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Rotten Fruit Detection using Artificial Intelligence and CNN

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***Abstract*— Spoiled fruits can be detected in the agricultural sector for the segregation of defective produce from fresh ones with an objective to sustain the quality of the product and consumer confidence. In this research work, a deep learning technique in the form of Convolutional Neural Network (CNN) has been presented for image classification of fruits as fresh or rotten.The Kaggle dataset was applied to carry out research. It has trained, validated and tested the model into three varieties of fruits namely apples, bananas, and oranges. The authors were able to develop their model correctly at 98.99%. This model can examine fruit images using CNNs and thus detect which fruit is rotten.It is a reliable and efficient alternative solution to manual inspection. Such an approach could better enhance quality control in agriculture by being able to deliver safe, high-quality products to consumers while reducing the risk of contamination and health problems from spoiled produce.**

I. Introduction

Ensuring the quality and safety of produce is essential in agriculture for maintaining consumer trust and minimizing food waste. Traditional methods for assessing fruit health rely on manual inspection, which is labor-intensive, time- consuming, and often inconsistent. With rising demand for high-quality produce, there is an urgent need for automated solutions to streamline and enhance quality control.

Methods taken by AI-driven models which involve the integration of image processing with machine learning models in evaluating picture of fruits for signs of spoilage such as changes in color, texture, and shape can accurately classify the fruits as fresh or spoiled. CNNs are especially effective in applications within image analysis since they constitute one type of deep learning model.

A CNN-based model to detect and classify rotten fruits, including apples, bananas, and oranges, was developed and tested within this research study. A labeled dataset was used to train the model to discriminate well between fresh and spoiled fruits. The benefits of this approach are as follows: scalability, cost effectiveness, improvement in operational efficiency, minimization of wastes, better food safety, and improved consumer satisfaction and trust.

II. Literature Review

AI and CNNs have greatly made progress in determining rotten fruit, and recent studies have focused more on improving model accuracy and scalability as well as achieving real-time performance. Growing fields of work are related to multiple sensing modalities, transfer learning, and applying data augmentation techniques to challenge difficulties of scavenging, data scarcity, and fruit variability.

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All these innovations will play a critical role in enhancing food safety, reducing waste, and optimizing the agricultural supply chain in a market where demand for high-quality produce continues to increase.

A. Comparison with Different AI Techniques

TABLE I

AI Technique	Strengths	Weaknesses	Why CNNs Are Preferable
Convolutional Neural Networks (CNNs)	-Automatically extracts features from raw images. - High accuracy in detecting subtle patterns like texture, color, and shape.	- Requires large datasets for training. - Computationally expensive.	-CNNs excel in handling complex visual data like fruit images, which is essential for detecting subtle spoilage indicators.
Support Vector Machines (SVM)	- Effective with smaller datasets. - Can work well with high-dimensional data.	- Not ideal for big image data. - Feature extraction must be manually done.	CNNs automatically learn the best features from images, while SVM requires manual feature extraction.
k-Nearest Neighbors (KNN)	Simple to implement and understand. - Good for small datasets.	- Slow during inference, especially with large datasets. - Sensitive to irrelevant features.	CNNs can handle large datasets efficiently and learn high-level features, unlike KNN which struggles with scalability.
Random Forest	Handles high dimensional data well. - Robust to over fitting and noise.	- Performance depends on the quality of features. - Not as effective for raw image data	- CNNs automatically extract features from images, which is more effective for picture based tasks.

III. METHODOLOGY

this research applied a structured approach in data preprocessing, model architecture, training, and evaluation, using a convolutional neural network (cnn) to classify fruit images as fresh or rotten.

A. Data Preparation

- Image Collection: The dataset consists of fresh and rotten fruits categorized into freshness con ditions and type.

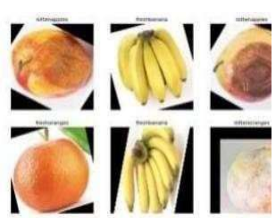

Figure1:Collected Dataset

- Preprocessing: Each image is resized to 100x100 pixels and converted to RGB format to standardize inputs for the CNN model.

B. Model Architecture

- CNN Layers: The model is built with sequential convolution layers using 3x3 filters with ReLU activation to capture features like color and texture associated with spoilage.

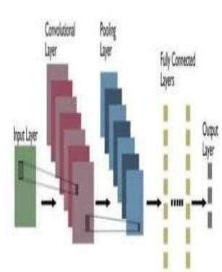

Figure 2: CNN Architecture

- Pooling and Dropout: MaxPooling layers reduce spatial dimensions, while Dropout layers mitigate overfitting by randomly dropping neurons during training.

