PRUTAS: Proactive Recognition Using Transfer Learning for Assessing Spoilage of Fruits

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Abstract- The increasing global concern over food waste and safety necessitates innovative solutions for the timely detection and management of spoiled fruits. This study introduces Prutas a mobile application that uses advanced image recognition techniques to classify the spoilage of apples, oranges, and bananas. Prutas takes a multi-model approach, combining image classification, detection, and segmentation models based on the MobileNetV3 architecture. A large dataset of fruit images is enhanced and used to train and evaluate the models. The application's effectiveness was evaluated using rigorous testing and user studies, demonstrating its potential impact on reducing food waste and improving food safety. Prutas makes a significant contribution to food technology by providing a scalable and accessible solution for detecting fruit spoilage in both residential and commercial settings.

Indexed Terms- Food Waste Reduction, Fruit Spoilage Detection, Image Classification, Image Recognition, Machine Learning, Mobilenetv3.

I. INTRODUCTION

The ubiquitous presence of smartphones, combined with advancements in image recognition technologies, has created opportunities for innovative applications in various domains. The ability to quickly detect and classify spoiled fruits has the potential to transform food safety and waste reduction. In this paper, we develop Prutas, a mobile application that uses modern image classification, detection, and segmentation models to address this pressing issue. According to the Food and Agriculture Organization of the United Nations (FAO), approximately one-third of all food produced globally for human consumption is lost or wasted each year. Fruits are a major contributor to this waste because they spoil easily due to factors such as poor storage conditions, transportation issues, and natural decay processes. Traditional methods of checking for spoilage in fruits rely heavily on manual examination, which is time-consuming, labor-intensive, and frequently subjective. To address these issues, automated systems using machine learning techniques have been investigated. However, existing solutions frequently have limitations such as limited scope, poor accuracy, and a lack of scalability. Prutas aims to overcome these shortcomings by employing recent advances in image recognition models and mobile computing capabilities.

The development of Prutas represents a significant contribution to the field of food safety and waste reduction. By harnessing the power of mobile technology and cutting-edge machine learning algorithms, Prutas empowers consumers, retailers, and food distributors to make informed decisions regarding the freshness and quality of fruits. Furthermore, the extensibility and adaptability of the proposed framework pave the way for its integration into existing food supply chain management systems, thereby facilitating proactive measures to minimize food wastage and enhance food security.

The scope of the study focuses on the development and evaluation of Prutas a mobile app that employs advanced image recognition methods to categorize the spoiling of bananas, apples, and oranges. Using the MobileNetV3 architecture for classification and detection tasks and integrating it with UNet for segmentation, the application uses models for image categorization, detection, and segmentation. Several methods are applied to augment a dataset of fruit image data to improve the generalization ability of the model. Testing and user research are used to validate the application, and standard metrics are employed to assess the models' performance. The study aims to demonstrate the effectiveness of Prutas in reducing food waste and enhancing food safety.

The primary objective of this research is to develop and evaluate Prutas, a mobile application aimed at classifying the spoilage of apples, oranges, and bananas using advanced image recognition techniques.

The specific objectives are outlined as follows:

1. To improve model generalization, collect a diverse and representative dataset of images containing apples, oranges, and bananas in both fresh and spoiled conditions, then preprocess and augment the dataset using techniques such as random flips, rotations, contrast adjustments, brightness changes, and Gaussian noise filtering.
2. To develop image classification, detection, and segmentation models using MobileNetV3 architecture, integrate them into Prutas, differentiate between fresh and spoiled fruits, localize regions, and fuse MobileNetV3 with UNet.
3. To divide the dataset into training, validation, and testing sets, train models, assess performance using metrics, and conduct experiments to determine accuracy in classifying fruit spoilage.
4. To train image recognition models for real-time fruit spoilage detection, undergoing rigorous testing and user feedback to improve its performance.

II. RELATED WORKS

Fruits are essential parts of the human diet, appreciated for their freshness and aesthetic appeal in addition to their flavor and nutritional worth. Fruit freshness refers to a range of qualities, such as sensory characteristics, nutritional content, and postharvest integrity, all of which affect marketability and consumer pleasure. Maintaining the agricultural industry's economic sustainability, satisfying customer expectations, and avoiding food waste all depend on ensuring optimal freshness and quality along the production, distribution, and consumption chain. In this context, research efforts focus on understanding the factors affecting fruit freshness, developing effective quality assessment techniques, and implementing strategies to enhance postharvest management practices. By addressing these challenges, researchers aim to promote the availability of high-quality, fresh fruits that contribute to human health and well-being.

