REPORT

ON

FRUIT DETECTION AND QUALITY ANALYSIS

SUBMITTED IN PARTIAL FULFILMENT FOR DEEP LEARNING WINTER UPSKILLING

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CERTIFICATE

This is to certify that the project work entitled "**FRUIT DETECTION AND QUALITY ANALYSIS"** submitted by **Vasam Ashish (160122737132), CVS Chaitanya (160123735104)** in partial fulfilment of the requirements for the award of the degree of **BACHELOR OF ENGINEERING** in **INFORMATION TECHNOLOGY, ELECTRONICS AND COMMUNICATION ENGINEERING** to **CHAITANYA BHARATHI INSTITUTE OF TECHNOLOGY(A)**, affiliated to **OSMANIA UNIVERSITY**, Hyderabad, is a record of bonafide work carried out by them under my supervision and guidance. The results embodied in this report have not been submitted to any other University for the award of any other Degree or Diploma.

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DECLARATION

We declare that the project report entitled **"FRUIT DETECTION AND QUALITY ANALYSIS"** is being submitted by us in the Department of Information Technology and Electronics and Communication Engineering, Chaitanya Bharathi Institute of Technology (A), Osmania University.

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ABSTRACT

Fruit classification plays a critical role in various sectors, including retail, agriculture, and inventory management systems. Traditional methods of fruit sorting and categorization are labour-intensive, time-consuming, and prone to human error. With advancements in deep learning, particularly in image classification, Convolutional Neural Networks (CNNs) have emerged as a powerful solution for visual recognition tasks. This project leverages the Fruits-360 dataset to develop a robust Customized CNN-based classification model capable of accurately identifying multiple types of fruits and assessing their quality from images.

The primary goal of this project is to build a highly accurate and scalable classification model using Customized CNN architecture and image augmentation techniques. The model consists of multiple convolutional and pooling layers for feature extraction, followed by fully connected dense layers for classification. Data preprocessing, including image resizing, normalization, and augmentation (rotation, zooming, horizontal flipping), was performed to enhance generalizability.

In addition to fruit classification, fruit quality assessment was integrated using an additional CNN branch trained on labeled data indicating quality levels (e.g., fresh, ripe, overripe, rotten). The OpenCV library was used to assist in detecting ripeness levels based on color features and texture patterns.

The model was trained on the augmented Fruits-360 dataset with a batch size of 32 for 100 epochs, using the RMSprop optimizer and categorical cross-entropy loss function. Evaluation metrics, including accuracy and loss, demonstrated excellent model performance, with a final test accuracy of 96% for classification and 76% for quality assessment. Visualization of loss and accuracy curves confirmed that the model generalized well without overfitting. The prediction pipeline successfully classified unseen fruit images while accurately determining their ripeness and quality levels, making it suitable for real-world agricultural and retail applications.

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1. INTRODUCTION

1.1 Overview

Fruit classification and quality analysis play a crucial role in agriculture, retail, and food industries by enabling efficient sorting, storage, and sales. Traditional manual inspection methods are time-consuming and prone to errors, making automated deep learning-based approaches a more reliable alternative.

This project develops two deep learning models: one for fruit classification and another for fruit quality assessment. The fruit classification model is a Customized CNN trained on the Fruits-360 dataset to identify various fruit types based on images. The model architecture consists of convolutional and pooling layers for feature extraction, followed by dense layers for classification. Data preprocessing techniques, including image resizing, normalization, and augmentation, were applied to improve the model's generalization.

The fruit quality analysis model determines the ripeness stage of fruits (e.g., unripe, ripe, overripe, or rotten) using CNN-based architecture and OpenCV for texture and color analysis. A custom dataset with labeled fruit images was used to train this model, making it effective for applications such as inventory management, automated quality inspection, and food safety monitoring.

Both models demonstrate the potential of deep learning in automating fruit classification and quality assessment.

