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

Rakesh J[1], Darshan DH[1], Deepak K[1], Manoj Kumar BM[1], Deepak. G[2*], Mahesh Kumar N[2]
[1]Undergraduate Student, [2]Professor, Department of Information Science and Engineering, Global Academy of Technology, Bangalore, Karnataka, India

[*]Corresponding Author: deepak.g@gat.ac.in

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Abstract
Mangoes, commonly known as the fruit king, play an important role in agriculture globally. Nevertheless, their quality is often impaired due to fungal contamination and the excessive use of pesticides. Manual examination traditionally requires substantial effort due to its reliance on human judgment, which can be inconsistent and prone to error. This work introduces an automatic mechanism designed to simultaneously recognize major mango diseases, such as anthracnose and black mold rot, and to detect pesticide residues on the fruit surface. The proposed hybrid system uses MobileNetV2 for deep feature extraction along with a Support Vector Machine (SVM) for classification. Empirical findings indicate superior performance compared to traditional CNN models, achieving 98% accuracy for pesticide detection and 94% for disease classification. A lightweight web tool enables farmers and buyers to perform instant quality assessments through an intuitive interface.

Keywords- Deep learning, Mango disease detection, MobileNetV2, Pesticide residue, Precision agriculture, Support Vector Machine (SVM), Transfer learning

INTRODUCTION

The mango (Mangifera indica) [1], an immensely valuable fruit in global trade, thrives as a staple crop throughout Southeast Asia, Sub-Saharan Africa, and North America due to its economic importance. It is crucial to ensure both economic viability and public health standards when conducting international agricultural transactions globally. Nevertheless, mango cultivation suffers greatly due to severe contamination caused by pathogens like anthracnose, alternaria, black mold rot, and stem-end rot, leading to diminished economic worth and hastening spoilage during storage processes [2], [3]. Concurrently, using pesticides in agriculture to combat diseases poses new hazards due to potential contamination of fruits' exteriors by high levels of chemicals, which may harm human health if ingested. Standard methods of evaluating fruits' nutritional value and detecting pesticides usually involve manual observation by humans looking for signs of diseases and subsequent testing using lab techniques like chemistry tests to identify residues. Despite their efficacy, these approaches require time-consuming resources and are not feasible on an extensive scale due to practical limitations, such as location for goods, warehouses, and logistics networks. Additionally, they experience subjectivity within their assessments and inconsistency among experts. Factors drive the creation of smart, self-operating, harmless monitoring tools capable of functioning instantly and aiding quick judgments.

Up-to-date developments in AI technology, especially through deep

Convolutional Neural Networks (CNNs), have significantly altered how we analyze images related to agriculture. These innovations allow for precise identification of various types of crop issues, such as disease outbreaks and physical flaws. Nevertheless, comprehensive end-to-end neural systems frequently demand extensive labeled data sets and commonly face challenges when applied broadly within various environments. Strategies combining advanced feature analysis with traditional Machine Learning (ML) models show enhanced flexibility and decreased risk of model oversensitivity in scenarios with scarce data points.

Our study introduces an integrated ML tool designed for both disease detection in mangos and assessing pesticides left on their skins through a fusion approach utilizing advanced neural network technology. This method utilizes MobileNetV2 in conjunction with transfer learning techniques to extract representations efficiently before employing Support Vector Machine (SVM) [4], [5] classifiers for comprehensive classification tasks, thereby improving overall system resilience.

Additionally, this system functions through an interactive online platform providing immediate access across all parties involved in agriculture: producers, traders, and customers alike. This proposal seeks to improve food safety tracking, encourage eco-friendly farming practices, and offer efficient, affordable inspections tailored for contemporary logistics networks.

LITERATURE REVIEW

The summary of the literature review is shown in Table 1. The study examines an in-depth analysis using Deep Learning (DL) techniques to interpret data related to fruits [1] 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 distinguishing fruits based on their characteristics and identifying them visually in images. Different types of DL architecture designs are examined; notable examples include CNNs along with specific applications such as object detection using methods like You Only Look Once (YOLO). In their work, the researchers outline the critical parameters employed for assessing system validity within practical scenarios. Significantly, this evaluation highlights multiple persistent problems within its domain, particularly concerning insufficient information resources and intricate procedures for precise object identification. Conclusively, this comprehensive study emphasizes significant avenues for further investigation into automated, visual assessment of fruits through rigorous research and innovation.

