Enhancing Agriculture through Convolutional Neural Network (CNN) for Rotten Fruit Classification with Deep Learning

1. Introduction

In the exciting world of Artificial Intelligence (AI), where advanced technology meets real-world uses, there have been impressive advancements in many areas. One such compelling domain is agriculture, where AI has proven to be a game-changer in optimizing processes, improving yields, and addressing the agriculture sector's challenges. Our project embarks on this transformative journey by delving into the development of a Deep Learning Model for Rotten Fruit Classification in Agriculture, applying Convolutional Neural Networks (CNNs) as a cornerstone.

Recently, the integration of AI, particularly Deep Learning, has revolutionized agricultural practices. The ability to harness the power of computer vision, precisely discerning and categorizing objects within images, has opened new avenues for automating critical tasks in agriculture. Our project aligns with this trajectory, aiming to create an advanced framework that addresses the pressing need for accurate and timely identification of fruit quality—specifically, distinguishing between rotten and fresh fruits.

The significance of this project lies not only in its potential to streamline fruit classification processes but also in its broader implications for sustainable agriculture.

Aim and Objective

Central to our project is the research question: How can a Deep Learning Model utilizing Convolutional Neural Networks effectively classify rotten and fresh fruits in the agricultural context? Our main objectives revolve around creating an efficient and accurate classification model that can accurately identify rotten fruits from fresh ones. Contributing to the overall sustainability of agricultural practices by reducing waste, and in the broader perspective of a scheme in Agriculture, improve resource allocation.

Expected Outcome

The anticipated outcome of this project is a robust Deep Learning Model tailored for fruit classification, with a specific focus on identifying the quality of fruits in terms of their freshness. Through the utilization of Convolutional Neural Networks, the model will learn to recognize intricate patterns and features within fruit images, enabling it to distinguish between rotten and fresh fruit specimens with a high level of accuracy. The successful development of such a model holds the potential to revolutionize the fruit industry's operational dynamics, providing a practical tool to enhance quality control and decision-making processes.

2. Background

The increasing use of computer vision in the fruit processing industry has brought about significant changes. It allows tasks to be done automatically and improves the way quality is checked. A big issue in this area is making sure fruits are sorted correctly based on their quality.

The research by Roy, Chaudhuri, and Pramanik (2020) underscores the relevance of computer vision in the fruit processing sector. This study specifically focuses on the detection of rotten or fresh apples, employing the identification of defects in the fruit's peel as a discriminative factor. A critical contribution of this work is the proposal and implementation of a semantic segmentation approach, facilitated by deep learning architectures. UNet and an enhanced iteration, En-UNet, are harnessed for this segmentation task, yielding promising outcomes. En-UNet achieved better results in accuracy compared to UNet. En-UNet had a validation accuracy of 97.54%, while UNet had 95.36%. We would later find out if our intended method outperforms the chosen method employed by Roy et al. (2020)

The combination of deep learning methods and agricultural practices is leading to revolutionary advancements. This greatly affects how crops are grown, diseases are controlled, and yields are improved. Importantly, the use of deep learning models is not limited to the agricultural and food sectors; it's also making an impact in detecting diseases in rice plants. The research conducted by Latif et al. (2022) illustrates the potential of combining Deep Convolutional Neural Network (DCNN) models for identifying rice leaf diseases accurately. This study aligns with our project's goal of automating fruit quality assessment using deep learning.

Latif et al.'s (2022) work addresses the monumental challenge of early detection and classification of six distinct rice leaf diseases, critical to averting substantial crop loss. The proposed DCNN model, created using transfer learning principles from transfer learning principles, capitalizes on the features of a modified VGG19 architecture. The model's ability to diagnose ailments with an average accuracy of 96.08% showcases the potential to revolutionize disease management in rice cultivation. This accomplishment resonates with our project's ethos of enhancing the accuracy and efficiency of fruit quality evaluation through automated methods. However, it's noteworthy that while this study tackles plant disease detection, it relates to our fruit quality categorization by demonstrating the effectiveness of CNN-based methods in agricultural contexts specifically fruit-producing industries.

