"AgriVision" a Flutter -Based Application for RealTime Detection of Pesticides Residues on Fruits ."

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Abstract : "AgriVision" is a mobile application developed using Flutter, aimed at tackling the serious concern of pesticide residue on fruits. It employs real-time image analysis and machine learning algorithms to identify chemical contaminants present on fruit surfaces, helping ensure compliance with health and food safety standards. By using the smartphone's camera, users can scan fruits, and the app instantly analyzes and reports the potential presence of hazardous substances. Its intuitive design and mobile nature make it a valuable tool for farmers, sellers, and consumers to evaluate fruit safety and encourage more sustainable farming practices. The project highlights how mobile platforms and artificial intelligence can be merged to deliver effective and scalable solutions in agriculture. Future developments may include linking the app to a centralized database, implementing predictive analytics to monitor pesticide usage patterns, and extending compatibility to a wider range of crops.

Keywords: AgriVision, Flutter app, instant detection, chemical residues, fruit safety, agricultural innovation, mobile technology, AI in agriculture, image-based analysis, smart farming, food hygiene, CNN-based detection, pesticide awareness.

INTRODUCTION

Pesticide residue on fruits and vegetables has become a widespread concern across the globe. Although pesticides play a crucial role in boosting crop production and managing pests, their improper usage or inadequate cleaning can leave behind toxic residues on fresh produce. These remnants pose serious threats to human health. Research has shown disturbing levels of pesticide presence in commonly consumed fruits and vegetables, with long-term exposure linked to illnesses such as cancer and neurological disorders. According to findings by the European Food Safety Authority (EFSA), a significant portion of fresh produce still carries detectable levels of these chemicals, emphasizing the need for improved detection techniques. While traditional testing tools like gas chromatography and mass spectrometry are accurate, they are also costly, time-intensive, and not readily available for everyday users. This highlights the demand for faster, affordable, and user-friendly solutions that both farmers and consumers can use to assess food safety in real-time. problem. Mobile technology is playing an increasingly vital role in agriculture, with applications now commonly used for monitoring crop health and identifying plant diseases. These advancements are also opening doors for innovations in food safety, particularly in the area of pesticide residue detection. AgriVision is a mobile app built using Flutter that addresses the urgent concern of pesticide contamination in fruits. The app leverages real-time image analysis and machine learning techniques to inspect fruit surfaces for chemical residues, helping ensure they meet safety guidelines. By utilizing the smartphone's

Mobile technology offers a promising solution to this

camera, users can scan fruits, and the app instantly assesses and reports any visible signs of pesticide presence. Its simple interface and mobile accessibility make it a convenient tool for farmers, consumers, and sellers to evaluate fruit quality. AgriVision not only encourages safer farming methods but also empowers users to make healthier dietary decisions, contributing to improved public health and food security.

I. LITERATURE REVIEW

The research work titled **"Detection of Pesticide Residues on Fruits Using Image Processing Techniques"** by Patil et al. (2021) explores the use of RGB-based image processing to identify pesticide contamination on fruit surfaces. The methodology involves analyzing changes in color tones and detecting visible surface irregularities that may be indicative of chemical residue. While the approach demonstrated the potential of visual features in contamination detection, its practical application was hindered by a strong dependence on controlled lighting and environmental conditions. This made the solution difficult to implement in real-world, variable settings such as farms or marketplaces. In contrast, **AgriVision** builds upon this concept by deploying a more adaptable and robust solution—utilizing a Convolutional Neural Network (CNN) trained on diverse, real-life fruit images collected under various conditions. This enhances the model's generalization ability, making it suitable for dynamic environments and varying light intensities.

Another relevant study, titled **"Deep Learning-Based Detection of Contaminated Fruits Using CNNs"** by Li et al. (2020), focuses on the classification of fruits into contaminated and uncontaminated categories through the use of deep learning models. Their research employed a CNN to detect subtle visual features associated with pesticide residues, achieving an impressive accuracy rate of approximately 92%.