S. Espinoza et al. [1] explores enhancing plant disease detection by first applying crucial image filtering and enhancement techniques—such as adjusting brightness, contrast, sharpness, and blur—to raw leaf images. These pre-processed images are then used to train and test two state-of-the-art deep learning models, such as MobileNetV2 and Xception. The core of the research involves assessing the effectiveness of these image enhancements on the models' performance in classifying and detecting plant health issues. Results indicate that filtering and enhancement significantly improve the models' ability to accurately determine plant leaf health, offering valuable insights for improving the reliability and foundational steps of intelligent agriculture systems.

M. M. Islam et al. [2] presents a two-step model designed to better detect mango leaf diseases, addressing the dependence of multiple countries on the quality and yield of this crop. The first stage employs an innovative handcrafted spatial feature extraction method to isolate important disease features, while the second stage uses a knowledge distillation process to train a small, efficient student network from a large, powerful teacher network. This combined approach results in a highly accurate system for rapid and reliable disease detection. The efficiency and special focus of the model make it a valuable and practical tool for precision agriculture and ensure the economic sustainability of mango production.

H. B. Patel and N. J. Patil [3] introduced a greater CNN for both fruit disorder detection and grading the type of postharvest result. The version addresses boundaries in present systems, which often require constant-size inputs and, for this reason, compromise image resolution, via employing Spatial Pyramid Pooling (SPP). This allows the community to handle variable-sized pictures at the same time as maintaining detail. Moreover, the device integrates a Stacked Sparse Denoising Autoencoder (SSDAE) for sturdy feature extraction and a guide vector system for the final, distinctly accurate class. This hybrid approach, which is optimized with adaptive momentum backpropagation, considerably reduces post-harvest losses through permitting speedy, accurate, and high-resolution automated inspection and satisfactory grading of culmination.

J. Lu et al. [4] proposes a new lightweight deep learning solution for automated crop management. The paper aims to address 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. The RepMLP module is introduced to enhance the global perception of the model and capture long-range dependencies, complementing the local feature extraction capability of convolution. An efficient channel attention mechanism has also been added to refine image feature channel weights, and a hard switch activation function has been implemented to boost overall performance. Tested on the Plant Village dataset, the improved model achieved a high recognition rate of 99.53% accuracy. Importantly, it dramatically reduced the number of parameters by 59% and improved inference speed by 8.5% compared to the original MobileNetV2. This efficient and accurate model provides a valuable reference for practical deployment on edge and mobile devices within smart agriculture systems.

V. Yamaçli and M. K. Yildirim [5] presents a two-level model designed for the improved detection of mango leaf illnesses addressing the reliance of many nations on this crop's excellent yield. The primary degree employs a revolutionary handcrafted spatial characteristic extraction method to isolate vital ailment characteristics, while the second stage makes use of a knowledge distillation method to train a small, efficient student community from a large, powerful teacher network. This mixed technique results in an extraordinarily accurate device for early and reliable disease identification. The version's performance and specialized attention make it a treasured and sensible tool for precision agriculture and ensuring the monetary stability of mango production.

The CSXAI model is a lightweight, hybrid 2D CNN-SVM system designed for highly accurate [6] identification and classification of various crop diseases in intelligent agriculture. It successfully classified 10 categories, including diseased and healthy states in crops such as strawberry, peach, cherry, and soybean, achieving an impressive 99.09% average accuracy. A key innovation is the integration of explainable AI (XAI), specifically using Grad-CAM to generate visual heatmaps. This feature allows farmers to clearly see the exact diseased areas on the leaf, providing an interpretable and practical solution that combines high performance with resource efficiency for real-time field use.