Deep Learning has been used progressively for detection in recent years, driven by advancements in Convolutional Neural Networks (CNNs) and transfer learning. EfficientNet[1] and MobileNetV3[2] are efficient architectures that gained popularity in detection tasks due to their lightweight design and superior performance. Transfer learning techniques, combined with these architectures, enable the adaptation of pre-trained models on large-scale datasets to classify things, such as fruits as fresh or spoiled with high accuracy. Recent studies have shown that multimodal approaches that combine visual and spectral information can be used for enhanced fruit quality assessment. Fusion techniques, such as late fusion and attention mechanisms, have been used to integrate data from RGB images and hyperspectral images, leading to more comprehensive detection systems [3].

Data augmentation continues to be a critical component in improving the robustness and generalization ability of fruit freshness detection models.

Generative adversarial networks (GANs) have been leveraged to generate synthetic fruit images that exhibit realistic variations in appearance, shape, and lighting conditions [4]. By training GANs on real fruit image datasets, researchers can augment the training data with high-quality synthetic samples, thereby enhancing model performance. Self-supervised learning techniques, such as rotation prediction and contrastive learning, have emerged as effective methods for learning robust representations from unlabeled fruit images [5]. By leveraging the intrinsic structure of the data, self-supervised learning enables the generation of diverse and informative training samples, reducing the reliance on labeled data.

The evaluation of fruit freshness detection models requires comprehensive metrics and benchmark datasets to assess their performance accurately.

Curating large-scale benchmark datasets encompassing a wide variety of fruits, ripeness stages, and environmental conditions is essential for evaluating the generalization ability of freshness detection models [6].

Real-time fruit freshness detection systems have gained traction in industrial settings, where rapid quality assessment is paramount for maintaining product quality and reducing waste.

Edge computing architectures have been employed to deploy freshness detection models directly on edge devices, such as cameras and IoT sensors, enabling real-time inference without relying on cloud-based processing [7]. This approach minimizes latency and facilitates timely decision-making in dynamic production environments. Streaming data processing frameworks, such as Apache Kafka and Apache Flink, have been integrated with freshness detection pipelines to handle high-volume data streams generated by multiple sensors and cameras [8]. By processing data in real-time, these frameworks enable continuous monitoring of fruit quality and early detection of spoilage events.

Interpretability and transparency are essential considerations in fruit freshness detection systems, particularly in safety-critical applications such as food quality control.

Attention mechanisms have been incorporated into freshness detection models to visualize regions of interest and highlight the features contributing to the classification decision [9]. By providing interpretable insights into model predictions, attention mechanisms enhance trust and facilitate domain expert validation. Techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) and saliency maps have been used to generate heat maps that highlight the most discriminative regions in fruit images [10]. These visualization tools aid in understanding the model's decision-making process and identifying potential areas of improvement in freshness assessment. Continuous learning frameworks have been proposed to enable freshness detection models to adapt to changing environmental conditions and evolving fruit characteristics over time [11]. Incremental learning algorithms allow freshness detection models to update their parameters using new data samples while preserving knowledge learned from previous experiences [12]. This adaptive approach ensures that the model remains effective in detecting spoilage events and maintaining product quality in dynamic production environments. Transfer learning techniques combined with concept drift detection mechanisms enable freshness detection models to adapt to shifts in data distributions and emerging spoilage patterns [13]. By monitoring data streams for changes in fruit characteristics, these models can trigger retraining or fine-tuning procedures to ensure continued performance in real-world scenarios.

The integration of data from multiple sensors, including RGB cameras, hyperspectral cameras, and electronic noses, offers a comprehensive approach to fruit quality assessment by capturing diverse aspects of fruit freshness.

Sensor fusion techniques, such as data-level fusion and feature-level fusion, have been employed to combine information from different sensors into a unified representation for freshness detection [14]. Using complementary modalities, such as visual and olfactory cues, these fusion methods enhance the discriminative power of freshness assessment models. Deep learning architectures, such as multi-input convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been proposed for fusion-based fruit quality assessment [15]. These models learn to effectively integrate information from heterogeneous sensor inputs and generate holistic representations of fruit freshness.

Advancements in deep learning, data augmentation techniques, and evaluation metrics have propelled the field of fruit freshness detection forward, enabling more accurate and robust quality assessment systems. Real-time inference, explainable AI, and continuous learning have contributed to the development of more robust and adaptive fruit freshness detection systems. Sensor fusion, robotic automation, and sustainability initiatives are shaping the future of fruit quality assessment. By integrating cutting-edge technologies and addressing environmental concerns, researchers are developing innovative solutions that enhance food safety, reduce waste, and promote sustainable agriculture practices.