However, the system's architecture required cloud-based inference, limiting its usability to locations with reliable internet access and increasing latency in response time. This server dependency made real-time field implementation impractical, especially in rural or low-connectivity areas. To overcome this limitation, **AgriVision** incorporates **TensorFlow Lite**, allowing the deep learning model to run directly on smartphones. This shift to on-device inference significantly enhances accessibility, supports offline usage, and delivers instant detection results, making it a more feasible and user-friendly solution for end-users in remote agricultural zones.

The paper titled *“Mobile-Based Application for Smart Agriculture using AI”* In their 2022 study, Chauhan et al. introduced a mobile application tailored for smart agriculture that leverages artificial intelligence to identify crop diseases and detect pesticide residues. Their Android- based solution relied on a cloud-hosted machine learning model, meaning that image data captured by the user was sent to a remote server for analysis. While this approach offered high computational capabilities, it introduced drawbacks such as latency in generating results and a dependence on stable internet connectivity—factors that limit its practicality in rural or low-network environments. In contrast, the “AgriVision’ application addresses these limitations by implementing on-device inference. By integrating a lightweight, optimized machine learning model directly within the mobile device, “AgriVision” allows for instantaneous pesticide residue detection without the need for constant internet access, making it more suitable for use in agricultural regions with limited connectivity.

The paper titled *“Intelligent Systems for Fruit Ripeness and Defect Detection Another relevant study, conducted by Ramesh and Das in 2020, explored the development of intelligent systems capable of evaluating fruit ripeness and identifying physical defects based on visual traits such as color, texture, and shape. Their work demonstrated the feasibility of using artificial intelligence for real-time quality assessment of fruits in field conditions, where laboratory equipment is unavailable.“AgriVision” builds upon this foundation by adapting the concept of visual inspection through AI for a more targeted purpose— detecting harmful pesticide residues. It not only performs surface analysis using advanced image processing techniques but also enhances usability by incorporating features such as scan history tracking, fruit-specific information, and safety alerts. These added functionalities make “AgriVision” a comprehensive and practical tool that goes beyond quality grading, directly contributing to consumer health and informed agricultural practices.*

The study titled **"Fruit Quality Classification using CNN and Edge Devices"** by Singh et al. (2021) explores the practical implementation of Convolutional Neural Networks (CNNs) on low-power edge devices such as smartphones and Raspberry Pi boards. The researchers focused on classifying fruits based on ripeness and surface defects, highlighting the technical limitations posed by these compact devices. Challenges such as limited memory, slower processing speeds, and energy constraints were key considerations in the study. To overcome these, the authors experimented with methods like model pruning (removing redundant parameters), quantization (reducing model precision), and the adoption of lightweight neural architectures optimized for mobile environments. Their work demonstrated that it is feasible to achieve real-time image classification on resource-constrained hardware without compromising much on accuracy. This research significantly shaped the architectural design of AgriVision, inspiring the integration of TensorFlow Lite and optimized CNN models. By adopting similar strategies, AgriVision ensures fast, efficient, and accurate pesticide detection directly on mobile devices, even in offline or rural settings.

The paper titled **"A Review on Food Safety: Detection of Pesticides in Fruits and Vegetables"** by Gupta et al. (2019), which provides a comprehensive overview of both conventional and modern techniques for detecting pesticide contamination. The authors examined traditional laboratory approaches such as gas chromatography, liquid chromatography, and mass spectrometry, emphasizing their high accuracy and sensitivity. However, these methods were also noted to be costly, time-intensive, and often inaccessible to the public, especially for routine screening or in rural agricultural zones. The paper also discussed emerging technologies like spectroscopic analysis, biosensors, and AI-driven image classification methods as more scalable alternatives. Importantly, Gupta et al. identified a significant gap between laboratory-grade testing and field-ready, consumer-friendly solutions. The study called for the development of portable, affordable tools that leverage artificial intelligence to enable non-specialists to assess produce safety quickly and reliably. AgriVision directly responds to this gap by offering a smartphone-based, AI-powered platform that empowers users to check for pesticide residues using only a camera—eliminating the need for complex lab equipment and making food safety assessments more accessible and real-time.