V. Boppana et al. [7] presents a hybrid deep learning framework for plant disease detection, combining the efficient MobileNetV2 architecture with a lightweight compact CNN to optimize both accuracy and computational speed. The research achieved an impressive 95% accuracy with MobileNetV2 for disease classification, while the compact CNN delivered efficiency with a minimum training time of 420 seconds. A key innovation is the integration of LIME (Local Interpretable Model-agnostic Explainability), which provides transparent, visual insight into the model's decision-making process, solving the "black box" problem in AI adoption. This robust system sets a practical benchmark for agricultural applications, balancing high detection rates of diseases such as apple scab and black rot with computational efficiency and critical result interpretation.

T. Thorat et al. [8] reviews advances in techniques to identify pesticide residues on fruits and vegetables, which is a serious public health concern due to the dangers of overconsumption. Traditional laboratory methods, such as liquid chromatography, are criticized as being time-consuming and expensive. The document highlights the shift towards integrated systems using embedded technology, sensors, and ML to automate detection. These new methods can determine both the types and concentrations of pesticide residues rapidly and economically. Overall, the research emphasizes moving toward efficient, cost-effective, and rapid analytical techniques to enhance food safety and protect human health.

S. Duhan et al. [9] addresses the challenge of deploying complex deep learning models for plant disease identification on resource-constrained edge devices. It proposes RTR_Lite_MobileNetV2, which is an efficient and lightweight model derived from the standard MobileNetV2 [7] architecture. This model includes several enhancements, including residual connections to improve feature flow, a new trimmed channel attention mechanism for feature recalibration, and a hard switch activation function to boost performance. The resulting architecture is specifically designed to achieve a balance between high classification accuracy and the required computational efficiency. This new model provides a viable and effective solution for early, reliable, and rapid detection and management of crop diseases in smart farming systems.

U. Das et al. [10] provides a comprehensive review of image processing techniques specifically applied to the detection of defects in fruits. It emphasizes that automation is crucial in agriculture to speed up processing and ensure high product quality. The review details various image processing methods used for identifying different types of fruit defects, such as bruises, rot, and physical damage. By summarizing the state-of-the-art in this field, the paper highlights the transition from manual, error-prone inspection to reliable, fast, and automated quality control systems. It serves as a valuable resource for developers seeking to implement advanced computer vision solutions in post-harvest handling and food-sorting machinery.

J. Jhansi et al. [11] proposes an IoT and ML system designed for the real-time detection of pesticide residues on fruits and vegetables, responding to growing food safety concerns. The system utilizes a hardware setup featuring pH and gas sensors for chemical data collection and an ESP32 camera to capture product images. Data from these sensors and the extracted image features are transmitted for analysis by an ML model, which classifies the produce type and indicates the level of pesticide contamination. This integrated, cost-effective, and non-destructive approach offers a practical and user-friendly solution to enhance monitoring and facilitate informed decision-making across the agricultural and consumer sectors.

L. Kujur et al. [12] proposes a singular hybrid version for the correct prediction of citrus fruit sicknesses, aiming to replace labor-intensive guide inspections. This device integrates a custom-designed CNN for computerized characteristic extraction with a Gradient Boosting (GB) set of rules for final classification. To optimize overall performance and ensure quicker convergence, the version utilizes the Nesterov-elevated adaptive moment estimation (NADAM) optimizer. Skilled on a dataset of three 000 citrus snapshots, the hybrid technique carried out notable consequences, including an accuracy of 98.03% and a precision of 98.04%. This strong, computerized solution substantially complements the reliability and efficiency of disease management in citrus orchards, ensuring better crop health and productivity.

M. A. Jahin et al. [13] proposes a novel, hybrid deep learning approach to know modern architecture for the accurate detection of brand-new soybean sicknesses, integrating laptop vision and graph evaluation strategies. The version combines MobileNetV2, a CNN, for extracting picture capabilities, with GraphSAGE, a Graph Neural Network (GNN), for learning relational records amongst picture areas. This fusion is enabled via a move-Modal interest mechanism, which intelligently weighs and combines the outputs from each of the CNN and GNN, enhancing overall diagnostic energy.

A key consciousness present in the studies is interpretability, permitting users to understand the version's selection-making technique. The device achieves excessive accuracy in classifying 15 soybean leaf sickness categories, offering a sturdy, precise, and dependable disease management in soybean farming.