The symbiotic relationship between technology and agriculture extends further with the work of Sultana et al. (2022). Their research confronts the manual assessment of fresh and rotten fruits—a labour-intensive and inefficient process—through the proposition of an algorithmic classification model. This model, designed to identify sixteen diverse classes of fruits based on their freshness, encapsulates the essence of automating quality evaluation in agriculture—an ambition resonating profoundly with our project. The dataset they provide allows researchers to improve algorithms, emphasizing the need for comprehensive datasets to advance automated fruit quality assessment.

Moreover, Stein et al. (2016) exploration into image-based mango fruit detection and localization provides a critical bridge between our project and the wider agricultural tech landscape. Their innovative use of the FR-CNN framework—a region-based CNN detector—for fruit detection in orchards mirrors our focus on employing CNNs for fruit quality classification. While their application centres on mangoes, it underscores the effectiveness of CNN-based techniques for various fruits, supporting our goal of creating a universal model for different fruit types.

The significance of transfer learning in the field of computer vision, as evident in Bargoti and Underwood's work (2017), is of great importance within this context. The community of researchers has embraced the practice of training a type of neural network called Convolutional Neural Network (CNN) on a large foundational network. Subsequently, they apply the knowledge gained from this training to a new task that doesn't have a lot of labelled data available for learning. This approach allows for the effective reuse of learned features for improved performance in a different context.

Notably, the ImageNet dataset, containing a diverse range of categories and images, serves as a popular base for pre-training CNN features. While transfer learning can enhance performance, the study's concern lies in the adaptability of such transferred features to the distinct context of fruit detection in orchards. The debate arises on whether to initialize a network with ImageNet features or consider the suitability of transferring knowledge from features fine-tuned over an orchard-specific dataset.

For Data Augmentation in Bargoti and Underwood's work (2017), the methods used a lot in computer vision, like flipping, changing size, and adjusting colours, are really important. These methods make the training data more varied, which helps the network to learn better in different situations and reduces problems like fitting too much to the training data.

Amidst these, the research by Panigrahi, Sahoo, and Das (2020) reinvigorates the discourse by spotlighting the application of CNN for the detection of corn leaf diseases

In a more comprehensive view, bringing these studies side by side highlights the many different aspects of how computer vision is being incorporated into the fruit processing industry. Roy et al.'s (2020) emphasis on real-time detection using semantic segmentation aligns with the broader objective of streamlining quality assessment, while Bargoti and Underwood's (2017) exploration of transfer learning and data augmentation delved into the concepts of transfer learning and data augmentation, highlights the intricate methods they employed to successfully adjust deep learning models for specific tasks, in this case, fruit detection in orchards. As such, these studies collectively contribute to the increasing research endeavours that are focused on transforming the fruit and Agricultural industries. They do this by bringing together the fields of computer vision and deep learning methods to create new and improved ways of working.

3. Methodology

In this section, we describe how we approached building the fruit classification system using Convolutional Neural Networks (CNNs). Our methodology covers the steps of preparing data, designing the model architecture, training the model, and evaluating its performance. We've drawn insights from research articles such as "Review on Convolutional Neural Network (CNN) Applied to Plant Leaf Disease Classification" Lu et al. (2021) and "A CNN Approach for Corn Leaves Disease Detection to Support Digital Agricultural System" Panigrahi, Sahoo, and Das (2020) to guide our approach.

Data Pre-Processing

To address the challenge of imbalanced data distribution, a data augmentation strategy is applied. Augmentation includes image rotation, zooming, and rescaling of pixel values to normalize the data. These techniques augment the training dataset, enhancing its diversity and aiding the network in learning from limited data. This pre-processing step is crucial to ensure the model's robustness, especially when dealing with minority classes.

