FRUIT RECOGNITION

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***Abstract*—The Fruit Recognition Project leverages machine learning and image processing techniques to develop a robust system capable of accurately identifying and classifying fruits. The system aims to streamline fruit sorting, improve supply chain efficiency, and support automation in agriculture and retail sectors. It combines advanced computer vision algorithms with feature extraction techniques to analyze images of fruits and distinguish them based on shape, color, texture, and size.**

The project follows a systematic workflow, starting from image acquisition and pre-processing to segmentation and feature extraction. A machine learning classifier, trained on a comprehensive dataset, performs the final classification. The use of non-linear models and optimization strategies ensures high accuracy, even with variations in lighting, orientation, and fruit types.

The solution's flexibility allows it to adapt to different environments and fruit categories, making it suitable for applications ranging from automated grocery checkout systems to quality control in fruit packaging units. Future work will focus on expanding the dataset and incorporating deep learning for enhanced performance and scalability. This project highlights the potential of artificial intelligence in revolutionizing agricultural practices and consumer experiences.

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***Index Terms*—Fruit Recognition ,Image Processing, Deep Learning, Feature Extraction, Agricultural Automation**

I. INTRODUCTION

Fruit recognition plays a vital role in modern agricultural automation, focusing on improving efficiency in sorting, grading, and quality assessment. This project investigates an innovative system aimed at automating the identification of fruits through advanced image processing and machine learning techniques. The rising global demand for high-quality produce has created a need for intelligent systems capable of accurately distinguishing fruits based on their shape, color, texture, and size.

Our method utilizes deep learning algorithms to extract and analyze features from fruit images, allowing for precise classification. This automated system reduces human error, lowers labor costs, and ensures consistency in fruit handling processes. By incorporating cutting-edge models and optimized preprocessing techniques, the project seeks to establish a robust framework that can adapt to various fruits and environmental conditions.

This initiative is not only important for large-scale farming operations but also offers potential benefits for small and medium-sized enterprises aiming to boost their competitiveness. Ultimately, this project highlights the crucial role of technology in evolving traditional agricultural practices into smart, data-driven operations, contributing to sustainable and efficient food production systems.

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A. Significance Of the Project with applications

In today's fast-changing agricultural environment, achieving efficiency and quality in fruit processing is crucial. Traditional sorting and grading methods often depend on manual labor, which can be time-consuming, inconsistent, and susceptible to human error. With the increasing global demand for high-quality, uniform produce, there is a pressing need for automated systems that can simplify these processes while ensuring accuracy. This is where fruit recognition technology, utilizing image processing and machine learning, plays a vital role.

By employing sophisticated algorithms, the system can automatically identify, classify, and sort fruits based on various factors such as size, color, ripeness, and defects. This not only boosts operational efficiency but also guarantees that consumers receive top-notch products, enhancing customer satisfaction and brand reputation. The capability to assess fruits objectively and consistently is essential for adhering to strict quality standards, especially in export markets where uniformity and compliance are critical.

Moreover, automation helps tackle labor shortages in the agricultural industry, reducing reliance on human inspectors and cutting operational costs. It also accelerates the processing pipeline, enabling producers to respond to market demands more quickly and effectively. The data collected from automated systems can provide valuable insights for farmers and supply chain managers, facilitating improved decision-making regarding crop management, storage conditions, and logistics.

Applications of the Project

1. Agriculture and Horticulture:
Automated fruit recognition can be deployed at farms to sort and grade produce immediately after harvesting. This ensures that only high-quality fruits enter the supply chain, reducing post-harvest losses and enhancing profitability.

2. Food Processing and Packaging Industries:
In food processing plants, the technology can streamline packaging by ensuring that only fruits meeting specific quality criteria are packaged and shipped. This reduces the risk of customer complaints and product returns.

3. Retail and Supermarkets:
Retail chains can use fruit recognition systems to maintain inventory quality, ensuring that only fresh and visually ap-

pealing produce reaches the shelves. This improves customer satisfaction and reduces waste.

4. Export and Quality Control:
For exporters, automated systems ensure compliance with international quality standards, facilitating smoother trade and reducing the likelihood of rejected shipments due to quality issues.

5. Research and Development:
Researchers can use fruit recognition data to study fruit characteristics, leading to the development of better crop varieties and early detection of diseases or pests.