The research work titled *“Intelligent Systems for Fruit Ripeness and Defect Detection”* by Ramesh and Das (2020) explores the use of artificial intelligence for assessing fruit quality by analyzing external characteristics such as texture, color, and shape. Their study employs a range of image classification techniques to demonstrate how real-time analysis can be performed effectively on mobile devices, making such solutions practical for field use. However, the primary objective of their system was limited to identifying the maturity level and physical imperfections in fruits, without considering chemical contaminants. Building upon this foundation, the AgriVision project takes a more specialized approach by focusing on the detection of pesticide residues— elements that may not cause any visible changes but still present serious health concerns. By training its convolutional neural network model to recognize nuanced visual cues associated with pesticide contamination, AgriVision extends the capabilities of AI in agriculture beyond basic quality control, contributing to a more comprehensive food safety assessment system. This advancement broadens the role of mobile AI in smart agriculture by addressing both the aesthetic and chemical integrity of fruits.

*In the study titled **"Fruit Recognition from Images Using Deep Learning"**, Prasad et al. (2020) introduced a methodology for classifying various fruit types using image-based datasets and deep learning techniques. They employed a Convolutional Neural Network (CNN) model, which was trained to recognize fruits based on distinguishing visual features such as color, contour, and surface texture. The dataset used in this study was comprehensive and well-organized, contributing significantly to the model's high accuracy rate of approximately 95%. This research demonstrates the robustness of CNNs in managing image variability caused by differences in lighting, background, and positioning—common challenges in real-world image data. The outcomes of this study closely align with the objectives of the AgriVision project, where accurate fruit classification serves as a foundational step before assessing those fruits for potential* *pesticide contamination.*

In another relevant study titled **"Real-Time Fruit Detection Using YOLOv3"**, Sharma and Jadon (2021) explored the capabilities of the YOLOv3 (You Only Look Once, version 3) object detection framework for identifying multiple fruit types in both still images and continuous video feeds. YOLOv3 is known for its speed and efficiency, making it suitable for real-time applications. The authors trained the model on a customized dataset consisting of various fruit classes and evaluated its performance in dynamic environments such as markets and orchards. The algorithm achieved high levels of precision and recall, indicating reliable object detection in diverse conditions. While AgriVision currently employs CNNs for static image classification, this study suggests promising avenues for future development—such as integrating real-time detection through models like YOLO to support live scanning capabilities in environments like farms, sorting centers, or marketplaces. This would allow AgriVision to evolve from a static diagnostic tool into a dynamic, real-time monitoring system.

Wang and Zhang (2022), in their study titled *"Pesticide Detection in Agricultural Products using Deep Convolutional Networks,"* explored the use of advanced deep learning techniques for identifying pesticide contamination in agricultural produce. Their approach utilized deep convolutional neural networks (CNNs) trained on datasets enhanced through spectral imaging, a method known for its high sensitivity in detecting chemical compounds. Although spectral imaging can be costly and less accessible for everyday use, the researchers also evaluated RGB-based imaging models. Remarkably, these conventional image inputs yielded an accuracy rate of 87%, showing promise for more practical, low-cost solutions. This work is directly relevant to the AgriVision project, as it supports the feasibility of using visual data alone—without chemical tests—for detecting pesticide residues with reliable accuracy.

In another study, Singh and Thakur (2021) introduced an *AI-based smart farming application* tailored for rural Indian farmers. Built with Flutter, the mobile app offered essential features such as crop planning recommendations, soil quality analysis, and pest alerts. While the app did not focus specifically on detecting pesticide residues or assessing fruit safety, it provided valuable insights into the design and functionality of mobile agricultural solutions. The authors emphasized the importance of making apps lightweight, supportive of regional languages, and intuitive to use—factors that are essential for widespread adoption in resource-limited settings. These principles greatly inform the user interface and accessibility goals of AgriVision.