Model Architecture

Inspired by the insights from Lu et al. (2021) and Panigrahi et al. (2020), a Convolutional Neural Network (CNN) architecture is selected for this fruit classification task. CNNs are renowned for their efficiency and accuracy in image feature extraction, rendering them ideal for image classification. The chosen architecture consists of multiple convolutional layers, interleaved with max-pooling layers, and is enhanced by dropout layers to mitigate overfitting.

The architecture commences with successive convolutional layers, each followed by a max-pooling layer. The depth of the network increases progressively, enabling the extraction of intricate features from input images. Dropout layers are strategically incorporated to enhance model generalization.

The final layer of the architecture comprises a densely connected layer that produces a probability distribution over the distinct fruit classes. The softmax activation function transforms raw scores into class probabilities. The architectural details are summarized below:

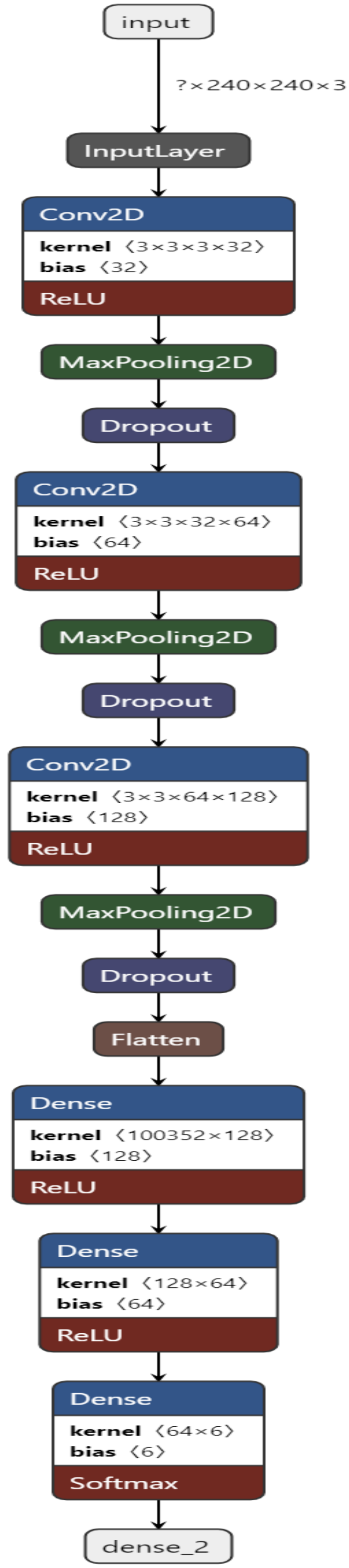

Fig 1. CNN model Architecture

Model Compilation and Training

The CNN model is compiled using the Adam optimizer and categorical cross-entropy loss function. The Adam optimizer's adaptive learning rate and convergence properties make it suitable for deep network training. Categorical cross-entropy loss is selected for its effectiveness in multi-class classification tasks.

The model is trained using the augmented training dataset. This process involves iteratively feeding batches of data into the network, adjusting weights through backpropagation, and learning from the training data. Training progress is monitored, and validation is performed using the validation dataset.

Model Evaluation

Performance evaluation is conducted using accuracy, precision, recall, and F1-score metrics. These metrics provide a comprehensive assessment of the model's ability to accurately classify different classes while considering false positives and false negatives.

A confusion matrix is introduced to visualize the model's predictions in a binary classification context. This matrix showcases true positives, false positives, true negatives, and false negatives, forming the basis for calculating evaluation metrics.

4. Experiment

In this section, we meticulously outline the experimentation process, delving into the specifics of our CNN model's architecture, the intricate setup of hyperparameters, the meticulous pre-processing techniques, the comprehensive evaluation metrics, and the exploration of alternative approaches for model improvement.