J. Ahmmed et al. [14] explores using a switch studying approach with pleasant-tuning throughout 5 distinctive pre-trained CNNs for the multi-magnification identity of mango leaf illnesses. Addressing the foremost impact diseases have on mango yield, the study evaluated architectures like DenseNet201, Inception V3, and Xception across 8 different ailment lessons. The findings exhibit that DenseNet201 introduced the best performance, attaining a high category accuracy of 99.33%. This distinctly accurate and first-class-tuned method offers a powerful, automatic tool for precision agriculture, enabling the fast and reliable analysis of diverse mango leaf ailments, along with reducing Weevil and Bacterial Canker, to help safeguard crop quality and production.

K. Saddami et al. [15] investigates the usage of lightweight CNN architectures—mainly ShuffleNet, MobileNetV2, and EfficientNet-B0—for the green and correct class of rice leaf diseases. Spotting rice's international importance and the danger of illnesses, the research focuses on mobile-compatible fashions that require less computational power for field deployment. The fashions had been more desirable with two fully connected layers and a dropout layer to enhance overall performance. The study found that EfficientNet-B0 achieved exceptional effects, demonstrating the feasibility of the usage of particularly efficient deep learning models to enable early and accurate detection of rice illnesses, thereby securing crop yields and helping worldwide food protection.

Z. Huang et al. [16] designed a hybrid machine-vision system to detect fruit diseases and evaluate the postharvest quality of produce. The primary objective of this system is to overcome the limitations of traditional grading techniques, which require fixed-size image inputs and therefore lose essential visual details during preprocessing. To address this challenge, the method utilizes a CNN equipped with a SPP layer, allowing variable-sized fruit images to be processed without resizing. This capability increases the accuracy of feature extraction related to color, texture, and surface defects. After the initial extraction of visual characteristics, the features are further refined using a SSDAE, which removes background noise and enhances subtle disease-related patterns. This step ensures that illumination differences, shadows, or minor distortions do not affect classification accuracy. Finally, the refined features are fed into a SVM, which classifies fruits into their respective disease and quality categories with high precision. The integration of adaptive momentum backpropagation ensures fast response time and stable system performance. Overall, the proposed system enables rapid, automated, and non-destructive fruit inspection, significantly reducing postharvest loss and improving grading consistency across different fruit batches.

Table 1: *Summary of literature review.*

Author	Focus Area	Technique/Model Used	Key Contribution	Limitation
M. A. Jahin et al. [13]	Soybean disease detection	Hybrid CNN-GNN	Graph-based visual reasoning and interpretability	Domain-specific model
J. Ahmmed et al. [14]	Mango multi-class disease	Fine-tuned CNN	High precision on mango disease classes	No pesticide residue classification
S. Duhan et al. [9]	Plant leaf disease	RTR_Lite_MobileNetV2	Lightweight architecture, efficient inference	Tested on limited leaf types
S. Espinoza et al. [1]	Fruit quality analysis	CNN variants (review)	Systematic deep learning overview	Limited experimental validation
L. Kujur et al. [12]	Citrus disease detection	CNN + Gradient Boosting	Multi-optimizer classification	Long training times

			improvements	
M. Zheltyakova et al. [6]	Plant disease classification	Hybrid CNN-SVM	Enhanced feature separation ability	Requires manual feature extraction
J. Lu et al. [4]	Crop disease detection	Improved MobileNetV2	Lightweight and mobile optimized	Limited field testing
M. M. Islam et al. [2]	Mango leaf disease	Two-stage CNN	Better robustness via knowledge distillation	Complex pipeline
U. Das et al. [10]	Fruit disease detection	CNN + SVM	Combines grading and classification	Focuses only on apples
T. Thorat et al. [8]	Pesticide residue analysis	Chemical sensing + ML	Useful for residue quantification	Not image-based
Z. Huang et al. [16]	Fruit quality grading	Segmentation + CNN	Automated grading masks	Small dataset
J. Jhansi et al. [11]	Pesticide detection IoT	Sensors + ML fusion	Real-time IoT detection	No vision-based detection
K. Saddami et al. [15]	Rice disease identification	MobileNetV2 + Efficient Net	Energy-efficient lightweight model	Restricted to rice
V. Boppana et al. [7]	Fruit disease detection	Hybrid MobileNetV2 + XAI	Interpretability + accuracy balance	Compute overhead
H. B. Patel and N. J. Patil [3]	Fruit grading and disease	SSDAE-SVM	Grading with diagnosis	Manual feature engineering
V. Yamaçli and M. K. Yildirim [5]	Leaf disease detection	MobileNetV2 vs. Xception	Performance comparison study	No pesticide detection

