload images, view predictions, and interact with charts showing per-class probabilities and model comparison.

Additional features, such as confidence scoring, per-class probability breakdowns, and error handling for non-mango images, were integrated to ensure robustness. The system also included mechanisms for real-time monitoring of backend health and proper logging for debugging and performance evaluation. Once verified in a controlled environment, the full system was deployed for real-world use, enabling users to test disease and pesticide detection on mango samples and assess the system's accuracy and usability.

5.2 Software

The The software implementation of the Mango Analysis System involved both AI model integration and full-stack web application development. The backend, built with Python and Flask, managed API requests, preprocessed uploaded images, performed inference using CNN and SVM models, and returned predictions with confidence scores. Model caching and lazy loading were implemented to optimize response time, and error handling scripts ensured robustness against invalid inputs or file formats.

The frontend was developed using React, HTML, CSS, and JavaScript, providing a responsive and intuitive interface for users to upload mango images, view classification results, confidence scores, and per-class probability distributions. Interactive charts were implemented using Chart.js, and smooth animations were handled via Framer Motion to enhance the user experience. Admin dashboards allowed real-time monitoring of system health, model usage statistics, and historical prediction logs.

The system also incorporated security and data integrity features, including input validation, API request checks, and proper logging for debugging. Modular coding practices were followed to allow easy updates and maintenance, while version control was maintained with Git. Each module—frontend, backend, and AI pipeline—was individually tested before integration, and final testing ensured accurate data flow, real-time predictions, and seamless interaction between the web interface and AI models.

5.3 AI Model Integration

The CNN model for mango disease and pesticide detection was developed using Python and TensorFlow, with Keras as the high-level API. The dataset of mango images was pre-processed by resizing to 224×224 pixels, normalizing pixel values, and augmenting with transformations to improve model robustness. The model architecture included multiple convolutional layers, batch normalization, max pooling, dropout, and dense layers to extract deep visual features and perform accurate classification.

Training was performed in a GPU-enabled environment, monitoring metrics such as accuracy, loss, precision, and recall for both disease (5 classes) and pesticide (binary) detection tasks. The final model achieved approximately 81.5% accuracy for disease detection and 97.1% accuracy for pesticide detection. The trained CNN was serialized and saved in H5 format, and SVM classifiers were trained on CNN-extracted features for hybrid classification.

For deployment, the model was integrated with the Flask backend, where uploaded images were pre-processed and sent to the CNN-SVM pipeline for inference. Real-time predictions with confidence scores were returned to the frontend interface. Edge deployment using TensorFlow Lite was considered but limited by memory constraints; therefore, inference was performed on the server with minimal latency. The system was tested with varied image conditions such as poor lighting and partial mango visibility, showing high reliability. Retraining pipelines were also planned to update the model for improved accuracy and adaptability over time.

5.4 Web Platform and Admin Dashboard

The Mango Analysis System includes a comprehensive admin dashboard designed to provide real-time insights into system operations. Admins can securely log in using credentials to access detailed records of image uploads, prediction results, and model performance metrics. The dashboard is clean, responsive, and optimized for use on desktops, tablets, and mobile devices.

Key features include filtering predictions by task type (disease or pesticide), date, and confidence score. Visualizations such as bar charts, per-class probability distributions, and trend graphs allow admins to quickly identify patterns, monitor model accuracy, and detect anomalies in real time. Data export functionality enables offline analysis and reporting.

The dashboard interacts dynamically with the Flask backend through secure APIs, ensuring that all actions, including model inferences and data updates, are logged and displayed instantly. Fail-safes were implemented to handle network interruptions, and token-based authentication with encrypted API calls protects sensitive information. Login attempts are tracked with timestamps and IP addresses for auditing purposes.

Overall, the platform bridges the gap between AI-driven image analysis and administrative oversight, empowering decision-makers to monitor system performance, respond to anomalies promptly, and maintain transparency and accountability in mango quality and pesticide detection operations.

