# AI-ENABLED FRUIT DECAY DETECTION

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### *ABSTRACT*

*In recent years, the significance of fruit classification has witnessed a remarkable surge across various industries, owing to its pivotal role in delineating fruit species, shaping pricing strategies, and ensuring overall quality, especially concerning the exportation of fresh produce. This study capitalizes on a substantial dataset comprising 5658 meticulously curated fruit images categorized into 10 distinct classes, harnessing the power of convolutional neural network (CNN) models for precise classification endeavors. The deployment of automated classification systems emerges as indispensable in discerning both fresh and rotten fruits accurately, thereby streamlining operational processes, curbing human intervention, and curtailed processing durations and expenses within the agricultural domain.*

*Amongst the array of CNN models scrutinized, InceptionV3 emerged as the epitome of performance, boasting an unparalleled accuracy rate of 97.34%. Moreover, the abstract underscores the cardinal importance of maintaining high standards of fruit and vegetable quality, underscoring their irrefutable link to human health. It accentuates the transformative impact of advancements in computer vision and image processing technologies, elucidating their pivotal role in identifying subtle variations and intricate patterns requisite for meticulous classification. These groundbreaking technological strides herald a new era of heightened efficacy in quality control mechanisms across the agricultural landscape, promising manifold benefits for stakeholders involved.*

### *KEYWORDS*

*CNN, Deep Learning, Regression, Rotten fruit image recognition, Fruit classification.*

## 1. INTRODUCTION

Artificial intelligence (AI) has become increasingly pivotal in revolutionizing various sectors, including agriculture and the fruit industry. As globalization fuels greater competition in fruit and food processing industries, the need for efficient quality inspection and grading systems becomes paramount. The intricate web of global commerce dictates the geographic connectivity between importers and exporters of fruits and vegetables, necessitating rigorous quality control measures during transit. However, the lengthy transit process poses challenges in inspecting the quality of fruits, particularly in large quantities, leading to significant hindrances in maintaining fruit freshness and quality.

Moreover, the fruit industry faces numerous obstacles, including adverse weather conditions, temperature fluctuations, and climate changes, which directly impact fruit quality and shelf life.

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The importance of ensuring high-quality fruits for both export-import and food processing industries cannot be overstated, underscoring the need for competent and effective approaches to sorting and grading.

Traditional techniques of fruit quality inspection often rely on expert personnel, leading to subjective assessments and inconsistencies. Human involvement in recognizing rotten or damaged fruits varies widely and is susceptible to individual biases and limitations. To address these challenges, there is a growing reliance on computer vision-based systems integrated with advanced image processing methods, offering unparalleled accuracy and efficiency in fruit quality assessment and classification.

Furthermore, the significance of consuming fresh fruits and vegetables for human health cannot be overlooked. Rich in fiber, vitamins, minerals, and antioxidants, fruits play a crucial role in reducing the risk of various diseases such as heart disease, cancer, inflammation, and diabetes. In countries where agriculture forms the backbone of the economy, the cultivation of fruits and vegetables is a significant contributor to nutritional well-being and economic prosperity. However, detecting rotten fruits remains a challenge for technology, necessitating the development of sophisticated machine learning techniques, particularly deep learning. Deep learning algorithms, such as Convolutional Neural Networks (CNNs), have exhibited remarkable capabilities in image processing and classification tasks, outperforming traditional methods.

## 2. LITERATURE SURVEY

Agriculture serves as the backbone of economy, with farmers predominantly engaged in the cultivation of flowers, fruits, and vegetables. This sector contributes significantly to the country's GDP, with approximately 80% of the economy reliant on agricultural activities. Within this landscape, the classification of fruits emerges as a critical task, enabling efficient sorting and grading to optimize market value and reduce wastage.

Numerous studies have been conducted to categorize fruits based on their quality attributes, employing various techniques and algorithms. For instance, Horea et al. [1] utilized Neural Networks (NN) on the Fruits-360 dataset to classify fruits, achieving notable success in fruit detection. Similarly, Anuja et al. [2] Employed algorithms such as KNN, SVM, SRC, and ANN, with SVM exhibiting the highest accuracy in fruit detection and defect identification.