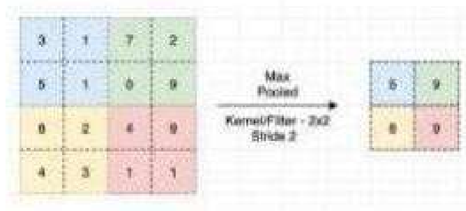

Figure 3:Pooling Layer

- Batch Normalization: Batch normalization layers are added after convolution layers to stabilize and accelerate learning.
- Fully Connected Layer: A final dense layer with sigmoid activation provides binary classification for freshness, while softmax is used for fruit type classification.

Training Strategy

- Optimization and Loss: The model uses binary cross-entropy loss for freshness classification and categorical cross-entropy for type classification. The Adam optimizer updates model weights.
- Callbacks: Training includes learning rate adjustment via ReduceLROnPlateau saves the model with the best validation performance.

Evaluation And Visualization

- Performance Metrics: Accuracy and loss are observed for both training and validation sets across epochs. Additional metrics (precision, recall, F1 score) assess classification performance.
- Visual Analysis: Training progress is visualized with plots of loss and accuracy, and predictions are validated visually on sample images from the validation set.

IV. RESULTS

The trained model outperforms the data with robust performance, considering the sparse categorical cross-entropy loss function and even evaluates all results from the Adam optimizer, the major performance metric being accuracy. It reached a test loss of 8.53% and an impressive test accuracy . Below, we'll show the comparative results from training versus validation accuracy and loss on the model, which displays the excellent consistence in its performance with good generalization capability over the datasets. This consisitent representation, therefore, depicts the ability of the model to distinguish between classes without such overfitting or underfitting.

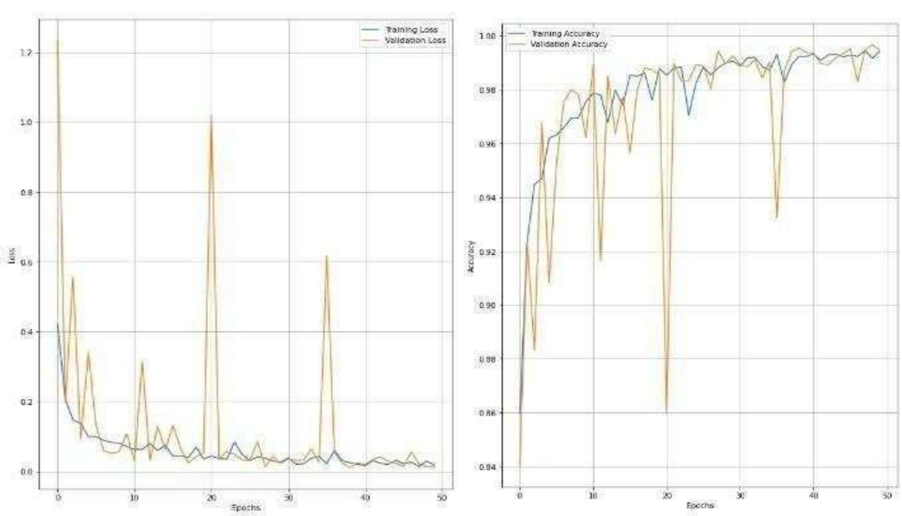

Figure4: comparison between i)training data and validation loss ii)training data and validation accuracy

```
model.evaluate(X,Y)
```

```
341/341 [==============================] - 3s 9ms/step -
s: 0.0131 - accuracy: 0.9955


[0.013103034347295761, 0.9955049753189087]
```

Figure 5:Accuracy During testing

To evaluate the model's performance, we tested several images by comparing their actual labels with the predicted labels. Based on the results, it was concluded that the model is functioning accurately.

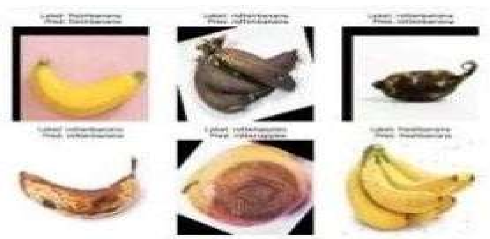

Figure 6:Result of predicted data

V. CONCLUSION

Altogether, CNNs can be considered to be a promising approach for fruit health assessment, given the strengths of deep learning and image processing. It has shown a lot of potential to transform the quality control of fruits by providing precisely automatic measurements about fruit health.

By training CNN models on diversified fruit image datasets, this project has been able to extract the key features from the imagery for the precise classification and prediction of various factors including freshness, ripeness, and disease presence. Generalizing to new fruit samples becomes thus feasible with CNNs.

Major outcomes of the project have broad implications in saying that it can really be useful for agriculture, food processing, and consumer goods industries, because through this approach, fruit health is evaluated in an efficient and objective manner to lessen waste, increase productivity, and offer consumers fruit which is fresher and healthier.

More research in the future could concentrate on improving CNN models, increase the dataset size with more varieties of fruits, and implement real-time applications for its practical use. Over all, the CNN- based fruit health assessment methodology holds tremendous promise to enhance quality control processes and to address the changing needs of this industry.

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