A particularly innovative method is detailed in the research titled *"Rapid Detection of Residual Chlorpyrifos and Pyrimethanil on Fruit Surfaces Using SERS and Deep Learning."* This study integrated Surface-Enhanced Raman Spectroscopy (SERS) with deep learning models to detect multiple pesticide residues on fruits such as apples and strawberries. SERS significantly boosts the sensitivity of the detection process by amplifying molecular signals, while deep learning algorithms accurately classify the type and presence of contaminants based on spectral patterns. Although such advanced equipment may not be practical for mobile deployment, the study demonstrates a powerful fusion of AI and spectroscopy for non-invasive residue detection, potentially influencing future AgriVision upgrades for enhanced precision.

The study titled *"Machine Learning-Enhanced Color Recognition of Test Strips for Rapid Detection of Pesticide Residues"* proposed a fast and cost-efficient method for identifying pesticide residues using colorimetric test strips. In this approach, users apply chemical reagents to fruit surfaces, producing color changes that are then analyzed by machine learning algorithms. These models interpret the intensity and hue of the color patterns to determine the likelihood of pesticide presence. This solution offers an accessible and low-cost alternative for field testing and aligns with AgriVision's vision of providing real-.time, user-friendly pesticide detection through mobileTechnology.

"Colorimetric Sensing for Pesticide Detection in Fruits: A Machine Learning Approach" study focuses on colorimetric sensing techniques, where chemical reagents cause color changes on fruit surfaces in the presence of pesticides. The color changes are analyzed using machine learning algorithms to detect the level of pesticide contamination. This low-cost and quick method directly relates to AgriVision's approach of enabling users to detect pesticides through an easy-to-use mobile interface.

"Leveraging IoT Devices for Real-Time Monitoring of Pesticide Residues in Fruits".This research explores the use of Internet of Things (IoT) devices for real-time monitoring of pesticide residues in agricultural produce. The IoT sensors provide immediate feedback to mobile applications, allowing users to instantly know the safety of their food. This concept is in line with AgriVision's aim of providing a real-time, mobile solution for pesticide detection that is both accessible and user-friendly.

"Deep Learning for the Detection of Pesticide Contaminants in Agricultural Produce".This study uses deep learning techniques to identify pesticide residues in fruits, with the model trained to distinguish between different pesticide types and contamination levels. The findings highlight the potential of deep learning to enhance detection accuracy, a key feature that AgriVision aims to incorporate into its mobile application to provide accurate pesticide detection for everyday users.

"Rapid Field Detection of Pesticide Residues Using Smartphone-Based Microfluidics".This paper discusses a smartphone-based system integrated with microfluidic chips that detect pesticide residues in fruits within minutes. The system uses chemical reactions that result in visible changes, which are then analyzed by the smartphone camera. This concept aligns with AgriVision's goal of enabling quick and easy pesticide residue detection using a mobile platform.

"Advancements in Portable Sensors for the Detection of Pesticide Contamination in Fresh Produce".This research investigates the development of portable sensors that can quickly detect pesticide contamination in fresh fruits and vegetables. The sensors detect changes in the chemical properties of fruits caused by pesticide exposure, providing immediate feedback to the user. This technology aligns with AgriVision's commitment to providing real-time, on-site pesticide detection for consumers via a mobile app.

II. Problem Statement

In modern agriculture, the excessive and unregulated use of pesticides on fruits poses a serious threat to public health, food safety, and the environment. Consumers often lack accessible tools to determine whether the fruits they purchase and consume are contaminated with harmful chemical residues. Traditional laboratory testing methods for pesticide detection are time-consuming, expensive, and inaccessible to the average consumer or farmer, especially in rural areas.