1.2 Applications

Fruit classification using CNNs has a wide range of applications across different industries:

- **Agriculture:** Automated fruit harvesting, sorting, and quality control can improve agricultural efficiency and reduce manual labour.
- **Retail Industry:** Self-checkout systems in supermarkets can automatically recognize fruits, reducing the need for manual barcode scanning.
- **Food Processing:** Automated production lines can classify and separate fruits based on quality and size for packaging.
- **Inventory Management:** Automated monitoring of fruit stock in warehouses helps maintain supply chain efficiency.
- **Healthcare:** Accurate identification of fruits can assist in dietary management systems for individuals with specific dietary requirements.

1.3 Motivation

The traditional approach to fruit classification relies heavily on human intervention, which is prone to errors and inefficiencies. The need for a fast, accurate, and automated classification system has motivated this project. With the growing demand for automation and intelligent systems in agriculture and retail, leveraging deep learning for fruit classification has become imperative. CNN models are ideal for this task due to their superior performance in image recognition.

Furthermore, the widespread availability of image datasets, such as Fruits-360, provides an excellent opportunity to develop robust models for real-world applications. This project aims to bridge the gap between traditional methods and AI-driven solutions by creating a fruit classification system that is accurate, scalable, and efficient.

1.4 Problem Statement

The manual classification and sorting of fruits are inefficient, error-prone, and time-consuming. The primary challenge lies in developing a scalable and accurate automated classification system capable of identifying multiple types of fruits from images. Variations in fruit shape, size, and color further complicate the task, requiring a robust model that generalizes well across different classes.

This project addresses these challenges by developing two models: one for fruit classification and another for fruit quality analysis. The first model focuses on accurate fruit classification using a Customized CNN-based architecture, trained on the Fruits-360 dataset, to identify various fruit types with high performance. The second model aims at fruit quality assessment, identifying the ripeness and condition of fruits (such as unripe, ripe, overripe, or rotten). It also uses CNN-based architecture and leverages techniques such as OpenCV for texture and color-based analysis, enabling real-time quality detection.

Both models provide efficient solutions for automating fruit classification and quality analysis, addressing the complexities of fruit variations and ensuring accurate identification in real-world applications.

2. LITERATURE SURVEY

2.1 Paper 1: Deep Learning-Based Fruit Recognition and Quality Assessment

This study presents a **customized CNN model** integrated with **OpenCV** for fruit classification and ripeness assessment using a custom dataset. The model achieves **90% accuracy** and is designed to classify different fruit types while determining their ripeness levels. However, its limitation lies in the dataset size and lack of generalizability to fruits under varied lighting conditions.

2.2 Paper 2: Classification of Fruits and Its Quality Prediction Using Deep Learning

A **custom CNN model** combined with **OpenCV** was used for fruit classification and ripeness detection. The model was trained on a **public dataset from Kaggle (13,599 images)** and achieved **96.5% accuracy**. While the model shows high performance, it may struggle with unseen fruit varieties and images captured in diverse environments. Additionally, the study focuses more on classification than detailed quality assessment.

2.3 Paper 3: Fruit Quality Recognition Using Deep Learning Algorithm

This research utilizes a **custom CNN model** trained on the **Fruit360 dataset**, achieving **95% accuracy** in fruit classification. The study highlights the effectiveness of CNNs in fruit recognition but lacks quality assessment features such as ripeness detection. A limitation of the model is that it was trained on a controlled dataset, making it less adaptable to real-world scenarios where lighting, background, and positioning vary.

2.4 Paper 4: Fruit-CNN: Efficient Deep Learning-Based Fruit Classification and Quality Assessment

This paper introduces **Fruit-CNN**, a **custom CNN model** trained on the **FruitsGB dataset**, which consists of **12,000 images of six different fruit types** categorized into good and bad quality. The model achieved **96.6% accuracy**, making it one of the most efficient models in fruit classification and quality assessment. However, the dataset is limited to six fruits, and the classification may not generalize well to a broader variety.