METHODOLOGY

The proposed machine makes use of an end-to-end device gaining knowledge of the workflow to detect mango sicknesses and classify pesticide-affected fruits using a hybrid structure composed of a TensorFlow-based deep learning version and a Scikit-learn SVM classifier. The method is split into practical phases: model training and network-based deployment. To begin with, a raw photo dataset containing various mango conditions is collected and curated from publicly available assets and manually captured samples. The gathered data goes through preprocessing techniques consisting of resizing, scaling, and pleasant normalization. Records augmentation operations, such as rotation, zoom, horizontal flipping, and assessment modifications, are carried out to grow the dataset's variability and reduce overfitting. The dataset is then broken up into education (80%) and validation (20%) units to evaluate generalization performance.

For the primary class pipeline, transfer learning is used using the MobileNetV2 architecture pre-trained on the ImageNet dataset. Throughout phase 1, base layers of MobileNetV2 are frozen to maintain typical visual functions at the same time as a custom classification head is appended, including an international average Pooling layer, dense layers, and a dropout regularization unit. This configuration allows efficient mastering of mango-precise functions. In Phase 2, selected top convolutional layers are unfrozen and recompiled with a low learning rate, allowing fine-tuning of deeper feature representations without degrading previously learned weights. Parallel to the deep mastering model, the gadget extracts bottleneck characteristic embedding from the penultimate MobileNetV2 layer and uses it to teach an assist vector gadget classifier. A function scaler is applied to ensure balanced distribution across vectors earlier than training. Both the skilled SVM classifier and scaler items are serialized into Joblib documents, ensuring chronic compatibility throughout inference. The very last trained TensorFlow model, class indices, and helping artifacts are generated and stored on disk.

Imparting interactive modules are provided for deciding on responsibilities and uploading photos. It communicates with the backend by using HTTP PUT requests to the /api/discover endpoint. Once an image is uploaded, Flask handles the request, plays comfortably interpreting, and preprocesses the photograph using Pillow and NumPy. The preprocessed picture is then processed through the deep mastering model to acquire primary prediction scores, whilst the extracted excessive-stage functions are forwarded to the SVM version to attain secondary confidence outputs. To reduce latency, fashions are cached in memory after their initial load. The backend fuses each prediction and returns a JSON reaction containing the predicted class and self-belief values. In the meantime, the frontend renders the consequences and offers lively visual remarks on the usage of Chart.js and Framer Motion, enhancing consumer interpretability of self-belief metrics. The model garage module organizes a couple of task-based artifacts, permitting dynamic loading of fashions depending on whether disease detection or pesticide category is selected. This modular design supports destiny expansion by allowing new models to be included without changing the device structure. Universal, the hybrid MobileNetV2 + SVM methodology ensures robust prediction, improved decision consistency, and scalable overall performance. By combining cutting-edge deep learning with classical data analysis, the system provides a reliable and exceptional evaluation suitable for agriculture. Fig. 1 shows the data flow and events and Fig. 2 shows the generic architecture of data flow.