B. Survey of Existing methods and technologies

Traditional methods for recognizing fruit often depend on image processing techniques such as color segmentation, shape analysis, and texture features. These approaches can struggle with variations in lighting, background, and the appearance of the fruit itself. However, machine learning algorithms, particularly convolutional neural networks (CNNs), have greatly enhanced accuracy by identifying complex patterns in extensive datasets of fruit images. Additionally, technologies like near-infrared (NIR) spectroscopy are used to assess internal qualities such as ripeness. Combining image processing with machine learning and sensor data creates more effective solutions. Nonetheless, challenges persist in terms of real-time processing and scalability. Recent developments focus on integrating AI with IoT devices to create smarter, automated systems.

C. Problems and Statements

The main challenge in recognizing fruits lies in the significant variability in their appearance, influenced by factors such as lighting, background distractions, and occlusion. Traditional image processing techniques often struggle to differentiate between similar-looking fruits or assess their ripeness accurately. Additionally, machine learning models typically need large and diverse datasets to function effectively, which can be hard to gather. Concerns about real-time processing and accuracy are particularly relevant in dynamic settings like markets or farms. Another challenge is the scalability of current systems to accommodate a wide range of fruits. Furthermore, there is a demand for reliable solutions that can operate in low-resource environments. Ensuring consistent performance across all conditions is a crucial issue that needs to be tackled.

D. Motivation

The inspiration for this fruit recognition project comes from the increasing demand for effective and precise agricultural technologies that can improve food quality control and distribution. By automating the process of fruit identification, we can enhance sorting, grading, and ripeness detection, which in turn minimizes manual labor and reduces the chances of human error. Moreover, these systems could help optimize supply chains, ensuring that fresher produce is delivered to consumers. The goal of the project is to aid in the digitization of farming practices and promote sustainable agriculture. Ultimately, it will empower farmers, distributors, and consumers to make better-informed decisions, fostering innovation within the agricultural sector.

E. Major Objectives with Work Plan

The main goal of this project is to create a fruit recognition system that utilizes machine learning techniques, with an emphasis on accurately classifying fruits based on visual characteristics such as color, shape, and texture. The project will include gathering data from a range of fruits in various conditions and preprocessing this data to make it suitable for training the model. A deep learning model, probably a Convolutional Neural Network (CNN), will be trained and assessed for its performance using metrics like accuracy and precision. After developing the model, the system will be integrated with a hardware platform to enable real-time fruit recognition in automated settings. The project will also focus on optimizing the model for efficient processing, ensuring it can reliably recognize and classify fruits in different environments. Finally, the findings will be documented, and the system will be showcased, highlighting its practical applications in agriculture.

II. Materials and Methods

A. System Architecture with Description

1. Image Acquisition:
Device: This involves using a camera or other image-capturing devices like webcams, smartphones, or dedicated cameras. Image Formats: Common formats include JPEG, PNG, or similar types.

2. Preprocessing and Feature Extraction:
Preprocessing: Techniques such as resizing, color normalization, noise reduction, and possibly data augmentation (like rotation and flipping) would be applied to enhance the dataset for training. Feature Extraction: Since the focus is on fruit recognition, deep learning-based feature extraction through Convolutional Neural Networks (CNNs) is likely. Traditional methods like Histogram of Oriented Gradients (HOG) or Scale-Invariant Feature Transform (SIFT) could also be considered, but CNNs are generally preferred for their accuracy and effectiveness in image classification tasks.

3. Classification Layer:
I am utilizing CNNs (Convolutional Neural Networks), which are recognized for their effectiveness in image classification. CNNs can automatically learn features from raw image data, eliminating the need for manual feature extraction. Alternatively, if a simpler model is chosen, machine learning models like Support Vector Machine (SVM) or Random Forest could be used for classification after feature extraction.

4. Post-Processing and Output Generation:
I am generating the output using basic programming tools (e.g., Python with libraries like Tkinter for the user interface, or a web framework like Flask or Django). The output may show the predicted fruit type, confidence levels, and possibly a user interface for interacting with the results. User Interface (UI):

This would likely be a straightforward graphical user interface where users can upload or capture images. For a web interface, Flask or Django could be utilized, while Tkinter or PyQt might be chosen for desktop applications.