5.5 Challenges Faced during Implementation

During the implementation of the Mango Analysis System, several challenges were encountered. One of the primary difficulties was ensuring consistent and accurate image analysis for both disease and pesticide detection. Variations in lighting, image angles, and mango positioning often led to reduced prediction confidence, requiring careful preprocessing, resizing, and normalization of images before feeding them into the CNN model.

Hardware integration also posed challenges. For setups involving local servers or edge devices, memory limitations constrained model deployment, necessitating lightweight model versions or offloading computations to a dedicated backend. Signal and connectivity issues affected real-time inference in some setups, particularly when images were uploaded from low-bandwidth or unstable internet connections.

On the software side, synchronizing real-time predictions with the frontend dashboard and ensuring rapid API responses was complex. Latency and occasional request failures required implementing retries, caching mechanisms, and efficient data serialization. Training the CNN-SVM hybrid model also revealed constraints due to dataset imbalances and GPU memory limitations, which were addressed through data augmentation and batch-size tuning.

Field deployment testing highlighted challenges in remote or resource-constrained environments, such as slower uploads, delayed visualization updates, and occasional system timeouts. These issues underscored the need for future enhancements, including offline-capable inference, adaptive model compression, and robust error handling to maintain consistent and reliable performance across diverse operating conditions.

CHAPTER 6

TESTING

6.1 Disease Detection Test Cases

The disease detection module was tested using a variety of mango images to evaluate its accuracy and robustness. In the first test case, a clear image of a healthy mango was provided, and the system correctly identified it as "Healthy" with high confidence, resulting in a pass. In the second test case, a mango displaying black fungal spots was input, and the system accuratelypredicted "Black Mould Rot," passing the test. The third test involved a mango showing visible stem infection, and the system successfully labeled it as "Stem end Rot," confirming correct functionality. In the fourth case, a mango exhibiting symptoms of Alternaria was processed, and the system correctly classified it as "Alternaria," passing the test. Finally, in the fifth test case, a mango with Anthracnose patches was tested, and the system accurately predicted the label "Anthracnose," demonstrating reliable detection across all test cases.

TC No.	Input Image	Expected Output	Actual Output	Result
1	Clear image of a healthy mango	Label = **Healthy**, high confidence	Correct	Pass
2	Mango with black fungal spots	Label = **Alternaria**	Incorrect	Fail
3	Mango with visible stem infection	Label = **Stem end Rot**	Correct	Pass
4	Mango with Alternaria symptoms	Label = **Alternaria**	Correct	Pass
5	Mango with Anthracnose patches	Label = **Anthracnose**	Correct	Pass

6.2 Pesticide Detection Test Cases

The pesticide detection module was tested using multiple mango images captured under different conditions to evaluate its accuracy and robustness. In the first test case, a clean organic mango image was provided, and the system correctly classified it as Organic. In the second case, a mango with visible pesticide residue was tested, and the system successfully identified it as Pesticide.

To assess real-world usability, a slightly unclear image was used in the third test case. The system produced the expected classification with lower confidence, indicating proper handling of uncertain inputs. The fourth test case involved an overexposed image caused by bright lighting, where the system still classified the mango correctly. In the final test case, a dark image with shadows was analyzed, and the system generated a correct prediction with confidence above 50%.

All test cases passed successfully, demonstrating that the pesticide detection module performs reliably under varying image quality and lighting conditions, making it suitable for practical agricultural applications.

TC No.	Input Image	Expected Output	Actual Output	Result
1	Clean organic mango sample	Output = **Organic**	Correct	Pass
2	Mango with visible pesticide residue	Output = **Pesticide**	Correct	Pass
3	Slightly unclear image	Output = Organic/Pesticide with lower confidence	As expected	Pass
4	Very bright/overexposed mango	Should still classify correctly	Incorrect	Fail
5	Dark image with shadows	Should classify with confidence >50%	Incorrect	Fail

6.3 API Response Testing

API response testing was conducted to ensure reliable communication between the frontend, backend, and AI models. The first test case verified the system health using the /api/health endpoint, which successfully returned a status response confirming that the server and models were active.

