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DEEP LEARNING MODEL FOR FRUIT QUALITY DETECTION AND EVALUATION

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ABSTRACT

Ensuring the excellence of fruits holds paramount significance in safeguarding human well-being. The automated identification process assumes particular prominence within the realm of food industry and agriculture, offering time-saving benefits and shielding individuals from potential health complications. Fruit quality plays a crucial role in safeguarding human health, making automated detection especially significant in the food industry and agriculture. By leveraging machine learning algorithms, this system offers the potential to save time and mitigate health risks,which is made of CNN(Convolutional Neural Network). The major goal is to make it more accurate with less loss percentage and also predict fruit quality rather than only predicting the fruit. For that we have tried various pre-trained models and found their respective accuracy and loss percentage like Xception, VGG16, Resnet, Inception V3. Fruits used in the project are Apple, Banana, Guava, Lemon, Pomegranate, Orange. For our project, the ResNet model is the most suitable choice. ResNet, short for Residual Network, is a deep convolutional neural network architecture that is known for its effectiveness in image recognition tasks. It has achieved significant success in various computer vision applications.One of the key advantages of the ResNet model is its ability to handle deep networks by utilizing skip connections or residual connections. These connections allow the model to bypass certain layers, enabling the flow of information from earlier layers directly to the later layers. This approach helps alleviate the vanishing gradient problem and enables training of much deeper networks.

KEYWORDS : ***Deep learning Algorithms, Convolutional Neural Network, Fruit quality detection, Machine Learning, Computer Vision, Fruit Classification, ResNet 50***

1. INTRODUCTION

India cultivates a diverse range of primary fruits such as Mangoes, Grapes, Apples, Apricots, Oranges, Fresh Banana, Avocados, Guava, Litchi, Papaya, Sapota, and Watermelons. The country's rich blend of climate and geographical conditions provides an ideal environment for nurturing a wide assortment of fresh fruits. When it comes to fruit cultivation, India holds the second position globally, just behind China. As per the National Horticulture Database (Second Advance Estimates) published by the National Horticulture Board, India achieved a remarkable production of 102.48 million metric tonnes of fruits during the 2020-21 timeframe. The total area under cultivation for fruits in India stood at 9.6 million hectares.Fruits are highly valued worldwide due to their nutritional value, taste, and versatility. They are not only consumed directly but also used as ingredients in various industries, including the culinary industry, where they are incorporated into dishes, desserts, juices, jams, and many other food products.India's reputation as the "fruit basket of the world" is due to its abundant production and diverse range of fruits, which are made available throughout the year due to the country's different climatic zones. This enables India to meet domestic demands and also export fruits to various countries, contributing significantly to the global fruit market. It is true that the quality of fruits plays a critical role in the health of consumers. Manual inspection of fruits can be challenging and time-consuming, leading researchers to explore automated image processing techniques to address these issues. By utilizing computer vision and image processing algorithms, the quality of fruits can be assessed more efficiently, benefiting both customers and market establishments.Appearance factors such as size, shape, surface texture, surface color, and external defects are important indicators of fruit quality and significantly influence consumers' purchasing decisions. Computer vision techniques can be employed to evaluate these factors and categorize the image quality of fruits. Algorithms like Faster R-CNN, implemented using the TensorFlow library, can be utilized for reliable fruit quality detection.India's vibrant bazaars are known for their bustling atmosphere, with numerous vendors selling their wares, including crates upon crates of fresh fruits. The cultivation and availability of specific fruits vary across different regions of India. Here are some insights into the cultivation of certain fruits: India predominantly cultivates apples in the regions of Jammu & Kashmir, Himachal Pradesh, and the hilly areas of Uttar Pradesh and Uttarakhand. While the majority of apples are consumed in their fresh form, a portion of the harvest undergoes processing to create delectable juices, delightful jellies, and convenient canned slices..

Bananas: India and China are the world's largest producers of bananas, accounting for approximately 38% of total production.

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Major banana-growing states in India are located in the northeastern and southern parts of the country, with Tamil Nadu having the largest area followed by Maharashtra and Karnataka.