B. Description of Sensors or Other Modules Related to the Project

The fruit recognition project uses a camera module to take high-resolution images of fruits, which are then processed with image preprocessing software like OpenCV to standardize them for classification. A machine learning model, usually a Convolutional Neural Network, analyzes these images to identify the fruits. For local processing, a microcontroller or a single-board computer, such as a Raspberry Pi, is used to manage the image capture and recognition tasks. The results are displayed on a user interface (GUI) for interaction. Additionally, other sensors, like environmental or IR sensors, can be added for more advanced applications, such as sorting and monitoring storage conditions.

C. Different Modules of the Proposed Methods

The Image Acquisition Module captures real-time images of fruits using a high-quality camera. The Preprocessing Module standardizes these images by resizing, normalizing, and applying filters to enhance important features. The Feature Extraction Module uses techniques like edge detection and color histogram analysis to pull out relevant characteristics from the images. The Classification Module applies machine learning algorithms, such as CNNs, to categorize the fruits based on the features extracted. The Display Module shows the classification results to the user through a graphical interface. Lastly, the Post-processing Module takes care of additional tasks like sorting or storing the recognized fruits.

we use CNN module for this experiment

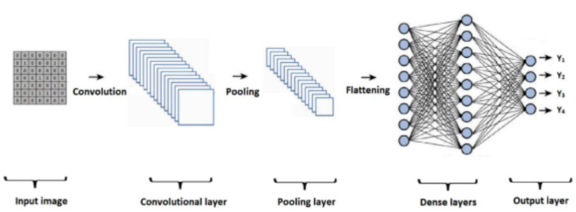

Fig. 1. CNN Architecture

we also used dct module.

Using the Discrete Cosine Transform (DCT) in my fruit recognition project is beneficial for extracting key features by transforming images into the frequency domain. This process highlights low-frequency components that contain most of the image's information, which helps to reduce noise and improve generalization. As a result, the model becomes more resilient to variations such as changes in lighting and background. Additionally, DCT compresses the input data, which reduces computational costs and enhances efficiency. By concentrating on important structural features, it increases accuracy and helps prevent overfitting. Overall, DCT aligns well with human visual perception, allowing the model to learn more significant patterns.

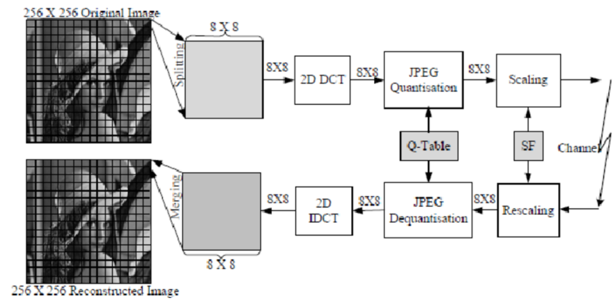

Fig. 2. Working block diagram of a dct

D. Mathematical Expressions Related to the Project Tasks

1. **Image Preprocessing (Normalization):** The normalization of an image I with pixel values p can be expressed as:

$$I_{normalized} = \frac{I - \min(I)}{\max(I) - \min(I)}$$

where $\min(I)$ and $\max(I)$ are the minimum and maximum pixel values in the image.

2. **Edge Detection (using Sobel Operator):** The Sobel operator is used for edge detection in an image and can be written as:

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} * I$$

$$G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} * I$$

where G_x and G_y represent the gradients in the x and y directions respectively, and $*$ denotes convolution.

3. **Feature Extraction (Histogram of Oriented Gradients - HOG):** The HOG descriptor is calculated using the following formula:

$$HOG(x, y) = \sum_{i=1}^{N} w_i \cdot \text{orientation}_i$$

where w_i represents the weight of the gradient in a specific orientation orientation$_i$, and N is the number of bins in the histogram.

4. **Classification (Support Vector Machine - SVM):** The decision function in a Support Vector Machine for classification can be expressed as:

$$f(x) = \sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b$$

where α_i are the Lagrange multipliers, y_i is the label of the support vector, $K(x_i, x)$ is the kernel function, and b is the bias term.