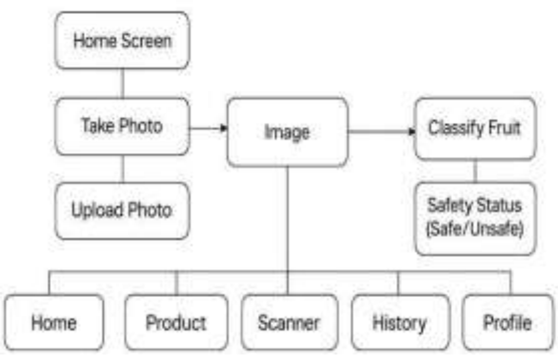
Moreover, existing mobile applications and digital solutions in the agricultural domain mostly focus on crop recommendations, weather updates, or general disease detection, but fail to offer real-time, on-device pesticide residue detection using accessible hardware like smartphones.

There is a critical need for a cost-effective, real-time, mobile-based solution that empowers both farmers and consumers to easily identify the presence of pesticide residues on fruits using commonly available mobile devices.

IV .Functional flow

buttons	Key Functionalities
Home	Quick intro, access to scanner, latest scan summary.
Product	Browse fruits, pesticide stats, safe handling info.
Scanner	Real-time image capture → preprocessing CNN detection → result → store history.
Profile	User data, preferences, feedback, theme toggle, about app.
History	Log of past scans, tap to view details, delete entries.

Agrivision



1. **Frontend (Mobile App)**

- Built with Flutter (iOS/Android).
- Screens: Home, Camera/Scanner, Upload, Results (Safety Status), History, Profile.

2. **Backend**

- ML Model: CNN for fruit classification + object detection (e.g., YOLO) for safety checks.
- Database: Firebase for user data and scan history.

3. **External Services**

- Auth: Firebase Authentication for sign up and login

4. **Data Flow**

1. User takes/upload photo → sent to backend.
2. ML model processes image → returns Fruit Type + Safety Status.
3. Results displayed on the screen.

5. **Key Tech Stack**

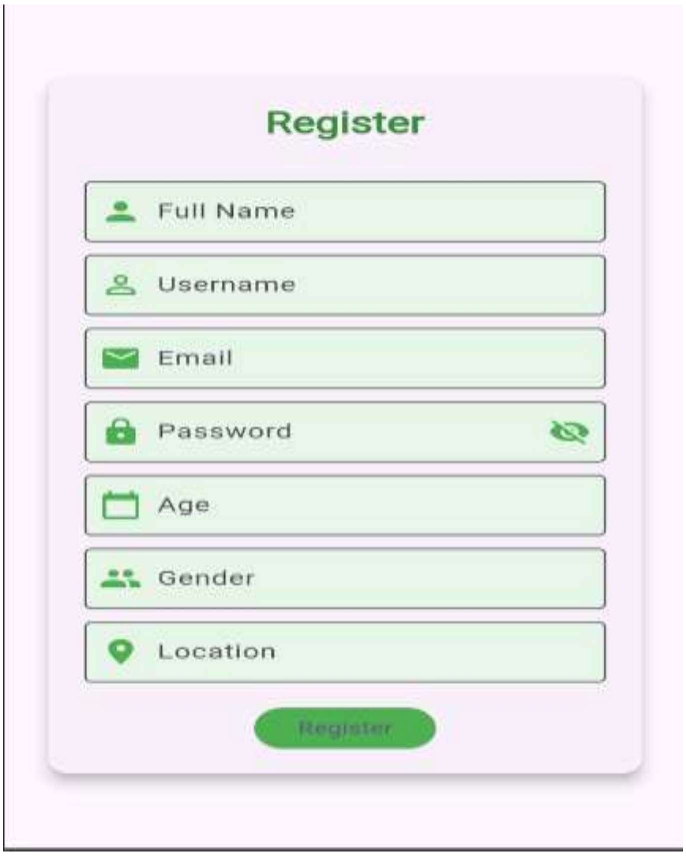
- Frontend: Flutter .
- Backend: TensorFlow/PyTorch.
- Database: Firebase.