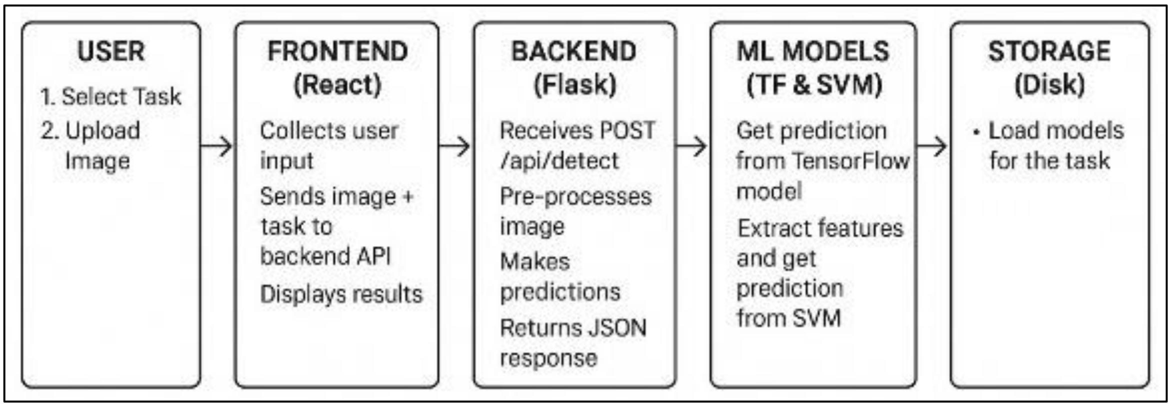

Figure 1: *Data flow and events.*

Fig. 1 explains this architecture, which shows a complete image-processing pipeline where the user uploads an image, the React frontend sends it to a Flask backend, which pre-processes it and uses TensorFlow and SVM models to generate predictions. The backend then loads the required models from storage, performs classification, and returns the result to the frontend for display.

Fig. 2 explains this workflow, illustrating the full training pipeline in which raw images undergo preprocessing. A pre-trained MobileNetV2 model is then fine-tuned using transfer learning, while an SVM classifier is trained on the extracted feature vectors. The final outputs include the trained TensorFlow model, SVM model, scaler, and class-indices file for deployment.