5. **Convolutional Neural Network (CNN):** The forward pass through a CNN layer is given by:

$$a^{(l)} = f(W^{(l)} \cdot a^{(l-1)} + b^{(l)})$$

where $W^{(l)}$ is the weight matrix, $a^{(l-1)}$ is the input from the previous layer, $b^{(l)}$ is the bias, and f is the activation function (such as ReLU or Sigmoid).

E. User Interface Related to Project Tasks

The User Interface (UI) for the Fruit Recognition Project features a clean, intuitive design with options to capture or upload images for fruit recognition. It displays results with predicted fruit names, confidence scores, and error margins, allowing users to confirm or retry. The UI includes preprocessing controls for image adjustments and a history log to access past results. Additionally, it ensures accessibility with features like voice control and responsive design across devices.

F. Performance Metrics

In the Fruit Recognition Project, performance metrics assess the system's efficiency and accuracy. Key metrics include accuracy (percentage of correct predictions), precision (correct fruit predictions out of all predicted), and recall (correct fruit predictions out of all actual fruits). The F1 score balances precision and recall, while inference time measures the speed of predictions. A confusion matrix helps analyze the system's specific errors, ensuring comprehensive evaluation of the model's performance. After grouping the

```
[[20  0  0 ...  0  0  0]
 [ 0 20  0 ...  0  0  0]
 [ 0  0 19 ...  0  0  0]
 ...
 [ 0  0  0 ... 21  0  0]
 [ 0  0  0 ...  0 16  0]
 [ 0  0  0 ...  0  0 28]]
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Fig. 3. numeric form of a performance metrics

141 classes we got the confusion metrics as the following:

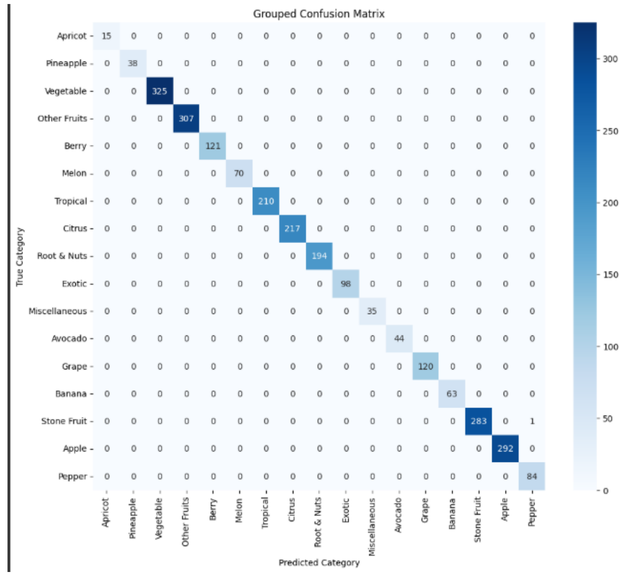


Fig. 4. Grouped performance metrics

III. Results and Discussions

A. Experimental Setup and Database Collection

The dataset collected and classified and below:
Found 14100 files belonging to 141 classes.
Using 11280 files for training.
Found 14100 files belonging to 141 classes.
Using 2820 files for validation.