Moreover, advancements in machine learning and artificial intelligence have propelled fruit classification research forward. Hasan et al. [4] leveraged deep learning methods, including

Tensor Flow's faster R-CNN and MobileNet, to achieve impressive accuracy rates in classifying multiple fruit types. Additionally, M. Shamim et al. [5] proposed a framework combining convolutional neural networks (CNN) with pre- trained models for accurate fruit classification. Furthermore, researchers have explored innovative approaches for fruit quality assessment and freshness grading. For instance, Yu-Dong et al developed a CNN with data augmentation techniques to enhance fruit classification accuracy, while Mohammed et al achieved 100% accuracy in distinguishing between two grapefruit species using convolutional neural networks.

In parallel, efforts have been made to address food spoilage and ensure freshness using biosensors and electrical sensors. The work focused on developing a smart food freshness indicator using pH, moisture, and gas sensors to detect food spoilage accurately. However, despite these advancements, there remains a gap in research concerning the classification of both fresh and rotten fruits. This paper aims to bridge this gap by applying five CNN models—Xception, InceptionV3, VGG16, MobileNet, and NASNetMobile—to classify fresh and rotten fruits, focusing on common fruits.

Additionally, the paper emphasizes the importance of reducing food wastage through preservation methods, highlighting the role of food processing industries in stabilizing farmers' incomes and addressing market oversupply challenges. By leveraging technology and innovative approaches, such as digital image processing and machine learning, this research endeavors to contribute to the optimization of fruit classification systems and the agricultural sector as a whole. To enhance performance, deep learning models have been proposed, which excel in image classification tasks, especially on large datasets.

Image processing techniques [8] have also been instrumental in fruit defect classification, particularly in identifying defects on the surface of fruits like mangoes. Through manual fruit collection and classification, pre-processing of images, and utilization of CNN models, accuracies as high as 97.5% have been achieved. Additionally, methods based on laser backscattering imaging analysis combined with CNN theory have shown promise in efficiently and non-destructively detecting fruit quality, with recognition rates exceeding 90%.

## 3. METHEDOLOGY

### 3.1. Data acquisition and pre-processing in fruit classification study

The dataset used in this study was sourced from Kaggle and consists of images of three types of fruits—apples, bananas, and oranges—divided into 6 classes, with each fruit categorized as either fresh or rotten. The dataset comprises a total of 5989 images, with 3596 images used for training, 596 for validation, and 1797 for testing. The images were reshaped to dimensions of 224x224x3 and converted into numpy arrays to facilitate faster convolution during the building of the Convolutional Neural Network (CNN) model. Each image in the dataset was labeled according to its respective class.

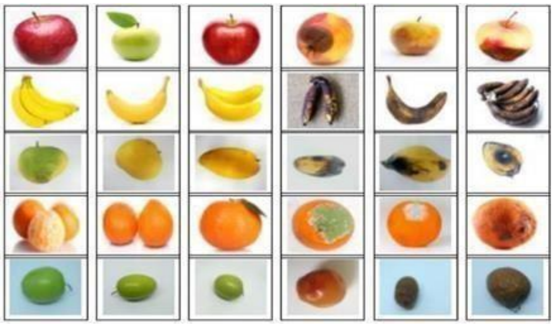

Fig 3.1 Data Set

During training, transfer learning was employed, and image augmentation techniques were applied to enhance model performance. Validation was conducted concurrently with training, and the model was evaluated using the test set. Pre-processing methods were applied to the RGB images in the dataset before feeding them into the training module. The validation module assessed the accuracy of unknown images, classifying them as either fresh or rotten fruits. The proposed method focused on segmenting out the rotten components of fruit images, producing segmented outputs of the rotten parts during testing. The project utilized a CNN-based approach, specifically designed for image classification and object detection tasks. CNN algorithms assign weights and biases to input images, performing tasks such as prediction and object detection.