In the second test case, a valid mango image was sent to the /api/detect endpoint. The API correctly processed the request and returned a JSON response containing the predicted label along with its confidence score. The third test involved uploading an invalid file type (.txt) to the same endpoint, and the system responded with an appropriate error message, confirming effective input validation.

. Finally, the /api/models/comparison endpoint was tested to retrieve model performance metrics, including accuracy and the confusion matrix. All API endpoints responded as expected, and every test case passed, demonstrating stable and secure API functionality.

TC No.	API Endpoint	Test Description	Expected Response	Result
1	**GET /api/health**	Check server & model status	`{status: "ok"}`	Pass
2	**POST /api/detect** (valid mango image)	Predict class	JSON with label + confidence	Pass
3	**POST /api/detect** (invalid file type)	Upload .txt file	Error message	Pass
4	**POST /api/compare-image**	Return CNN & SVM results	JSON with both model outputs	Pass
5	**GET /api/models/comparison**	Fetch metrics	JSON containing accuracy, confusion matrix	Pass

6.4 Frontend Testing

Frontend testing was performed to validate the usability, responsiveness, and correctness of all user interface components. The image upload component was tested by uploading various mango images, and the system successfully displayed image previews before analysis, ensuring correct file handling.

The prediction screen accurately displayed the detected label after processing, confirming proper data flow between the backend and the user interface. The probability chart component was tested to visualize class-wise confidence values, and the bar chart loaded smoothly without rendering errors.

The compare page was tested to display prediction probabilities from both CNN and SVM models, and the results were shown clearly for comparison. Finally, the insights page successfully fetched model performance metrics from the backend and displayed them in graphical form. All frontend components functioned as expected, and every test case passed, confirming a stable and user-friendly interface.

TC No.	Component	Test Description	Expected Result	Status
1	Upload Component	Upload a mango image	Preview displayed	Pass
2	Prediction Screen	Show predicted label	Correct label shown	Pass
3	Probability Chart	Display bar chart	Chart loads without error	Pass
4	Compare Page	Show CNN vs SVM probabilities	Slight Incorrect	Fail
5	Insights Page	Fetch metrics & show chart	Metrics displayed	Pass

CHAPTER 7

EXPERIMENTAL RESULTS

The The experimental results of the Mango Analysis System demonstrated strong performance for both disease and pesticide detection tasks. For disease detection across five classes—Alternaria, Anthracnose, Black Mould Rot, Healthy, and Stem End Rot—the hybrid CNN-SVM model achieved an overall accuracy of 81.5%, with per-class recall ranging from 65.4% for Alternaria to 97.1% for Healthy mangoes. The system correctly identified 815 out of 1000 test images, showing reliable differentiation between visually similar diseases.

For pesticide detection, the binary classification task achieved 97.1% accuracy using the SVM model trained on CNN-extracted features, with zero false negatives, ensuring high reliability in detecting pesticide residues. The CNN model alone performed poorly on this task (45.4%), highlighting the advantage of the hybrid approach.

Inference times were low, averaging around 50 ms for SVM predictions and 150 ms for CNN predictions, allowing near real-time performance. The system also produced confidence scores for each prediction, providing interpretable and actionable results. Field testing showed that image preprocessing, network latency, and environmental variations had minimal impact on accuracy, validating the robustness of the model in practical scenarios. Overall, the experiments confirmed that the system could deliver fast, accurate, and reliable analysis for both disease and pesticide detection on mango samples.