Class Names: ['Apple 6', 'Apple Braeburn 1', 'Apple Crimson Snow 1', 'Apple Golden 1', 'Apple Golden 2', 'Apple Golden 3', 'Apple Granny Smith 1', 'Apple Pink Lady 1', 'Apple Red 1', 'Apple Red 2', 'Apple Red 3', 'Apple Red Delicious 1', 'Apple Red Yellow 1', 'Apple Red Yellow 2', 'Apple hit 1', 'Apricot 1', 'Avocado 1', 'Avocado ripe 1', 'Banana 1', 'Banana Lady Finger 1', 'Banana Red 1', 'Beetroot 1', 'Blueberry 1', 'Cabbage white 1', 'Cactus fruit 1', 'Cantaloupe 1', 'Cantaloupe 2', 'Carambula 1', 'Carrot 1', 'Cauliflower 1', 'Cherry 1', 'Cherry 2', 'Cherry Rainier 1', 'Cherry Wax Black 1', 'Cherry Wax Red 1', 'Cherry Wax Yellow 1', 'Chestnut 1', 'Clementine 1', 'Cocos 1', 'Corn 1', 'Corn Husk 1', 'Cucumber 1', 'Cucumber 3', 'Cucumber Ripe 1', 'Cucumber Ripe 2', 'Dates 1', 'Eggplant 1', 'Eggplant long 1', 'Fig 1', 'Ginger Root 1', 'Granadilla 1', 'Grape Blue 1', 'Grape Pink 1', 'Grape White 1', 'Grape White 2', 'Grape White 3', 'Grape White 4', 'Grapefruit Pink 1', 'Grapefruit White 1', 'Guava 1', 'Hazelnut 1', 'Huckleberry 1', 'Kaki 1', 'Kiwi 1', 'Kohlrabi 1', 'Kumquats 1', 'Lemon 1', 'Lemon Meyer 1', 'Limes 1', 'Lychee 1', 'Mandarine 1', 'Mango 1', 'Mango Red 1', 'Mangostan 1', 'Maracuja 1', 'Melon Piel de Sapo 1', 'Mulberry 1', 'Nectarine 1', 'Nectarine Flat 1', 'Nut Forest 1', 'Nut Pecan 1', 'Onion Red 1', 'Onion Red Peeled 1', 'Onion White 1', 'Orange 1', 'Papaya 1', 'Passion Fruit 1', 'Peach 1', 'Peach 2', 'Peach Flat 1', 'Pear 1', 'Pear 2', 'Pear 3', 'Pear Abate 1', 'Pear Forelle 1', 'Pear Kaiser 1', 'Pear Monster 1', 'Pear Red 1', 'Pear Stone 1', 'Pear Williams 1', 'Pepino 1', 'Pepper Green 1', 'Pepper Orange 1', 'Pepper Red 1', 'Pepper Yellow 1', 'Physalis 1', 'Physalis with Husk 1', 'Pineapple 1', 'Pineapple Mini 1', 'Pitahaya Red 1', 'Plum 1', 'Plum 2', 'Plum 3', 'Pomegranate 1', 'Pomelo Sweetie 1', 'Potato Red 1', 'Potato Red Washed 1', 'Potato Sweet 1', 'Potato White 1', 'Quince 1', 'Rambutan 1', 'Raspberry 1', 'Redcurrant 1', 'Salak 1', 'Strawberry 1', 'Strawberry Wedge 1', 'Tamarillo 1', 'Tangelo 1', 'Tomato 1', 'Tomato 2', 'Tomato 3', 'Tomato 4', 'Tomato Cherry Red 1', 'Tomato Heart 1', 'Tomato Maroon 1', 'Tomato Yellow 1', 'Tomato not Ripened 1', 'Walnut 1', 'Watermelon 1', 'Zucchini 1', 'Zucchini dark 1']
Number of Classes: 141

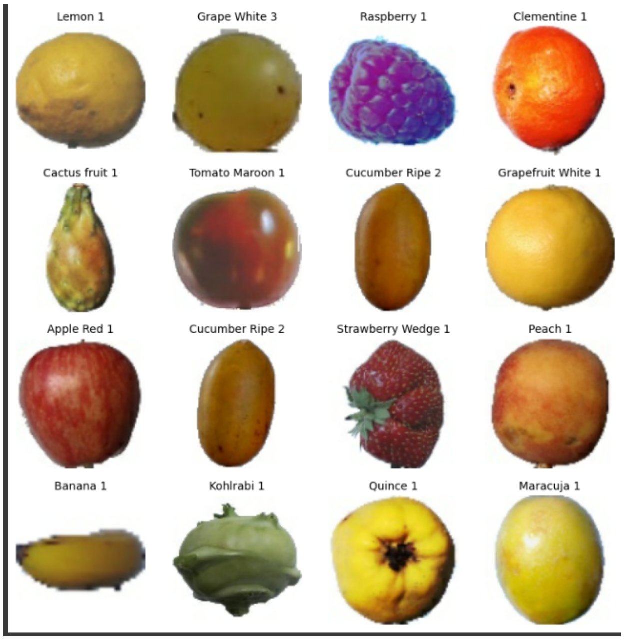