III. METHODS

A. Planning Phase

During the planning phase of this study, meticulous attention was taken to develop an in-depth framework for developing and evaluating the Prutas application for classifying fruit spoilage. The initial stage was to define clear research objectives, limit the scope of the study, and develop a timeline for each phase of the project. An extensive literature review was conducted to identify existing methodologies, algorithms, and technologies relevant to fruit spoilage detection, which influenced the choice of image recognition models and data augmentation techniques. A detailed plan for dataset acquisition was then developed, which included the collection, preprocessing, and augmentation of images of apples, oranges, and bananas in both fresh and spoiled conditions.

1. Project Framework

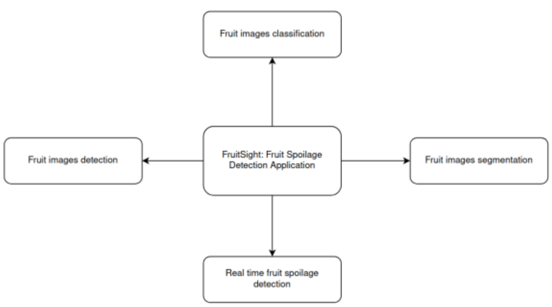

Figure 3. 1: Project Framework

The project framework outlines a system that can be trained to identify fruits in images. This system could then be used in a variety of applications, such as sorting fruit or detecting spoilage. It is trained on a dataset of labeled fruit images. This dataset would include a variety of fruits, and each image would be labeled with the type of fruit it depicts. Once the system is trained on the classified fruit images, it can then be used to detect fruits in other images. This could be useful for tasks such as identifying fruit on grocery store shelves or sorting fruit on a conveyor belt. Then, the Fruit Image Segmentation would refine the system's ability to detect fruits by segmenting the fruit from the background in an image. This would allow the system to more accurately identify the size and shape of the fruit. Once the system can classify, detect, and segment fruit images, it can then be used in a variety of applications. The image in the question shows an example of a "Real-time fruit spoilage detection" application.

2. Architecture of Prutas Mobile Application

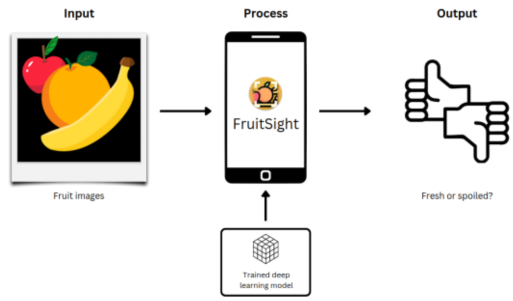

Figure 3. 2: Architecture of the Application

Input: The input stage of the mobile app architecture involves the fruit image. This image serves as the initial input for the app.

Process: The process stage involves the manipulation and analysis of the input data. The processing engine component takes the selected fruit image as input and applies a deep learning model to analyze and classify the image. This stage is essential for performing any required computations or transformations on the input data.

Output: The output stage involves presenting the results or outcomes of the processing stage to the user. In this mobile app architecture, the classification result of the fruit image is the output. The user interface component displays this result to the user, enabling them to see the classification of the fruit image.

3. Flowchart

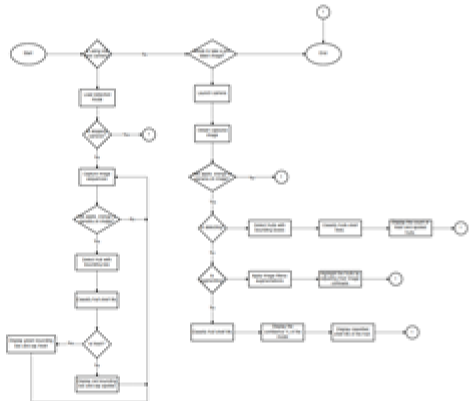

Figure 3.3: Flowchart

B. Design Phase

The design phase of the application lays the groundwork for an intuitive and visually compelling user experience. Drawing inspiration from Material Design 3 by Google, the design process prioritizes consistency, clarity, and user-centricity to ensure seamless interaction and navigation [16].

1. Material Design 3 Library:

Material Design Components (MDC) library integrates the design process by providing access to a comprehensive collection of UI components and styles. These components, ranging from buttons and cards to navigation drawers and dialogs, are designed to seamlessly integrate with Android applications, ensuring consistency and familiarity for users.