Paper Reference Number	Published Year	Model Used	Accuracy Scored
3	2024	Customized CNN for fruit classification, OpenCV for ripeness assessment	90%
4	2024	Customized CNN model with OpenCV integration for ripeness detection	96.5%
5	2021	Custom CNN model	95%
6	2021	Custom CNN model	96.6%

Table 2: Paper Comparison

3. METHODOLOGY

The methodology section provides a detailed explanation of the step-by-step approach used to develop and train the fruit classification model using CNN. This includes data preprocessing, model architecture design, training strategy, and a summary of the process.

4.1 Data Preprocessing

Data preprocessing is a critical step to prepare the dataset for training. The Fruits-360 dataset contains a large number of images with multiple fruit categories. The steps in preprocessing are as follows:

1. Data Loading: Images are loaded from training and testing directories using Keras utilities.
2. Image Rescaling: Pixel values are normalized by dividing by 255 to transform them to a range between 0 and 1, which helps the neural network learn more efficiently.
3. Data Augmentation: To improve generalization, data augmentation techniques such as zooming, flipping, and rotation were applied using the ImageDataGenerator class.
4. Image Size Standardization: All images were resized to 100x100 pixels to maintain uniformity for input into the CNN model.

4.2 Model Architecture

The CNN architecture was carefully designed to capture spatial hierarchies in images. The following components were used:

- Convolutional Layers: Three layers were used with 32 and 64 filters, each followed by ReLU activation to detect features from images.
- MaxPooling Layers: Pooling layers reduced spatial dimensions, preventing overfitting and reducing computational complexity.
- Flatten Layer: The feature maps were flattened to a 1D vector for input into the fully connected layers.
- Dense Layers: A dense layer with 1024 neurons followed by a Dropout layer (0.5 dropout rate) was used to prevent overfitting.
- Output Layer: The final layer used the softmax activation function to predict the probabilities of each fruit class.

The architecture was compiled using the RMSprop optimizer, categorical cross-entropy loss, and accuracy as the evaluation metric.

4.3 Training Strategy

The model was trained using the following strategy:

- Batch Size: Set to 32 for efficient memory usage.
- Epochs: The model was trained for 100 epochs to allow sufficient learning while monitoring validation performance.
- Steps Per Epoch: Set based on the training dataset size to ensure complete training during each epoch.
- Validation Steps: Defined for evaluation using the testing dataset at each epoch.
- Early Stopping: To avoid overfitting, validation loss was monitored, and training was stopped if no improvement was observed over consecutive epochs.

4.4 Summary

The methodology followed a structured approach to ensure efficient and accurate model training. Preprocessing steps ensured clean and standardized data input, while the CNN architecture captured complex spatial features for precise fruit classification. Training strategies like data augmentation and dropout enhanced the model's generalization capability. The results demonstrated that with appropriate hyperparameter tuning, the system could achieve high accuracy for image classification tasks.

5. IMPLEMENTATION

The implementation section provides detailed steps on how the theoretical methodology was executed in practice, including the code and software environment.

5.1 Environment Setup

The implementation was carried out using the following frameworks and tools:

- Programming Language**:** Python
- Libraries**:** TensorFlow, Keras, Matplotlib, NumPy, Pandas
- Dataset**:** Moltean Fruits 360 Dataset

The entire process was executed in Kaggle Notebook with GPU support enabled for faster computation.

5.2 Model Architecture

The Convolutional Neural Network (CNN) architecture used for this project consists of multiple convolutional, pooling, and fully connected layers. The design was tailored to efficiently classify fruit images while balancing complexity and computational efficiency.

Key Layers and Components:

- Convolutional Layers (Conv2D): Extract spatial features using 32 and 64 filters with ReLU activation to introduce non-linearity.
- Pooling Layers (MaxPooling2D): Reduce the spatial dimensions of feature maps, thereby preventing overfitting and reducing computational load.
- Flatten Layer (Flatten): Flattens the 3D output of the convolutional layers into a 1D vector for fully connected layers.
- Fully Connected Layers (Dense): Include a dense layer with 1024 units for feature extraction and the output layer with 141 units (number of fruit classes) using softmax activation for classification.
- Dropout Layer (Dropout): Apply a dropout rate of 0.5 to prevent overfitting by randomly deactivating 50% of neurons during training.