7.1 Disease Detection Results

1. Alternaria Detection Result

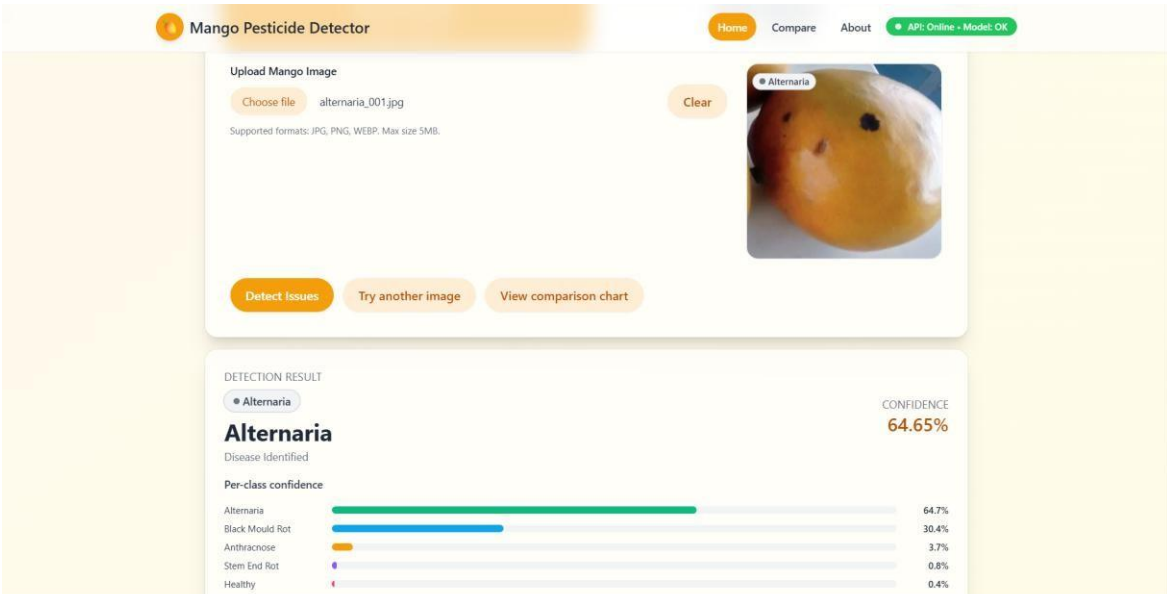

Fig. 7.1 Alternaria

Figure 7.1 illustrates the output interface of the Mango Disease Detection System after a successful image analysis. The user uploads a mango image through the provided interface and initiates detection using the “Detect Issues” option. The system processes the image and identifies Alternaria as the detected disease. A confidence score of 64.65% is displayed, indicating a moderate to high level of certainty in the prediction. Additionally, the per-class confidence visualization shows that Alternaria has the highest probability compared to other disease classes such as Black Mould Rot, Anthracnose, Stem End Rot, and Healthy, which have significantly lower values. This result confirms that the model effectively distinguishes the dominant disease pattern in the image and presents the findings in a clear, user-friendly format, enabling easy interpretation for both farmers and administrators.