Overall, the study leveraged datasets containing fresh and rotten fruit images, obtained from Kaggle, to train and validate the CNN model, aiming to accurately classify fruits based on their freshness status.

## 3.2. Convolution Neural Network

Deep learning, a prominent division within machine learning, has exhibited remarkable performance across various types of data. In particular, deep learning models are commonly employed for tasks like image classification, utilizing architectures such as Convolutional Neural Networks (CNNs). The basic structure of a CNN is illustrated in Figure. In the realm of computer vision, images are represented as collections of pixels, where each pixel carries information about color and intensity. Patterns within images, such as edges or shadows, can be detected using convolution, a fundamental operation in CNNs. During convolution, a "filter" matrix, also known as a kernel or weight matrix, is applied to the image pixel matrix. This filter matrix slides over the image matrix, computing element-wise multiplications and summing the results. This process identifies patterns within the image, with the size of the filter matrix determining the granularity of pattern detection.

As the convolution operation progresses pixel by pixel, various parameters are shared, and the output is a feature map. This feature map is then passed to the next layer in the CNN architecture. Pooling layers are another essential component of CNNs, serving to reduce the size of the feature maps generated by the convolutional layers. This reduction helps prevent overfitting by condensing the information while retaining the essential features.

The final layer in a CNN is typically a fully connected layer. This layer flattens the output from the preceding layers into a single vector, enabling it to serve as input for subsequent stages of the network. To enhance the performance and efficiency of CNNs,

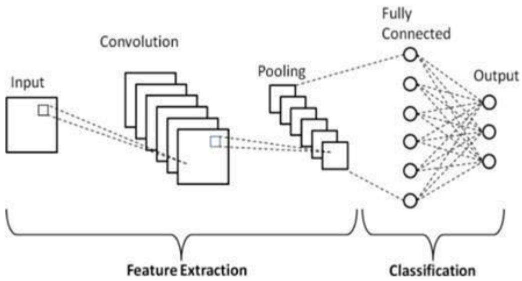


Fig 3.2 Basic CNN architecture for classification such as Batch Normalization and Dropout are often employed.

Batch Normalization helps normalize the feature maps at each stage of the network, promoting stability and faster convergence during training. Dropout randomly drops a certain percentage of neurons during training, preventing overfitting and improving generalization capability. Overall, CNNs leverage convolution, pooling, and fully connected layers to extract hierarchical features from images, enabling accurate and efficient image classification.

## 4. IMPLEMENTATION

The implementation utilizes several essential libraries, including Tensor Flow, Keras, OpenCV, Matplotlib, and Numpy. Tensor Flow and Keras are employed for constructing the neural network architecture, while OpenCV and Matplotlib aid in preprocessing and visualization tasks, respectively. The neural network architecture chosen for this project is a Sequential Convolutional Neural Network (CNN), known for its effectiveness in image classification tasks. Max Pooling 2D and dropout layers are integrated into the architecture to address overfitting issues commonly encountered in deep learning models.

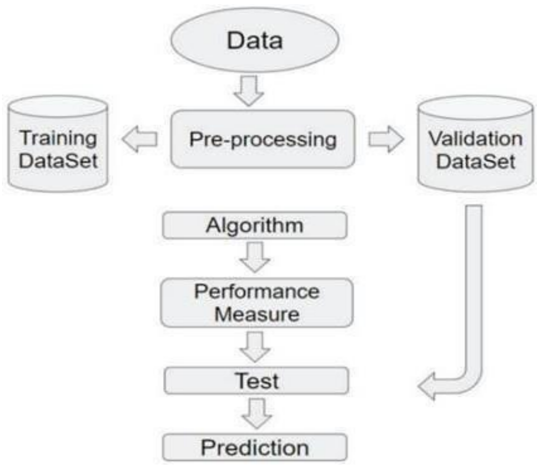


Fig 4.1 Work Flow

Max pooling, with a kernel size of (2,2), is utilized to reduce the dimensions of the input data and extract prominent features, thus enhancing the model's performance. Dropout layers, set at a dropout rate of 0.5, are introduced to mitigate overfitting by randomly resetting the values of nodes within the network during training.