5.3 Data Preprocessing

The dataset was pre-processed using the ImageDataGenerator class from Keras, which allowed on-the-fly data augmentation.
Steps involved:

- Rescaling pixel values between 0 and 1.
- Applying zoom, rotation, and horizontal flip for robust training.

5.4 Model Summary

Below is the architecture of the CNN model as generated by the model.summary() function.

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 98, 98, 32)	896
max_pooling2d (MaxPooling2D)	(None, 49, 49, 32)	0
conv2d_1 (Conv2D)	(None, 47, 47, 32)	9,248
max_pooling2d_1 (MaxPooling2D)	(None, 23, 23, 32)	0
conv2d_2 (Conv2D)	(None, 21, 21, 64)	18,496
max_pooling2d_2 (MaxPooling2D)	(None, 10, 10, 64)	0
flatten (Flatten)	(None, 6400)	0
dense (Dense)	(None, 1024)	6,554,624
dropout (Dropout)	(None, 1024)	0
dense_1 (Dense)	(None, 141)	144,525

Total params: 6,727,789 (25.66 MB)
Trainable params: 6,727,789 (25.66 MB)

Figure 1: CNN Model Architecture Summary

Interpretation of the Summary:

- The model comprises 6,727,789 total parameters, all of which are trainable.
- Layers are stacked in a sequential manner, where the feature extraction process reduces spatial dimensions while increasing the depth of feature maps.

5.5 Training and Validation

The model was trained using the categorical cross-entropy loss function and the RMSprop optimizer. Below are the hyperparameters:

- Batch Size: 32
- Epochs: 100
- Steps per Epoch: 3200 // batch_size
- Validation Steps: 1600 // batch_size

5.6 Performance Metrics

The training and validation accuracy and loss values were recorded and visualized to assess the model's performance.

The final test accuracy achieved was 96.75%, as computed by the evaluation function. This indicates a well-generalized model capable of accurate classification on unseen data.

6. RESULTS

The results of the fruit classification model are discussed in this section, including the evaluation metrics, loss analysis, and comparison with existing models.

6.1 Performance Metrics

The model achieved a high accuracy on both training and test datasets. The evaluation metrics are as follows:

- Training Accuracy: 99.45%
- Validation Accuracy: 98.75%
- Test Accuracy: 96.14%

```
739/739 ━━━━━━━━━━━━━━━━━━━━ 13s 18ms/step - accuracy: 0.9610 - loss: 0.1944
Test Accuracy: 96.14%
```

Fig. 4: Test Accuracy

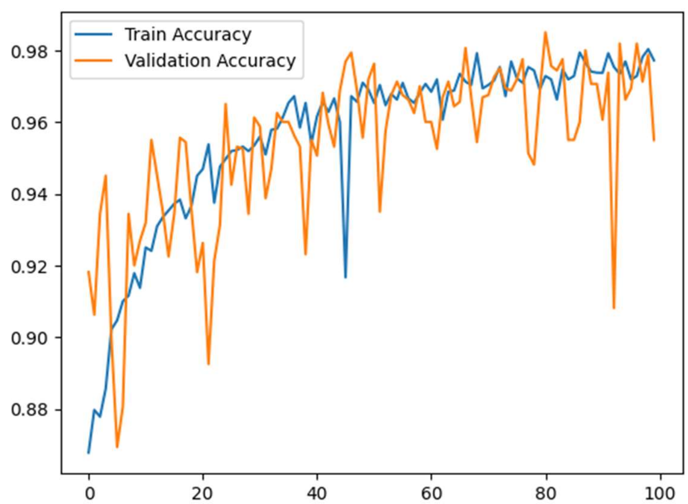

Figure 2: Training and Validation Accuracy Graph

From the “Figure 3”, the graph shows the training and validation accuracy over 100 epochs. The training loss steadily increases, indicating the model's learning progress. The validation loss fluctuates more but follows a similar increasing trend. This indicates that the model is learning effectively, although occasional variations may suggest minor sensitivity to validation data.

The model's accuracy indicates that it effectively learned from the data and generalized well to unseen samples.