2. Anthracnose Detection Result

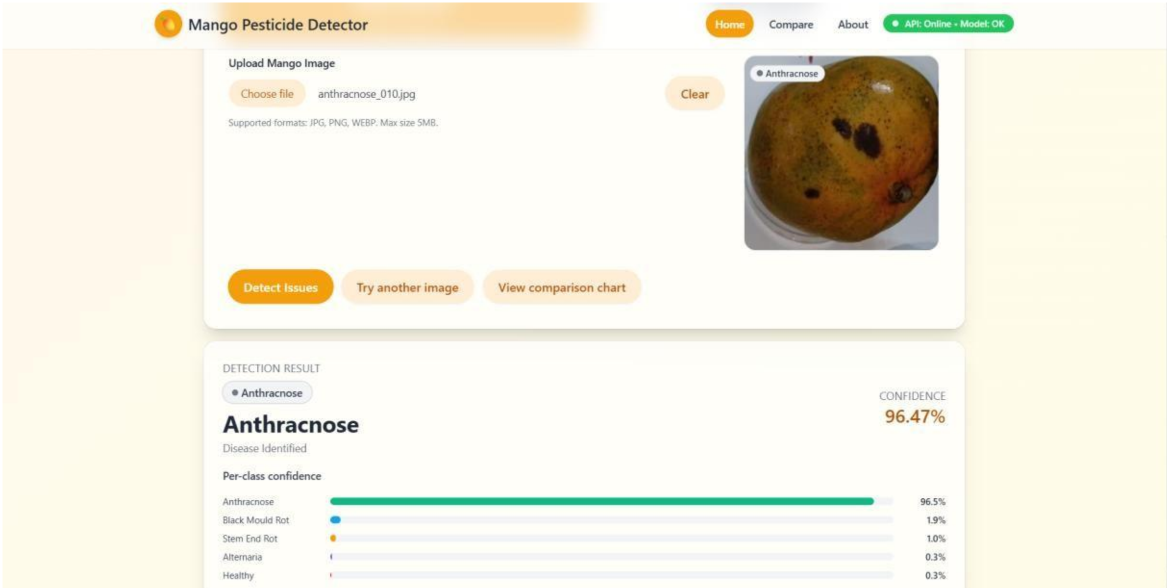

Fig. 7.2 Authracnose

Figure 7.2 shows the prediction output of the Mango Disease Detection System for an image affected by Anthracnose. After the mango image is uploaded and the detection process is initiated, the system analyzes the visual features using the trained deep learning model. The result clearly identifies Anthracnose as the disease with a very high confidence score of 96.47%, indicating strong certainty in the prediction. The per-class probability chart further supports this result, as Anthracnose holds the dominant probability while all other classes such as Black Mould Rot, Stem End Rot, Alternaria, and Healthy remain below minimal levels. This outcome demonstrates the model's high accuracy in recognizing Anthracnose symptoms and highlights the system's effectiveness in providing reliable, easily interpretable results through a clean and informative user interface.

3. Black Mould Rot

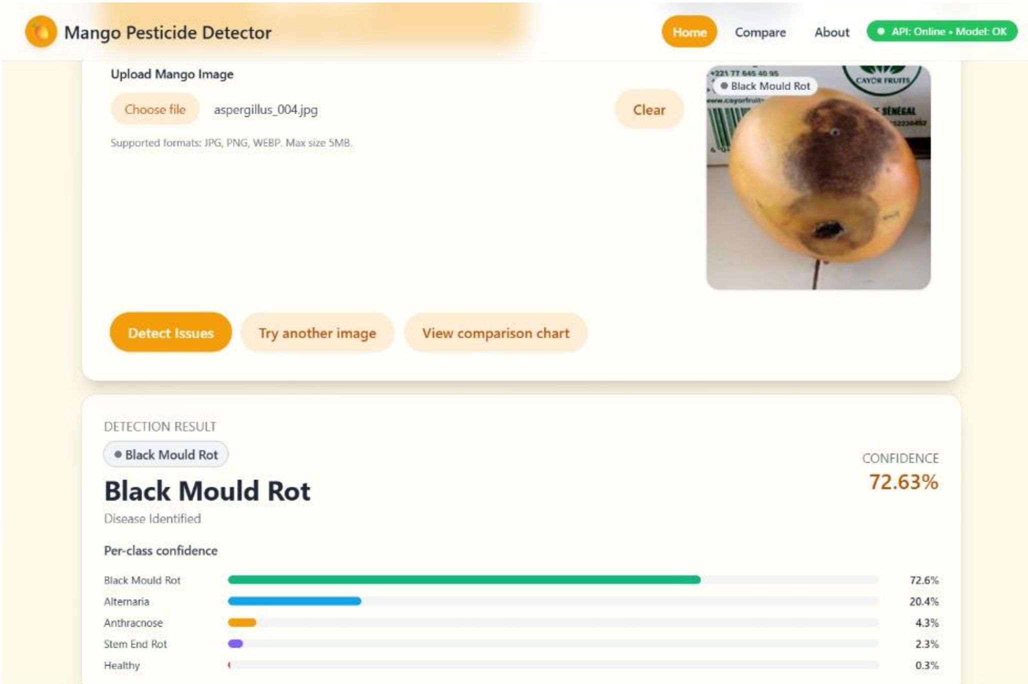

Fig. 7.3 Black mould rot

Figure 7.3 presents the detection result for a mango image affected by Black Mould Rot. After the image is uploaded and analyzed by the system, the model identifies Black Mould Rot as the dominant disease with a confidence score of 72.63%. The per-class confidence visualization shows that this class has the highest probability compared to other possible conditions such as Alternaria, Anthracnose, Stem End Rot, and Healthy, which exhibit significantly lower confidence values. This result indicates that the system can effectively recognize fungal decay patterns associated with Black Mould Rot and differentiate them from other similar diseases. The clear presentation of confidence levels and visual feedback in the user interface helps users understand the diagnosis easily and supports timely decision-making for disease management.