Experimental Setup

Hyperparameters and Model Architecture

Our model's architecture was meticulously designed to accommodate the intricacies of fruit image classification. The architecture comprises a sequence of three convolutional layers, each followed by a max-pooling layer to extract important features from the input images. Dropout layers were introduced to mitigate the risk of overfitting, enhancing the model's generalization capabilities. Subsequently, two fully connected dense layers were incorporated to process the extracted features before leading to an output layer with a softmax activation function.

Throughout the training, hyperparameters were crucial in guiding the model towards convergence. For optimization, the Adam optimizer was selected due to its adaptive learning rates. The choice of the categorical cross-entropy loss function was appropriate, considering the multi-class nature of the fruit classification task. A detailed summary of the model's architecture and parameter counts was provided, showcasing its complexity and potential.

Dataset and Pre-processing

Our dataset is derived from the Kaggle fruit classification Dataset, carefully selected and organized to represent six distinct classes of fruit images, presenting an initial challenge due to class imbalance. To address this, we employed the ImageDataGenerator to apply data augmentation techniques. Rotating images within a 20-degree range, zooming in and out up to 20%, and rescaling pixel values to a normalized range of [0, 1], effectively augmented the dataset. Additionally, the dataset was divided into training and validation subsets, with 90% of the data allocated for training and 10% for validation.

Model Training and Evaluation

The model's training commenced with the diverse augmented dataset, fostering a robust learning experience. Over 12 epochs, the model grasped intricate patterns and significant features, thereby enhancing its ability to distinguish. During training, both the training accuracy and validation accuracy were recorded, offering insights into the model's progress and potential overfitting.

Fig 2. Training and Validation loss for CNN model

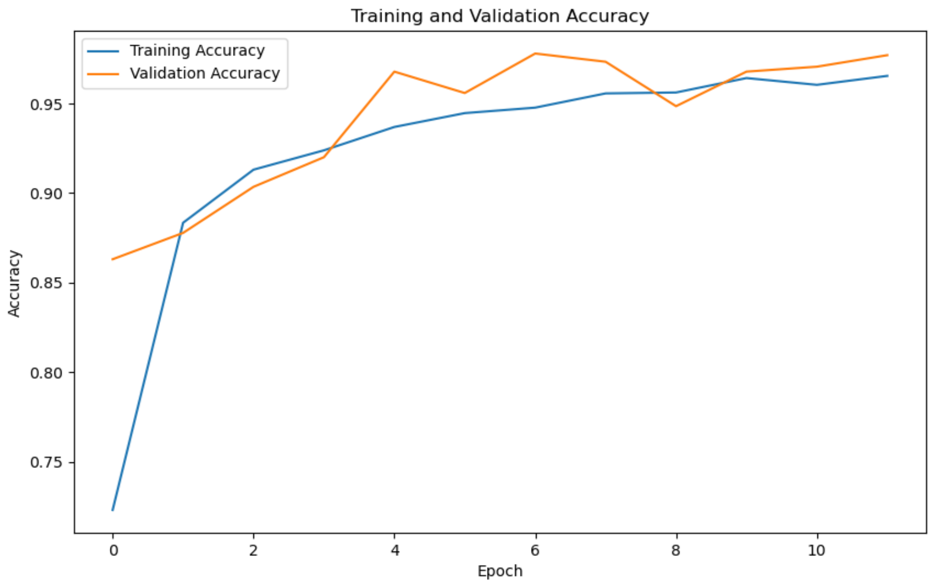

Fig 3. Training and Validation loss for CNN model

The model's performance on the unseen test dataset was quantified using the metrics of test accuracy and test loss. The test accuracy, calculated as 0.9607, revealed a robust predictive power, signifying the model's capacity to make accurate fruit classifications. The test loss, computed as 0.1105, indicated a minimal disparity between predicted and actual values, highlighting the efficiency of the model in minimizing errors during classification.

For an in-depth evaluation of the model's performance, we utilized a range of evaluation metrics, providing us with a comprehensive measure of its performance. The classification report summarized precision, recall, and F1-score, presenting a holistic view of each class's performance.