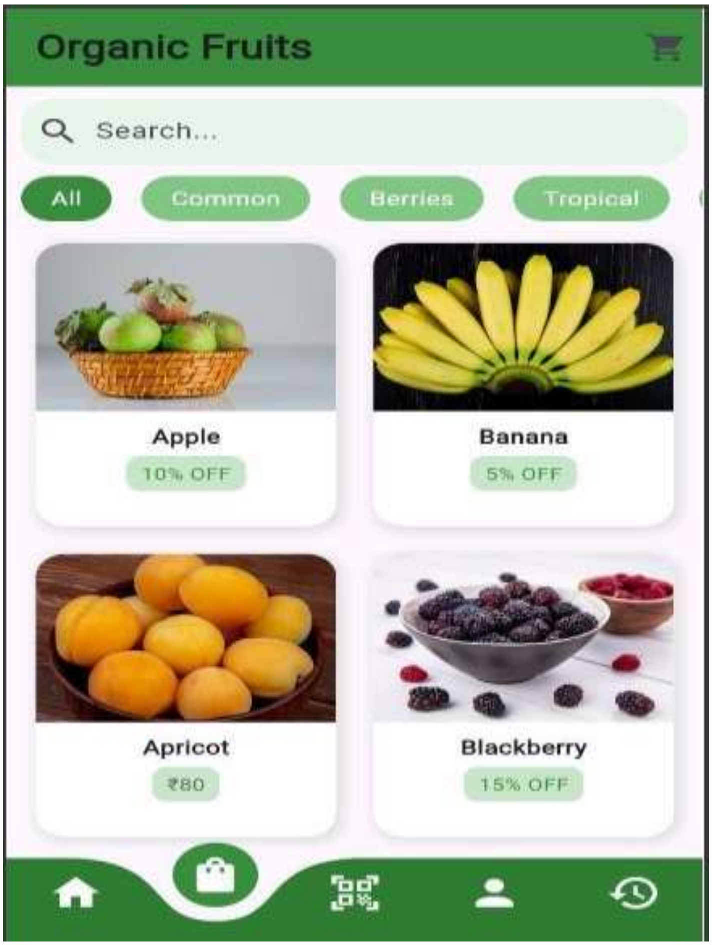
VI. Methodology

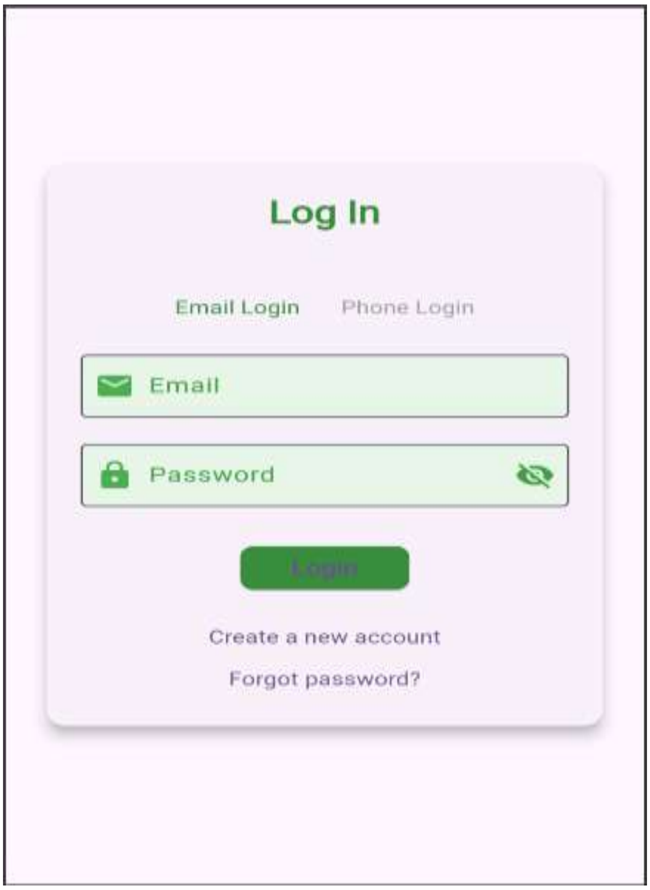
- **Data Collection and Preprocessing**: The project begins with gathering a dataset of fruit images, both with and without pesticide residues. These images are either sourced from public datasets or manually curated. The dataset is then labeled based on the presence or absence of pesticides. Preprocessing includes resizing images to a standard size, normalizing pixel values to a range (0 to 1), and applying augmentation techniques like rotation, flipping, and zooming to improve model robustness.
- **Model Development**: The next step involves selecting a Convolutional Neural Network (CNN) for fruit pesticide detection due to its effectiveness in image classification. A pretrained model, such as ResNet or VGG, may be fine- tuned, or a custom CNN architecture can be designed based on the dataset's characteristics. The model is trained by splitting the dataset into training, validation, and test sets. The training process uses a loss function, such as categorical cross-entropy, and an optimizer like Adam to minimize the error. Evaluation metrics like accuracy, precision, recall, and F1-score are monitored throughout the training process to ensure the model performs well.
- **Model Evaluation and Tuning**: After training, the model is validated using the validation dataset to fine-tune hyperparameters like learning rate and the number of layers. Testing is performed on the test set to assess the model's ability to generalize to new data. Performance metrics are used to confirm that the model is accurately detecting pesticide residues in fruits.
- **Backend Development**: The backend is developed using a framework like Flask or Django, exposing APIs that the Flutter mobile app will use. The trained CNN model is integrated into the backend, where it processes incoming images and returns predictions on whether the fruit contains pesticide residues. These predictions are then sent back to the mobile app.
- **Mobile App Development**: In parallel, the mobile app