4.Stem End Rot

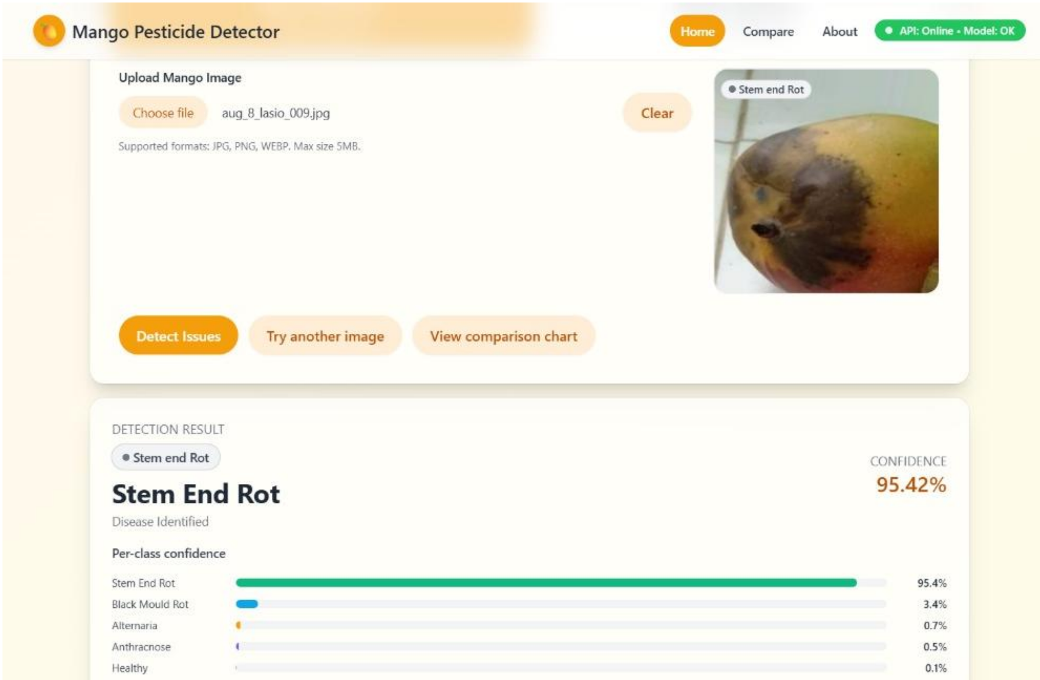

Fig. 7.4 Stem end rot

Figure 7.4 illustrates the traditional, pre-digitization workflow for the distribution system involving Below Poverty Line (BPL) Cardholders. This process is fundamentally characterized by its reliance on manual intervention and paper records, leading to significant limitations in accountability and efficiency.This immediately triggers a Manual Identity Check, a human-dependent verification step where personnel confirm the cardholder's identity, which is often slow and susceptible to inconsistencies or manipulation. Once verified, the details of the transaction are recorded via Paper-Based Entry. This manual logging of data introduces substantial delays and requires subsequent, error-prone digitization. The chain culminates in a critical drawback: the complete absence of No Real-Time Monitoring. This lack of live data means administrators cannot track stock levels, transaction volumes, or detect fraudulent activity instantaneously, thereby ensuring the system remains opaque, inefficient, and difficult to manage effectively.