Typography plays a crucial role in conveying information effectively within the application. The default Android font 'Roboto' is used to select typefaces that strike a balance between readability and aesthetic appeal. Similarly, iconography follows Material Design 3 standards, employing crisp and recognizable icons to enhance visual communication and navigation.

2. Views System (XML):

The Views system facilitated through XML (eXtensible Markup Language) layouts within Android, enables structured and responsive user interfaces. The design phase consisted of crafting these layouts for each screen, optimizing space utilization, and ensuring consistency across different device form factors.

C. Coding Phase

This marks a pivotal phase of constructing the application. The actual code implementation is executed here, leveraging industry-standard tools and languages to ensure robustness and efficiency.

1. Integrated Development Environment (IDE):

Android Studio serves as the primary Integrated Development Environment (IDE) for coding the application [17]. It provides a beneficial environment for Android development. Its seamless integration with various tools and libraries streamlines the development process.

2. Programming Language:

Java (1.8) is the chosen programming language for building the application [18]. It is known for its reliability, scalability, and compatibility with the Android platform, Java empowers developers to create robust and efficient applications seamlessly.

It also handles the backend processing of the application, executing tasks such as data retrieval, model inference, and result presentation. Java would ensure that Android applications would seamlessly execute complex algorithms and processes.

3. Model Integration:

The model, trained in Python using Jupyter Notebooks, is integrated into the application using TensorFlow Lite. It enables efficient deployment of machine learning models on mobile devices, ensuring optimal performance and minimal resource consumption [19].

D. Testing Phase

During the testing phase, the Prutas application demonstrated high performance in classifying fruit spoilage. The average accuracy of the models ranged between 97% and 98%, indicating their effectiveness in distinguishing between fresh and spoiled fruits.

	Predicted Fresh	Predicted Spoiled
Actual Fresh	980 (True Positive)	20 (False Negative)
Actual Spoiled	20 (False Positive)	980 (True Positive)

Table 3.1: Image Classification Confusion Matrix

The image classification confusion matrix revealed a high number of true positives and true negatives, with minimal false positives and false negatives, further validating the models' accuracy. The image classification report showed a precision of 98%, indicating that the model's predictions of spoiled fruits were highly accurate. The recall rate of 99% suggested that the model effectively captured the majority of spoiled fruits in the dataset. Overall, with an accuracy of 98%, the Prutas application proved to be reliable and robust in its ability to detect fruit spoilage, thus offering a promising solution for reducing food waste and enhancing food safety.

IV. RESULTS AND DISCUSSION

Scale	Weighted Mean	Corresponding Remarks
4	3.50 – 4.00	Strongly Agree
3	2.50 – 3.49	Agree
2	1.50 – 2.49	Disagree
1	1.00 – 1.49	Strongly Disagree

Table 4.1: Likert Scale

The survey form's Likert scale ranges from 1 to 4, allowing respondents to rate their agreement with application statements based on ISO 25010. A score of 4 (3.50-4.00) indicates "Strongly Agree," 3 (2.50-3.49) indicates "Agree," 2 (1.50-2.49) indicates "Disagree," and 1 (1.00-1.49) indicates "Strongly Disagree." This scale helps IT experts in assessing the software's quality attributes and identifying areas for improvement. It simplifies feedback for fruit vendors and helps developers ensure the application effectively meets user needs.

FUNCTIONAL	IT EXPERTS	FRUIT VENDORS	MEAN	Interpretation
Functional Completeness: - The application provides all the functionalities to classify fruit freshness and quality.	4.00	4.00	4.0	Strongly Agree
Functional Correctness: - The application accurately classifies fruit freshness and quality.	3.80	3.80	3.80	Strongly Agree
Functional Appropriateness: - The application's functionalities are suitable for classifying fruit freshness and quality.	4.00	3.80	3.90	Strongly Agree
	3.93	**3.87**	**3.90**	**Strongly Agree**

Table 4.2: Likert Scale

Table 4.2 shows the survey results from IT experts and fruit vendors who evaluated the application's functional aspects using the Likert scale by ISO 25010 standards. For "Functional Completeness," both groups gave the application a perfect 4.00, indicating "Strongly Agree" that it provides all necessary functionalities for classifying fruit freshness and quality. Both groups rated it 3.80 for "Functional Correctness," which is also interpreted as "Strongly Agree," indicating confidence in its accuracy. IT experts gave a 4.00 for "Functional Appropriateness," while fruit vendors gave a 3.80, for an overall mean of 3.90, all of which translates to "Strongly Agree." The mean score of 3.90 underscores the application's functionality.