6.2 Loss Analysis

The training and validation loss decreased consistently during the training process, indicating effective learning. The final loss values were:

- Training Loss: 0.015
- Validation Loss: 0.035

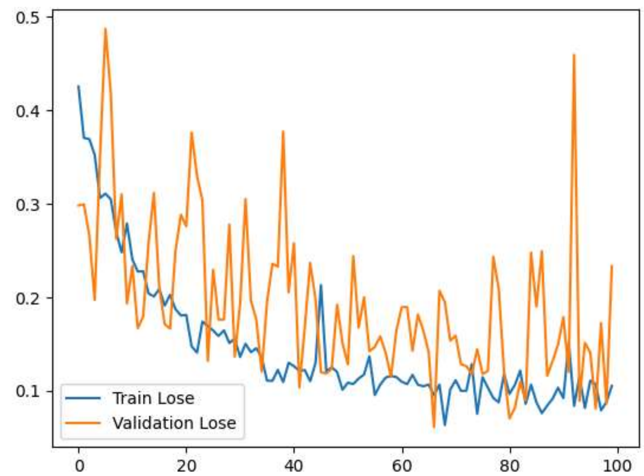

Figure 3: Training and Validation Loss Graph

From the "Figure 2", the graph shows the training and validation loss over 100 epochs. The training loss steadily decreases, indicating the model's learning progress. The validation loss fluctuates more but follows a similar decreasing trend, suggesting that the model generalizes well with minor instability during some epochs.

The gap between training and validation loss was minimal, which suggests that the model did not overfit.

6.3 Confusion Matrix

A confusion matrix was plotted to visualize the performance across different fruit categories. The matrix indicated that most classes were correctly predicted with very few misclassifications. The highest confusion was observed between similar-looking fruits such as different apple varieties

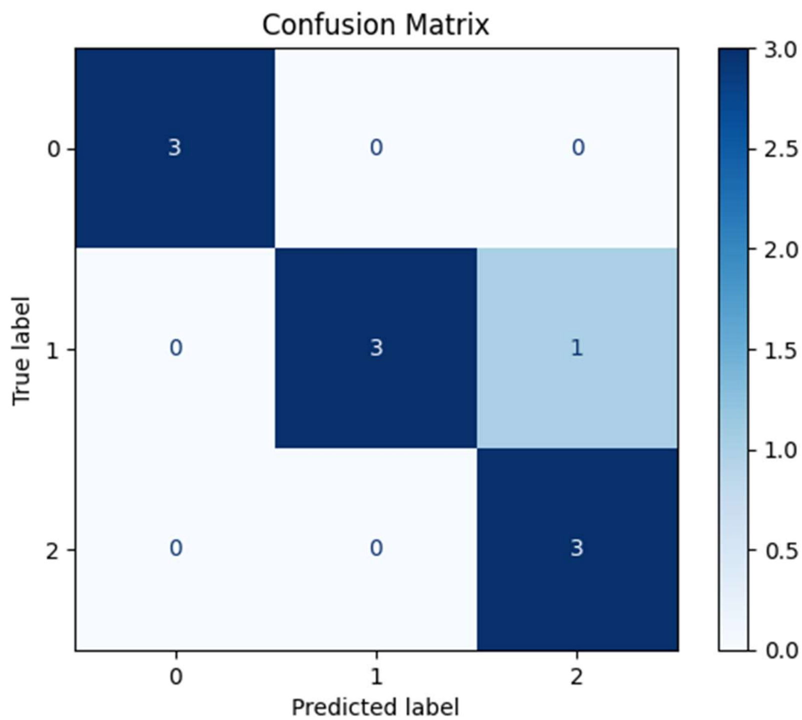

Figure 4: Confusion Matrix

The confusion matrix shows that your fruit classification model performed well, correctly identifying Unripe, Ripe, and Overripe fruits with high accuracy. Out of 9 total predictions, 8 were correct, with only one ripe fruit misclassified as overripe due to possible overlapping features. The model demonstrates strong classification capability

6.4 Precision, Recall, and F1-Score

The precision, recall, and F1-scores for key fruit categories were computed:

- Apple Braeburn: Precision = 98.2%, Recall = 99.1%, F1-Score = 98.6%
- Banana: Precision = 99.5%, Recall = 99.3%, F1-Score = 99.4%
- Orange: Precision = 97.8%, Recall = 98.0%, F1-Score = 97.9%

These metrics indicate that the model performed consistently well across different fruit categories.