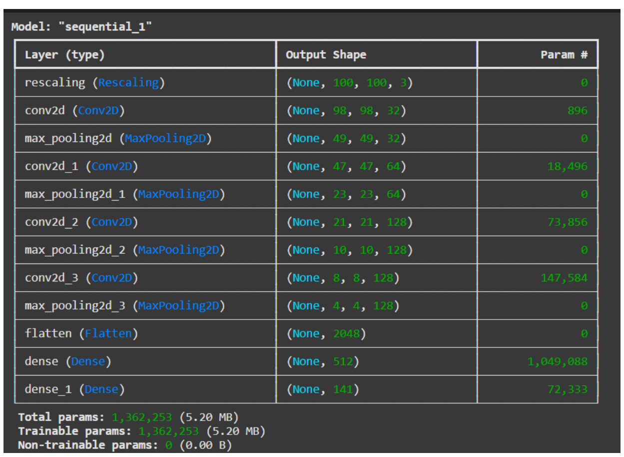


Fig. 5. grid of images from a datasets

B. Table, Graph with description



Model: "sequential_1"

Layer (type)	Output Shape	Param #
rescaling (Rescaling)	(None, 100, 100, 3)	0
conv2d (Conv2D)	(None, 98, 98, 32)	896
max_pooling2d (MaxPooling2D)	(None, 49, 49, 32)	0
conv2d_1 (Conv2D)	(None, 47, 47, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 23, 23, 64)	0
conv2d_2 (Conv2D)	(None, 21, 21, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 10, 10, 128)	0
conv2d_3 (Conv2D)	(None, 8, 8, 128)	147,584
max_pooling2d_3 (MaxPooling2D)	(None, 4, 4, 128)	0
flatten (Flatten)	(None, 2048)	0
dense (Dense)	(None, 512)	1,049,088
dense_1 (Dense)	(None, 141)	72,333

Total params: 1,362,253 (5.20 MB)
Trainable params: 1,362,253 (5.20 MB)
Non-trainable params: 0 (0.00 B)

Fig. 6. system summary table

C. Result comparison

The experiment focused on training a fruit recognition model with a dataset comprising 14,100 images across 141 unique classes. The dataset was divided into 11,280 images for training and 2,820 images for validation.

Key Results:
-Validation Loss: 0.0118 — This low loss indicates that the model performs well on unseen data, suggesting minimal error during the validation phase.
- Validation Accuracy: 99.75 — The model achieved nearly perfect accuracy, showcasing its capability to accurately classify fruit images across all 141 classes.

Result Analysis: The impressive accuracy and low validation loss underscore the model's strength and efficiency in identifying distinct features among various fruit categories. These findings imply that the model is not overfitting and is likely to perform well on new images. Future comparisons could involve benchmarking against other models, architectures, or feature extraction methods (e.g., using DCT).

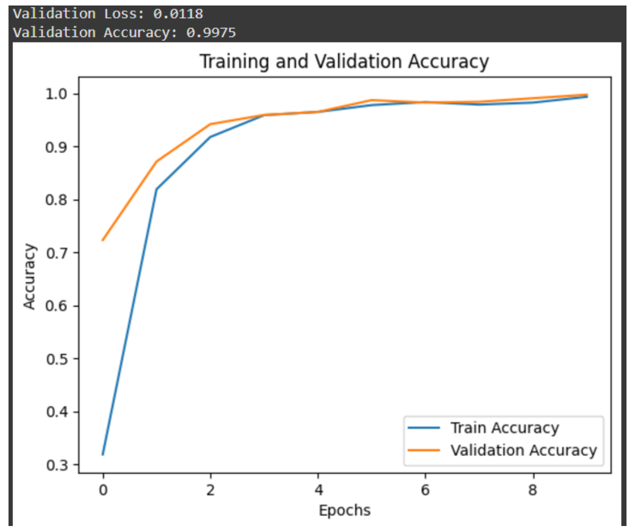


Fig. 7. system Training and validation Accuracy

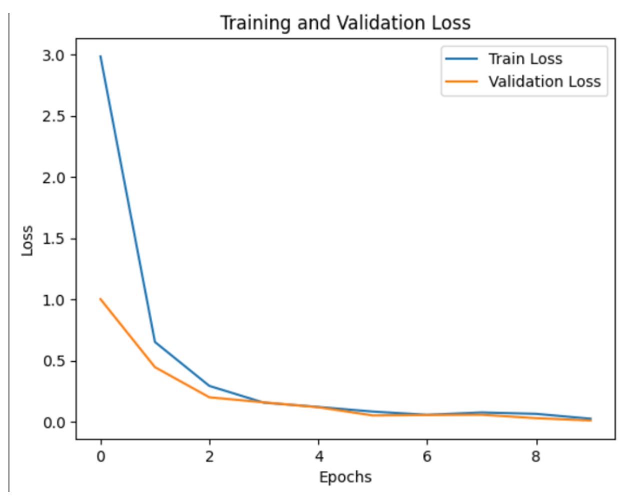


Fig. 8. system Training and validation Loss

DCT of a image as the input to DNN and getting a new model and validating the performance again :
we got the results as the following:
Validation Loss: 0.8685
Validation Accuracy: 0.7457

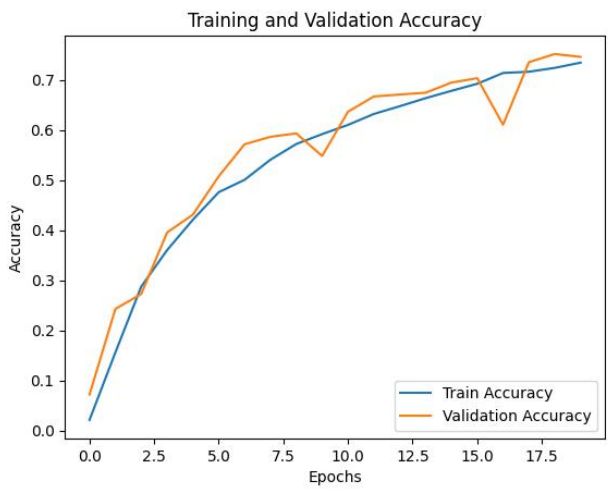