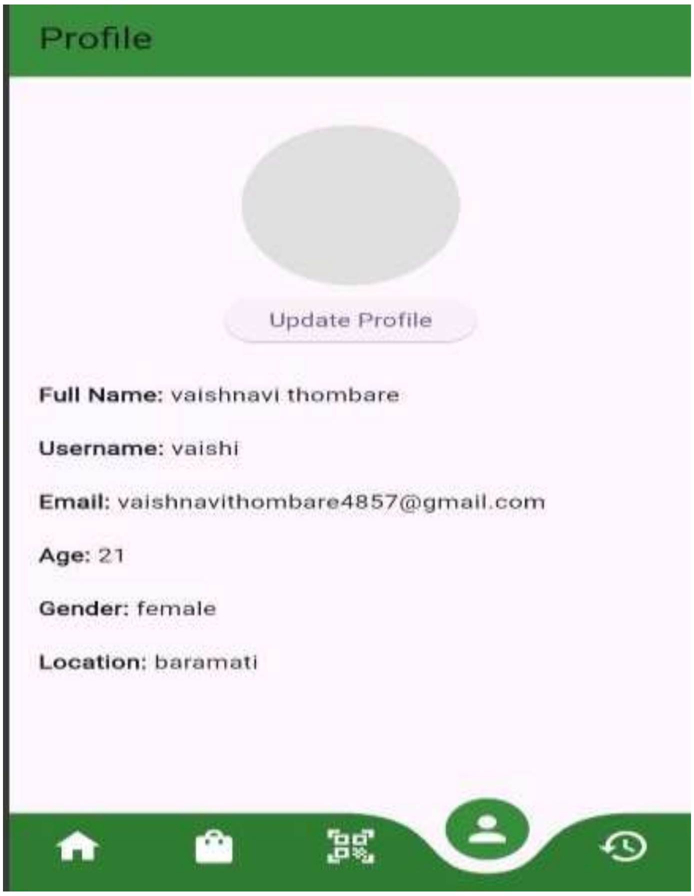
is developed using Flutter. It integrates with the device's camera to capture real-time images of fruits and preprocesses the images before sending them .