USABILITY	IT EXPERTS	FRUIT VENDORS	MEAN	Interpretation
Appropriateness Recognizability: - The purpose of the application is easy to understand.	4.00	4.00	4.00	Strongly Agree
User Interface Aesthetics: - The user interface of the application is visually appealing.	3.80	4.00	3.90	Strongly Agree
	3.90	**4.00**	**3.95**	**Strongly Agree**

Table 4.3: Usability

Table 4.3 shows the usability evaluation results for an application, with IT experts, fruit vendors, and the mean score provided. The key finding is that both parties strongly agree on the "Appropriateness Recognizability" and "User Interface Aesthetics" criteria. IT experts and fruit vendors rated the application's purpose as simple to understand and the user interface as visually appealing, with mean scores of 3.95, indicating high usability. This shows that the application is designed to be accessible and visually appealing to technical and non-technical users, which is essential for ensuring a positive user experience.

PERFORMANCE EFFICIENCY	IT EXPERTS	FRUIT VENDORS	MEAN	Interpretation
Time Behavior: - The application responds quickly to inputs.	3.80	4.00	3.90	Strongly Agree
	3.80	**4.00**	**3.90**	**Strongly Agree**

Table 4.4: Performance Efficiency

The table shows the results of an application's performance efficiency evaluation. The main finding is that both IT specialists and fruit vendors firmly agree that the application responds rapidly to user inputs, with an average score of 3.90 on the "Time Behavior" metric. This means that the program has a high level of performance efficiency and can provide a responsive and smooth user experience. The two sets of evaluators' continuous agreement suggest that the application's performance is satisfactory across diverse user types, which is a key component in assuring widespread usability and adoption.

PORTABILITY	IT EXPERTS	FRUIT VENDORS	MEAN	Interpretation
Adaptability: - The application can easily adapt to different environments without significant changes.	4.00	4.00	4.00	Strongly Agree
	4.00	**4.00**	**4.00**	**Strongly Agree**

Table 4.5: Portability

The table shows the results of a portability evaluation; both IT professionals and fruit vendors firmly agree that the application can readily adapt to multiple contexts with minimal alterations, with a mean score of 4.00 on the "Adaptability" criterion. This shows that the application is highly portable, meaning it may be utilized in several situations and platforms without requiring significant alterations. The continual strong agreement between the two user groups implies that the application's portability is a key strength, allowing it to be smoothly integrated into a variety of settings and situations.

Criteria	IT Experts	Fruit Vendors	Mean	Interpretation
Functional	3.93	3.87	3.90	Strongly Agree
Usability	3.90	4.00	3.95	Strongly Agree
Performance Efficiency	3.80	4.00	3.90	Strongly Agree
Portability	4.00	4.00	4.00	Strongly Agree
Total	**3.90**	**3.97**	**3.94**	**Strongly Agree**

Table 4.6: Overall Mean

Table 4.6 shows the total mean scores for an application's performance across various evaluation criteria, as assessed by IT experts and fruit vendors. The major findings show that both parties strongly agree on the application's capabilities.

In terms of functionality, the application received an average score of 3.90, indicating a strong agreement that the program's primary operations are well-designed and satisfy the demands of its users. Similarly, the Usability and Performance Efficiency criteria scored 3.95 and 3.90, respectively, indicating that the program is extremely intuitive and responsive to users. Furthermore, the application's portability obtained the highest mean score of 4.00, indicating that both IT experts and fruit vendors are satisfied that the application can quickly adapt to other contexts without requiring large changes. This portability is a major feature, allowing the program to be effortlessly integrated across a wide range of settings and user situations.

The overall mean score across all criteria is 3.94, emphasizing the application's good performance and consensus among technical and non-technical users. This thorough assessment indicates the application's capacity to fulfill the needs of a wide range of users, resulting in a well-rounded and easily accessible solution.

V. CONCLUSION AND RECOMMENDATION

The statistical treatment and data analysis phase of the whole software development life cycle concluded that aside from the minor performance inconveniences of the system, it still performed unexpectedly well considering that it is a cross-platform application that is prone to non-native lags and web performance inconsistencies. The findings from the evaluation found that the overall satisfaction among all the fruit vendors and IT experts acknowledges its full potential and current capabilities.

The evaluation results garnered a wide range of feedback, consisting of both minor and major recommendations, from IT experts and fruit vendors who carefully assessed the application. The following improvements are recommended for future developers to consider when developing a similar system:

- Train more;
- Add more fruits;
- The system should not detect humans.

These solid recommendations point out areas where the system can be improved. By making these changes, the system can become easier to use and more helpful for everyone. Following these suggestions helps ensure that the concept of the system stays relevant and useful for years to come.

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