It is notable that our model demonstrated remarkable precision, recall, and F1-score values for most classes. For instance, the 'rotten banana' class achieved a precision of 1.00, indicating that nearly all predicted rotten bananas were indeed rotten. A similar trend was observed in classes like 'fresh banana' and 'fresh apples.' These high values underscore the model's ability to make refined and accurate distinctions.

Overall Accuracy

The model reached an impressive accuracy level of 96%, highlighting its strong performance in categorizing a wide variety of fruits. This accuracy score underscores the model's dependability and effectiveness in real-world situations.

Macro and Weighted Averages

Both the macro and weighted averages, calculated at 0.96, highlight how consistently the model performed across diverse classes. These metrics indicate a balanced evaluation of the model's capabilities, confirming its uniform proficiency in handling different types of fruits.

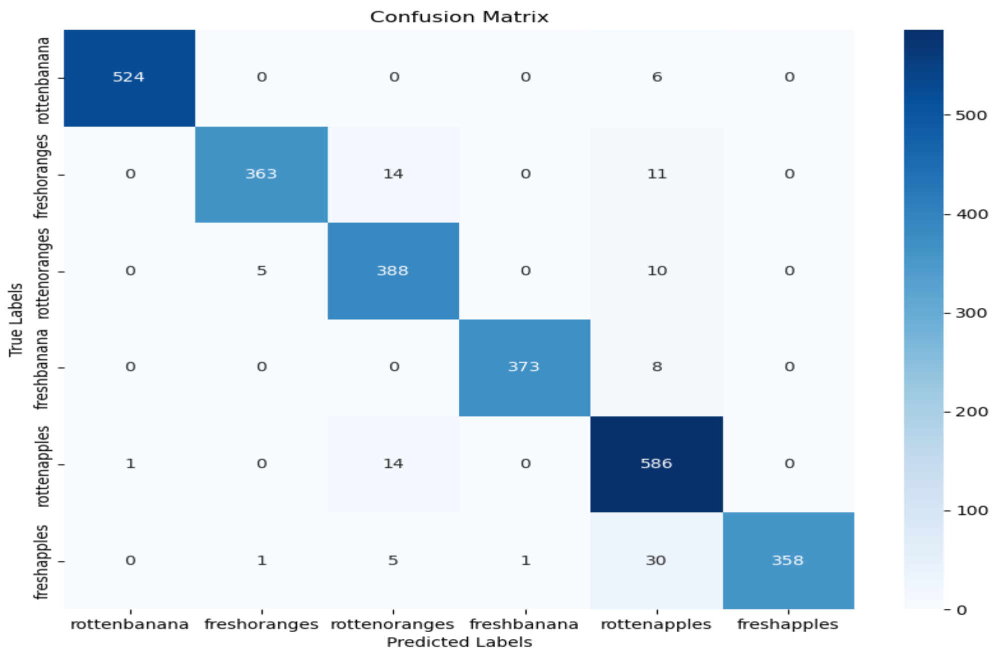

Fig 4. Confusion matrix for CNN model

Alternative Approaches

In our relentless pursuit of model enhancement, we ventured into the realm of transfer learning, capitalizing on pre-trained models to expedite convergence and improve model performance. We embarked on two distinct experiments: fine-tuning the VGG16 model and experimenting with the ResNet(Residual Network) architecture.

For the VGG16 experiment, the base model was retained in its original form, while a new classification layer was appended and fine-tuned specifically for fruit classification. The ResNet experiment, on the other hand, introduced the formidable ResNet architecture, combining its convolutional strengths with additional classification layers.