VII . IMPLEMENTATION RESULTS









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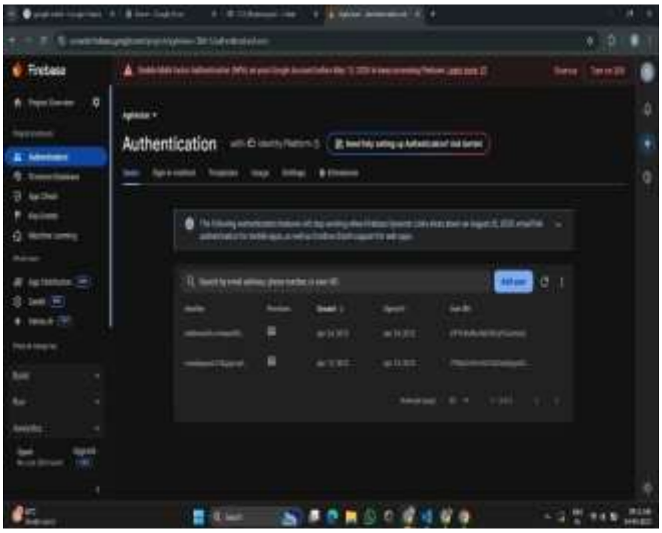

VIII. LIMITATIONS

- Limited Dataset Quality and Size The accuracy of pesticide detection depends heavily on the quality and variety of the training dataset. If the dataset is small, unbalanced, or lacks real-world variety (such as different lighting conditions, backgrounds, and fruit states), the model may perform poorly in real scenarios.
- Difficulty Detecting Invisible Pesticide Residues Many pesticide residues are not visibly detectable with standard cameras. AgriVision relies on visual features, so if pesticide traces do not cause any visible changes on the fruit's surface, the model might fail to identify them accurately.
- Hardware and Camera Limitations Mobile cameras may have limited resolution, especially under poor lighting or with user movement. Blurry or low-quality images can lead to inaccurate predictions by the model.
- Real-Time Processing Speed
Processing high-resolution images through a deep learning model, especially on low-end mobile devices, can be slow. Users may experience delays between scanning and receiving the detection result.
- Model Overfitting
The CNN model might overfit the training data if not properly regularized. As a result, the model may perform well during testing but poorly in real-world usage, where fruit appearances can vary significantly.
- Limited Scope of Fruit Types If the model is trained on only a few fruit types, it may not generalize well to other fruits. Users scanning fruits not included in the training set might get incorrect or unreliable results.
- Cloud Dependency and Internet Requirement Since the model is de loyed on a cloud server, an active and stable internet connection is required. In rural or remote areas where internet connectivity is poor, real-time detection may not be possible.
- Inability to Identify Specific Pesticides AgriVision can only classify the general presence or absence of pesticide residues. It does not detect the exact type of pesticide or quantify the level of contamination.
- Data Privacy and Security Risks Images captured by users are sent to cloud servers for processing. Without proper security measures, there is a risk of data leaks or unauthorized access to users' private data.
- Maintenance and Updating Requirements The model and app require periodic updates to maintain their effectiveness as new types of pesticides, fruits, or environmental conditions emerge. Continuous retraining with updated datasets is necessary to ensure high accuracy.

IX. CONCLUSION

The AgriVision project successfully demonstrates the use of deep learning and mobile technology for real-time detection of pesticide residues on fruits. By integrating a Convolutional Neural Network (CNN) model with a Flutter-based mobile application, the system provides an accessible and user- friendly tool for consumers and farmers to assess the safety of fruits. Through real-time image capturing, analysis, and instant feedback, AgriVision aims to promote healthier food choices and increase awareness about pesticide contamination.

While the system shows promising results, it also faces limitations such as dependency on the quality of images, internet connectivity for cloud-based model access, and challenges in detecting invisible pesticide residues. Despite these constraints, AgriVision lays a strong foundation for future advancements in smart agriculture and food safety technologies. With continuous improvements in dataset quality, model retraining, and expansion to a wider variety of fruits and pesticides, AgriVision can evolve into a highly reliable and essential tool in ensuring consumer health and promoting sustainable agricultural practices.

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