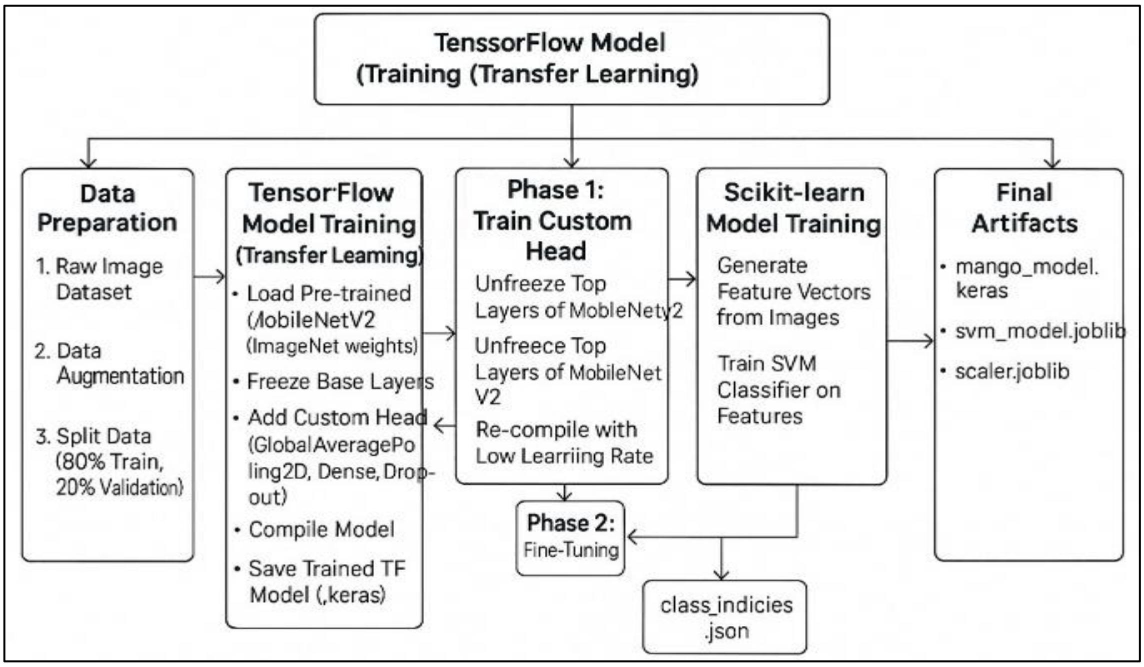

Figure 2: *MobileNetV2 model.*

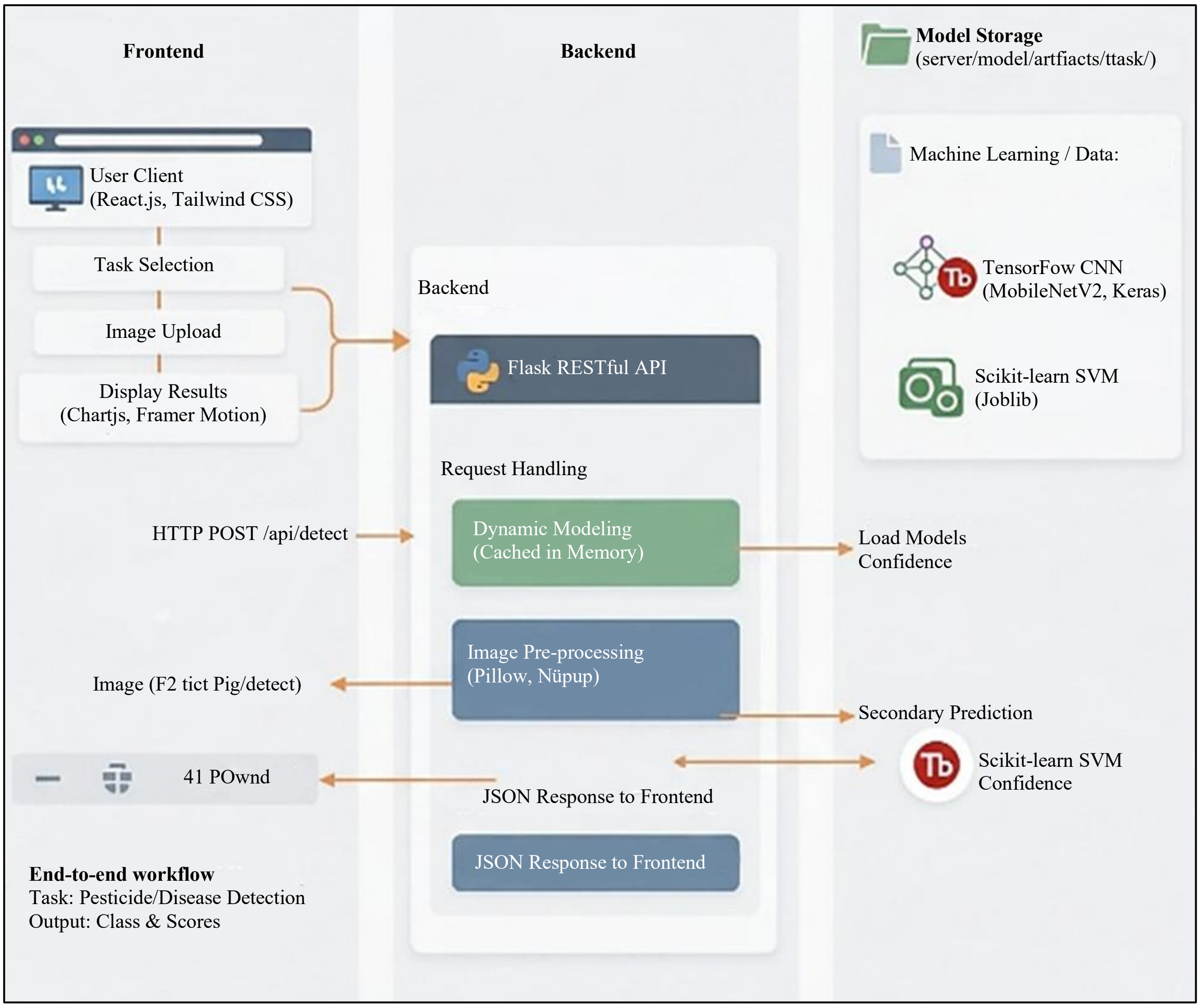

Figure 3: *React frontend.*

Fig. 3 shows how the React frontend sends an uploaded image to a Flask backend, where it is pre-processed and passed to TensorFlow and SVM models for prediction. The backend loads the required models from storage, generates confidence scores, and returns the final JSON result back to the frontend for display.