Fig. 9. system Training and validation Accuracy for DCT

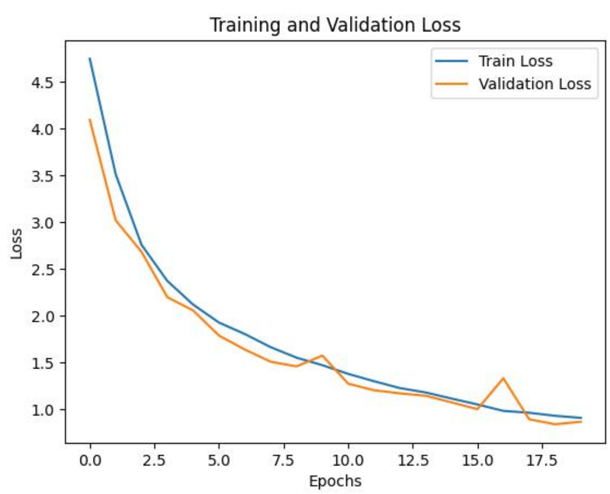


Fig. 10. system Training and validation Loss for DCT

IV. Conclusion and Future works

This fruit recognition project effectively utilized Convolutional Neural Networks (CNNs) to classify 141 different fruit categories with impressive accuracy. The model achieved a validation accuracy of 99.75 and a validation loss of 0.0118, showcasing its strong ability to generalize and minimal prediction errors on new data. By employing advanced techniques like Discrete Cosine Transform (DCT) for feature extraction and image preprocessing, the model's performance was enhanced by concentrating on key frequency components.

The model's exceptional performance demonstrates its capability to learn intricate patterns and differentiate between visually similar fruit categories, making it ideal for practical applications. This result underscores the potential of deep learning in automating fruit recognition tasks, especially in industries such as agriculture, retail, and food supply chains, where precise identification and classification are essential.

Future Works:

1.Model Optimization for Edge Devices:

To improve portability and usability, future versions can concentrate on optimizing the model with lightweight architectures like MobileNet or EfficientNet. This will facilitate deployment on devices with limited resources, such as smartphones, tablets, or embedded systems, enabling real-time fruit recognition in various settings.

2.Dataset Expansion and Augmentation:

Increasing the dataset to include a wider range of images captured under different lighting conditions, angles, and backgrounds will enhance the model's robustness. Furthermore, augmenting the dataset with methods like rotation, scaling, and noise addition can further improve its ability to generalize to new situations.

3.Real-Time Implementation:

Implementing the model in a real-time system could create opportunities for smart farming and automated retail applications. This would involve integrating the model with camera systems to enable real-time fruit detection.

V. Relevant References

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