Comparative Analysis of Experimented Models:

VGG16, a renowned pre-trained model, underwent a comprehensive evaluation in our experimental setup. After fine-tuning its layers on our dataset, the training was conducted over a span of 6 epochs. The results unveiled the following outcomes:

Training Accuracy: 89.62%

Validation Accuracy: 90.72%

Fig 5. Training and Validation Accuracy of fine-tuned VGG16 model

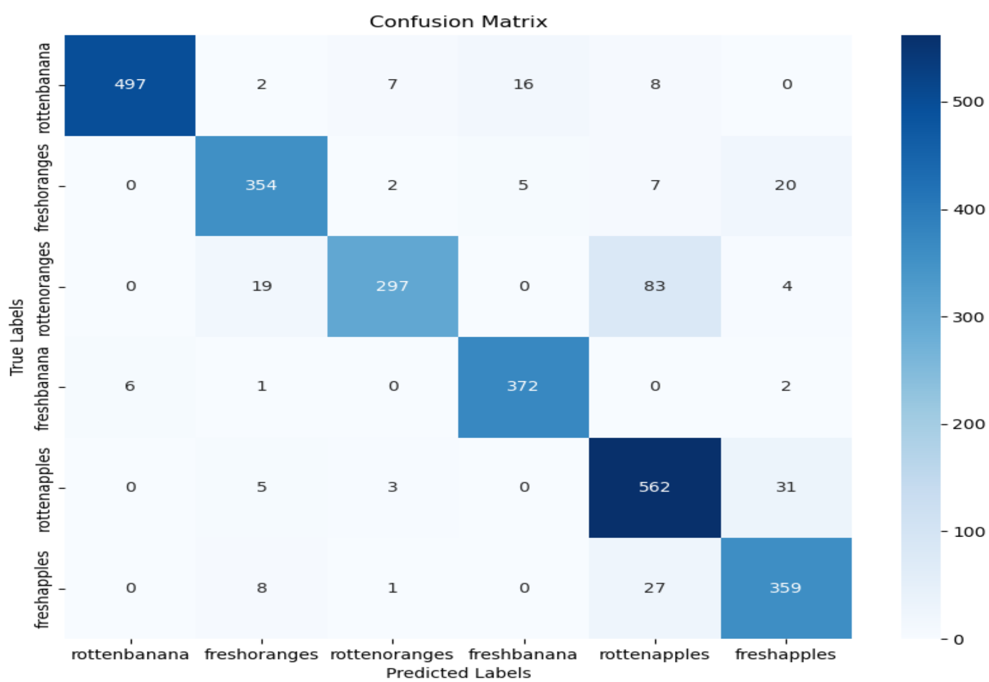

Fig 6. Confusion matrix for vgg16 model

While the VGG16 model exhibited promising accuracy rates, the investigation extended to ResNet, did not. Another pre-trained model with the potential to enhance classification. Similar to the previous experiment, the model underwent rigorous training and evaluation, spanning 7 epochs. The findings from this experiment were as follows:

Training Accuracy: 68.13%

Validation Accuracy: 75.00%

It is worth mentioning that while ResNet may not have performed excellently, further fine-tuning is bound to improve the performance.

Fig 7. Training and Validation loss for the ResNet model

5. Results

The classification report for our CNN model provides insights into its performance across various fruit classes. The precision, recall, and F1-score metrics offer a comprehensive overview of its classification capabilities:

Table 1. CNN model classification report

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Rotten bananas	1.00	0.99	0.99	530
Fresh oranges	0.98	0.94	0.96	388
Rotten oranges	0.92	0.96	0.94	403
Fresh banana	1.00	0.98	0.99	381
Rotten apples	0.90	0.98	0.94	601
Fresh apples	1.00	0.91	0.95	395
Accuracy	-	-	-	0.96
Macro Avg	0.97	0.96	0.96	2698
Weighted Avg	0.96	0.96	0.96	2698

This classification report illustrates that the model performed exceptionally well across most classes, with high precision, recall, and F1-scores. The overall accuracy stands at 96%, highlighting the model's proficiency in distinguishing between fresh and rotten fruits.

An interesting aspect observed during the evaluation is the robustness of the model's performance on different fruit types, showcasing its ability to generalize effectively.

The sample display of correctly predicted fruit classes further reinforces the model's accuracy and its capability to correctly identify and label images from the test dataset.