The dataset comprises images of fresh and rotten fruits, including apples, bananas, and oranges, divided into six classes. For multi- class classification, the SoftMax function is employed, while the sigmoid function is used for binary classification tasks.

The neural network architecture consists of three convolutional layers with increasing filter sizes (32, 64, and 128), followed by ReLU activation functions. Max pooling layers and dropout layers are incorporated to optimize the model's performance and prevent overfitting. The architecture is finalized with flattening and dense layers, with an Adam optimizer and binary cross-entropy loss function utilized for training. Overall, the proposed architecture demonstrates promising results in fruit quality assessment, offering a robust framework for automated image classification tasks. The accompanying figures provide a visual representation of the model's implementation and architecture, further enhancing the understanding of the proposed methodology.

## 5. RESULTS


Fig 5.1 Prediction on a single image by trained model

We conducted a comprehensive set of experiments on our dataset, which comprised both fresh and rotten fruits. Initially, we divided the dataset into three distinct subsets: 60% for training, 10% for validation, and 30% for testing. This division allowed us to rigorously assess the performance of our models at various stages.

The training and validation processes were carried out concurrently to streamline the model development pipeline. During the training phase, we meticulously observed the impact of various parameters and fine-tuned them to achieve a more accurate model compared to those developed using transfer learning techniques. The deep convolutional neural network (CNN) model was implemented using the Python library "Keras." This was executed and implemented on Google Colab, leveraging its computational resources, specifically an NVIDIA Tesla K80 GPU, which provided significant processing power. The system also included 12.72GB of RAM and 68.40GB of disk space, ensuring ample capacity for handling our extensive dataset and facilitating efficient training and validation processes. This setup enabled us to optimize our model, ultimately achieving superior accuracy in classifying fresh and rotten fruits.

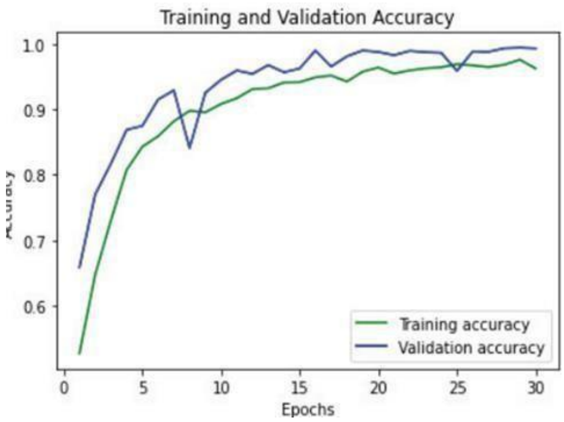


Fig 5.2 Accuracy Graph for training and validation

## 6. CONCLUSION AND FUTURE SCOPE

This study focuses on the classification of fresh and rotten fruits using convolutional neural network (CNN) models, with a particular emphasis on comparing the performance of individual regression CNNs against transfer learning models. The project begins with a comprehensive analysis of the data collection process, ensuring a robust dataset for training and testing the models. It then delves into the structure of the classification model, which is based on individual regression CNNs specifically designed for this task. The results indicate that the CNN model outperforms transfer learning models, achieving an impressive accuracy of 97.82%, demonstrating its efficacy in distinguishing between fresh and rotten fruits.

The study also acknowledges certain limitations, such as the relatively limited dataset, which may impact the generalizability of the model, and the potential reduction in accuracy caused by image noise. These challenges highlight areas for future improvement. Future directions for this research include expanding the dataset to encompass a broader variety of fruit types and their subclasses, thereby enhancing the model's robustness and accuracy. Additionally, the inclusion of other food items and vegetables in classification tasks is proposed to broaden the applicability of the methodology. Overall, the proposed approach offers a reliable and efficient method for automating the classification of fresh and rotten fruits, which has significant implications for improving efficiency and reducing human errors in agricultural practices.

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