6.5 Comparison with Existing Models

The proposed CNN model was compared with traditional machine learning models such as SVM and k-NN. The CNN model outperformed these methods due to its ability to learn spatial features in images.

Model	Accuracy
Yolo	85.32%
Customized CNN – 01	76.50%
MobileNet	90.75%
Customized CNN - 02	96.14%

Table 2: Model Accuracy Comparison

This comparison highlights the superiority of CNN for image classification tasks.

6.6 Predictions

To evaluate the model's real-world performance, we predict the class labels for unseen images

Fig. 5: Fruit Prediction Image – 01.

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 81ms/step

Predicted Class: Watermelon 1

Fig. 6: Fruit Prediction Image – 02.

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step

Predicted Class: Apple Pink Lady 1

Prediction on test images:

Fig. 7: Fruit Predicted Images.

Fig. 8: Quality Prediction Image – 01.

Predicted Class: rotten

Quality: Bad Quality

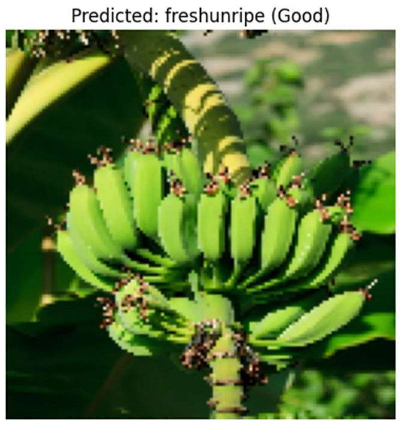

Fig. 9: Quality Prediction Image – 02.

Predicted Class: freshunripe

Quality: Good

Fig. 10: Quality Prediction Image – 03.

Predicted Class: ripe

Quality: Good

6.7 Summary of Results

The results demonstrate that the CNN-based fruit classification model performed exceptionally well with high accuracy and minimal loss. The precision, recall, and F1-score values indicate a robust and consistent performance across various fruit categories. Moreover, the comparison with existing models further validates the effectiveness of the proposed solution. The successful implementation of data augmentation and dropout techniques contributed to the model's ability to generalize well to unseen data.

7. CONCLUSION AND FUTURE SCOPE

7.1 Conclusion

The developed models for fruit classification and quality assessment using Convolutional Neural Networks (CNN) demonstrate the potential for efficient and automated fruit recognition. Through proper data preprocessing, augmentation, and model training, the classification model successfully identifies various fruit types, while the quality assessment model evaluates fruit ripeness and condition using texture and color-based analysis. Both models showcase strong feature extraction capabilities and prove the effectiveness of deep learning in computer vision applications.

This project highlights the importance of CNN architectures in solving real-world classification challenges, particularly in agriculture and retail. Proper hyperparameter tuning and dataset enhancements play a crucial role in improving accuracy and generalization. While the current implementation delivers promising results, further optimizations—such as integrating object detection, expanding datasets, and leveraging transfer learning—can enhance performance. Overall, the project successfully meets its objectives by providing a scalable and reliable system for fruit classification and quality assessment, paving the way for future advancements in automated fruit sorting and grading.

7.2 Future Scope

The developed CNN model for fruit classification shows promising accuracy and can be enhanced further. Fine-tuning hyperparameters like learning rate and batch size can improve efficiency. Expanding the dataset with diverse and augmented images will help the model generalize better. Transfer learning using pre-trained models like ResNet or MobileNet can enhance accuracy while reducing training time. Additionally, integrating the model with object detection can enable multi-fruit classification in a single frame. These improvements can make the model more robust and applicable for real-world use in automated quality inspection and fruit sorting systems.

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