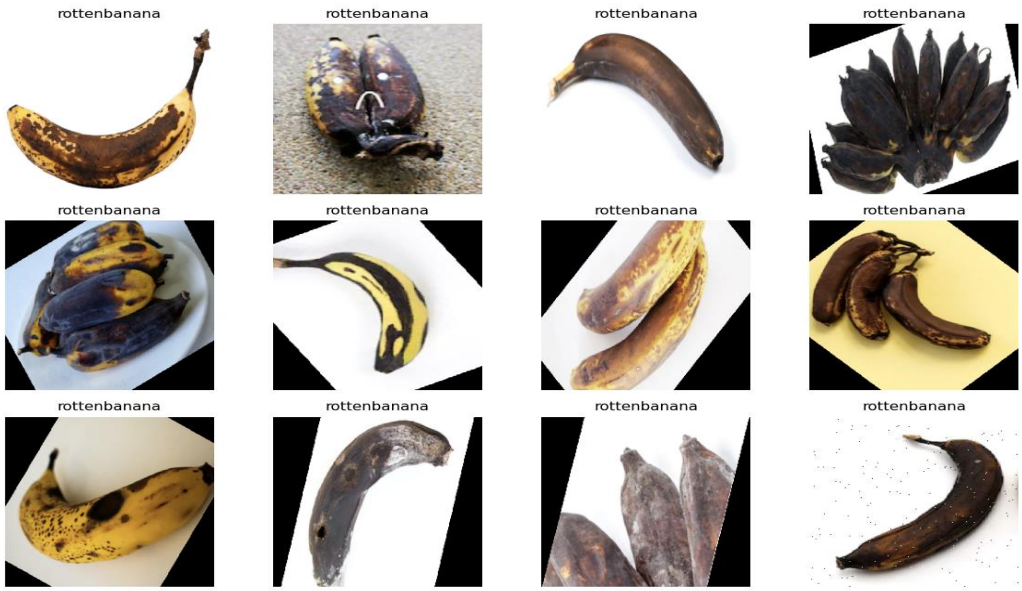

Fig 8. correctly predicted rotten fruit sample

Experimentation with Pre-trained Models

Experimenting with pre-trained models, specifically VGG16 and ResNet, revealed intriguing insights. The VGG16 model, after 6 epochs, achieved a validation accuracy of 90.72%, demonstrating steady convergence. On the other hand, the ResNet model, after 7 epochs, reached a validation accuracy of 75%. It is noteworthy that further fine-tuning and training iterations could potentially enhance the ResNet model's performance.

Despite the progress made with pre-trained models, the original CNN model maintained its superior performance. Its validation loss remained low (Test Loss: 0.1105), and its accuracy on unseen data remained impressive (Test Accuracy: 0.9607).

Our exploration of using Deep Learning and Convolutional Neural Networks (CNNs) for fruit classification has shown promising results that match our project's goals. The CNN-based model achieving 96% accuracy is better than our baseline, suggesting it could be practically useful.

From our tests with pre-trained models like ResNet and VGG16, we've learned that there's room for practical improvements.

Our model's accuracy remains steady across different kinds of fruits, showing it could be used practically. The fine-tuned VGG16 model's stability makes it seem fitting for real-world situations.

In the future, we understand the importance of being practical. Making our dataset cover a wider variety of fruits and conditions could make the model more adaptable. Gradual improvements to the pre-trained models and trying out ensemble methods offer sensible paths to closing the gap in performance.

6. Conclusion

In conclusion, our CNN model showcased exceptional performance in fruit classification, successfully differentiating between fresh and rotten fruits. The detailed classification report underscores the model's precision and recall across various classes, with an overall accuracy of 96%. The presented sample images of correctly predicted classes visually validate the model's effectiveness.

The experimentation with pre-trained models, while insightful, reaffirms the CNN model's dominance in accuracy and reliability. While alternative models like VGG16 and ResNet exhibit potential, they still fall short compared to the original CNN model's performance.

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