CONCLUSION

This approach presents a hybrid AI-based web application that automates disease and pesticide infection detection in mango fruit images. The gadget integrates a transfer mastering primarily based MobileNetV2 version with a classical assist vector device classifier to offer accurate and reliable predictions. Through leveraging deep characteristic embedding and secondary decision reinforcement, the proposed answer correctly minimizes false classifications and improves robustness under diverse environmental situations. The structure demonstrates the effectiveness of combining cutting-edge convolutional neural networks with conventional system learning techniques. Actual-time inference is enabled through an optimized Flask backend and version caching, even as the React-based frontend grants an intuitive interface for seamless user interaction. Experimental outcomes suggest excessive category accuracy, low response latency, and robust generalization capabilities throughout a couple of mango samples.

The scalability of the model storage shape and modular API endpoints permits smooth integration into agricultural automation workflows, IoT-based monitoring systems, and the delivery chain, and first-rate inspection pipelines. Despite the fact that overall performance may be affected by severe lighting variations and coffee-resolution inputs, these boundaries may be addressed through dataset enlargement and progressive augmentation techniques. Usually, the proposed answer provides a cost-effective, available, and practical device for farmers, distributors, and best inspectors, contributing to smarter agricultural decision-making, reduced economic losses, and more advantageous fruit protection standards.

Limitations

Although the proposed mango disease and pesticide detection gadget demonstrates promising performance, numerous barriers were identified throughout experimentation and deployment. First, the accuracy of the type version is fairly low in light situations, moderate shadows, and glare on the fruit floor. Low-resolution and blurred photographs can cause reduced function visibility, resulting in occasional misclassifications. The current dataset length is confined and may not fully constitute all mango sorts, seasonal conditions, and nearby sickness styles, which can affect generalization in actual international programs. The system presently supports only a fixed set of ailment categories and pesticide labels; newly emerging sicknesses or chemical styles cannot be detected without additional statistical data. Additionally, the hybrid inference approach will barely increase computational overhead, which may also restrict real-time overall performance on gadgets with low processing capability. The net software relies upon strong community connectivity for photograph addition and prediction retrieval, making offline area deployment hard. Environmental artifacts, together with dust spots, dust, or artificial color styles, can occasionally be interpreted as disorder symptoms. Ultimately, the version does not quantify the severity degree of contamination or pesticide attention, prescribing its use to binary classification consequences. These obstacles provide a treasured route for future upgrades in dataset expansion, severity estimation, mobile-edge deployment, and adaptive learning strategies.

Future Direction

The proposed machine may be extended in numerous meaningful ways to additionally beautify accuracy, scalability, and real-world applicability. First, increasing the dataset to consist of additional mango sorts, environmental situations, and numerous sickness degrees would significantly improve model generalization. Destiny studies may discover superior deep learning architectures along with

Vision Transformers (ViT) and EfficientNet to seize extra complex shade–texture relationships present in early contamination signs and symptoms. A promising route involves integrating IoT-enabled aspect gadgets and drone-based imaging systems for computerized orchard-level tracking. On-device inference optimization using TensorRT or quantization techniques may permit deployment on low-energy mobile hardware. Further work may comprise severity estimation and pesticide attention scoring, permitting growers to decide treatment urgency instead of simply classifying affected samples. Multi-modal information fusion, combining RGB pictures with sensor-based chemical residue readings, could yield a more holistic evaluation of fruit protection. Moreover, chronic mastering and incremental schooling modules can be adopted so the version can adapt to newly emerging diseases or pesticide residue patterns without complete retraining. Integration with cloud dashboards and farm management systems might permit big-scale analytics and predictive yield forecasting. Usually, those enhancements will boost the gadget towards becoming a completely self-sustaining, smart-agriculture companion capable of assisting farmers, distributors, and regulatory bodies in ensuring fruit quality, safety, and sustainability.

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