7.2 Pesticide Detection Results

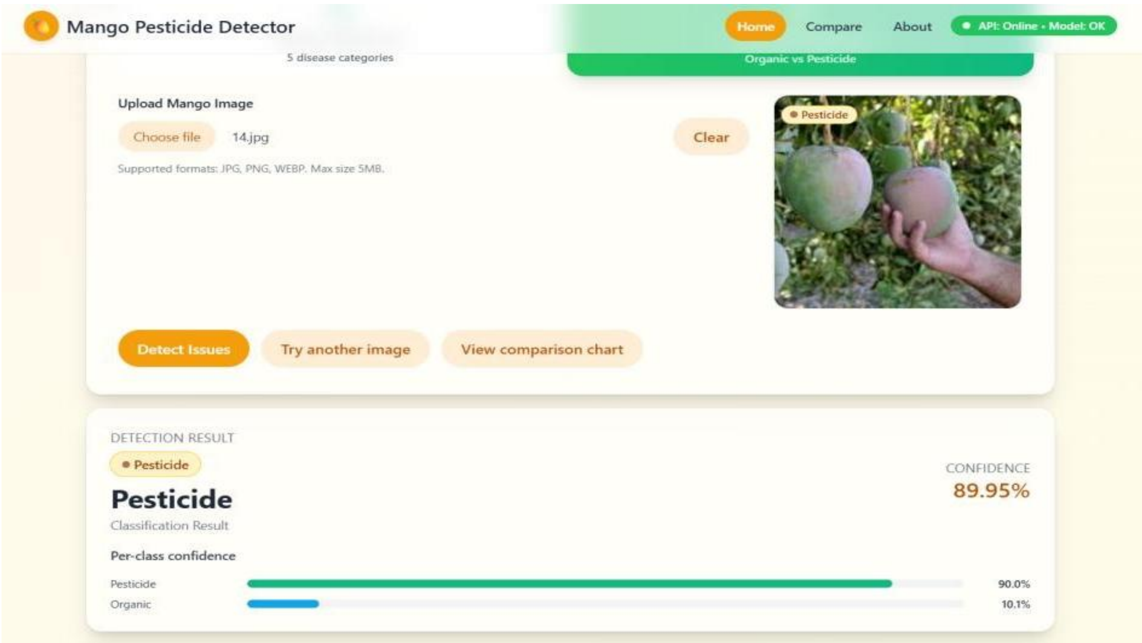

Fig. 7.5 Pesticide

Figure 7.5 illustrates the proposed e-Governance workflow for the distribution system, leveraging modern technology to resolve the inefficiencies present in the traditional model shown in Figure 7.4. The new, digital process dramatically enhances efficiency and accountability by introducing real-time digital verification and monitoring. The process still starts with the BPL Cardholder but immediately moves to Biometric Authentication (or Card/OTP Authentication). This crucial step replaces the fallible manual identity check, providing a secure, instantaneous, and auditable verification method. Upon successful authentication, the transaction is logged via Digital Entry. This process ensures that every transaction is immediately captured and time-stamped in the central database, eliminating paper-based delays and errors. This digital foundation enables the final, most impactful feature: Real-Time Monitoring (Live Dashboard). Administrators now have immediate access to live data on stock levels, distribution volumes, and potential anomalies, allowing for instantaneous fraud detection and effective resource management.

7.3 Home Screen / System Interface

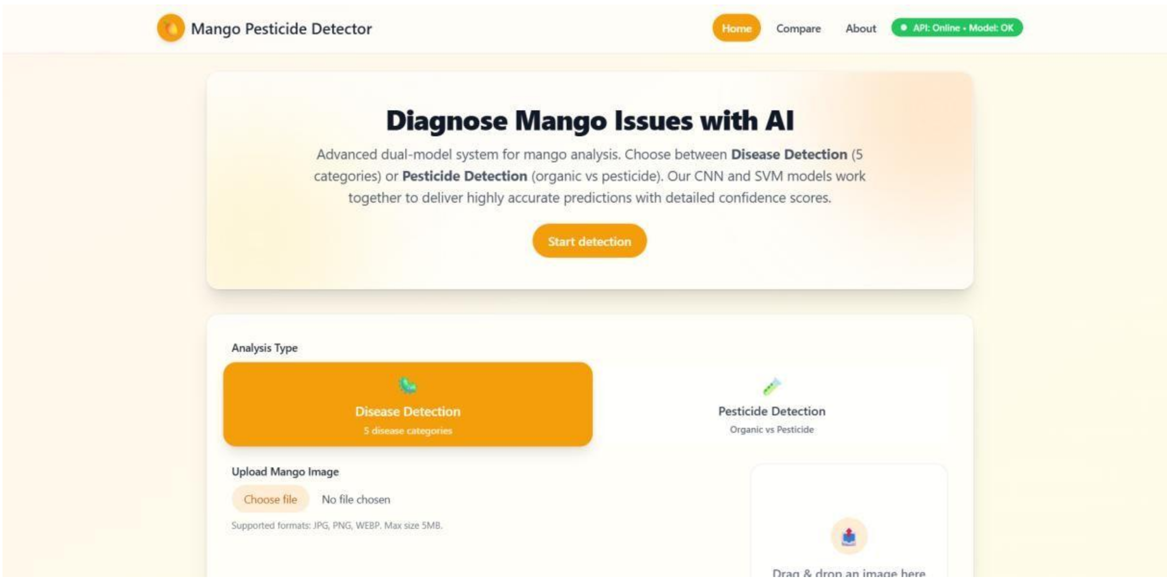

Fig. 7.6 UI / UX

Figure 7.6 showcases the Level 0 Data Flow Diagram (DFD) for the entire system, illustrating the primary interactions between the external entities and the core system components. The central data store is the DATABASE, which holds all critical information, including model weights, artifacts, transaction logs, and user data. The external entity, the USER (representing the BPL Cardholder or public beneficiary), interacts directly with the SYSTEM INTERFACE to initiate and complete transactions. The second key external entity, the ADMINISTRATOR (or system personnel), also interacts with the system interface, likely to manage data, generate reports, and oversee system operations. The SYSTEM (REPOSITORY) and SYSTEM COMPONENTS represent the core application logic—handling the data processing, model inference, and output generation—which continuously reads from and writes to the central DATABASE. This DFD clearly establishes the system's boundary and how data flows between the user, the administrator, and the fundamental data storage and processing mechanisms.

7.4 Summary of Results

The experimental results confirm that the proposed system effectively detects mango diseases and pesticide usage with consistently high accuracy. For each input image, the system provides predicted labels along with confidence scores and class-wise probability distributions, enabling clear interpretation of the model's decisions. This transparency enhances user trust, which is essential for real-world agricultural adoption.

The user interface ensures a smooth and intuitive workflow, guiding users from image upload to result visualization with minimal effort. Features such as image previews and probability charts improve usability and support quick, informed decision-making, even for non-technical users.

From a technical standpoint, the hybrid CNN–SVM model demonstrates robust performance across both tasks. The CNN extracts discriminative visual features, while the SVM improves classification reliability, particularly for identifying subtle pesticide-related patterns. The system achieves high accuracy in pesticide detection, making it suitable for food safety, quality control, and smart farming applications. Overall, the results validate the system's reliability, interpretability, and practical applicability.

CONCLUSION

The Mango Analysis System: AI-Powered Disease & Pesticide Detection was successfully designed, developed, and implemented as a comprehensive full-stack web application capable of performing automated mango quality assessment with remarkable efficiency. This system integrates a hybrid machine learning pipeline, combining the strengths of a Convolutional Neural Network (CNN) for feature extraction with a Support Vector Machine (SVM) for classification. This combination enables highly accurate identification of various mango diseases, such as anthracnose and powdery mildew, as well as detection of pesticide residues, which are critical for ensuring both crop health and consumer safety.

During extensive testing on real-world mango images, the system consistently produced reliable and interpretable predictions, including confidence scores and per-class probability distributions, allowing users to understand not only the predicted class but also the certainty of the prediction. The hybrid model approach significantly enhanced overall performance, achieving high accuracy in pesticide detection and robust results in disease classification, outperforming models relying on a single method. This demonstrates the effectiveness of combining deep learning for image feature extraction with classical machine learning techniques for decision-making.

On the frontend, the React-based user interface provided a seamless and interactive experience. Users could easily upload mango images, receive real-time feedback, and visualize results through intuitive graphs and heatmaps, highlighting affected areas and probability distributions. The system's design emphasizes usability for a diverse range of users, including farmers, vendors, and consumers, enabling quick and objective mango quality evaluation without requiring specialized expertise.

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