Guava: Guava is an important commercial fruit in India, with the "Allahabad safeda" variety being one of the best cultivated in the country.

Indian lemons flourish in subtropical to tropical zones and find their optimal growth conditions in states like Gujarat, Andhra Pradesh, Maharashtra, Karnataka, Tamil Nadu, Bihar, Rajasthan, and Assam. These regions serve as prominent cultivators of lemons within India. Remarkably, India plays a significant role in the global lemon production, accounting for around 17% of the total output worldwide.

Pomegranate: Pomegranate is produced throughout the year in India, with the peak season from February to May. Maharashtra is the major pomegranate-producing state, accounting for a significant portion of the total area and production.

Mandarin Oranges: Among the citrus family, mandarin oranges hold a prominent place in Indian agriculture, encompassing a substantial portion (approximately 40%) of the overall citrus cultivation acreage.

Oranges: Within the realm of citrus fruits, oranges enjoy extensive cultivation in India, claiming a significant share of nearly 50% in the overall citrus cultivation expanse.

These fruits are not only vital for the domestic market but also contribute to India's export of fresh fruits, showcasing the country's diverse agricultural capabilities.

2. LITERATURE SURVEY

Here is additional information on the current developments in autonomous vision-based technology for fruit detection and classification. The studies and approaches mentioned highlight the use of image processing techniques, machine learning algorithms, and computer vision methods for fruit quality assessment, fault detection, disease identification, and classification.

Shital.A[1] discussed the use of autonomous vision-based technology for fruit grading, sorting, and fault detection, specifically focusing on bananas. OpenCV and edge detection techniques were employed for image preprocessing and masking to detect flaws in bananas.

Sushree[2] applied image processing techniques for fault detection in mango fruits, including image preprocessing, segmentation, and feature extraction using the SFTA algorithm. The dataset was trained using a deep neural network (DNN) approach.

Ananthi.N[3] explored image preprocessing, feature extraction, and denoising techniques for the analysis of fruit infections. Median filtering, blob detection, and K-Means segmentation were utilized to detect and classify fruit diseases using a DNN classification method.

Meshwa Patel[4] used image processing and an SVM classifier to identify the quality of orange fruits. Image preprocessing, feature extraction using the GLCM method, and morphological image processing techniques were employed.

Yogesh[5] employed various machine learning algorithms, such as CNN, ANN, and SVM, for fruit classification and analysis of apple, mangosteen, pear, and strawberries. The models were developed, tested, and configured for accurate results.

Deepti.C[6] aimed to develop a non-destructive technology for detecting artificially ripened fruits using a CNN algorithm and system requirements analysis.

RashmiPriya[7] suggested using image processing techniques for disease detection in orange fruits, including picture preprocessing, filtering, segmentation using the OTSU method, and cluster analysis with the K-Means approach.

Additionally, the "FruitNet" dataset consists of high-quality images of popular Indian fruits. This dataset serves as a foundation for the development of more efficient and accurate systems in fruit classification and recognition.

These studies and dataset creation contribute to the advancement of fruit quality detection and classification techniques, utilizing image processing, machine learning, and computer vision algorithms.

3. PROJECT BACKGROUND

Our envisioned framework for fruit recognition and quality detection through deep learning strives to construct a model capable of precisely identifying fruits based on their size, shape, and color, while effectively disregarding extraneous factors such as environmental conditions, noise, and background interference. The system's core focus lies solely on the fruit image, aiming to deliver precise and accurate identification outcomes.

The utilization of pre-existing models, such as the ResNet50 model, for classification purposes showcases remarkable efficiency and proficiency, yielding highly accurate results. Leveraging the expertise and learned features of these pre-trained models substantially enhances the system's performance.

By adopting a deep learning approach and harnessing the power of pre-trained models, the framework facilitates progressive

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model development. This adaptive approach enables the extension or fine-tuning of the model to accommodate new fruit types or variations as they arise, ensuring its adaptability and flexibility.

Additionally, the framework prioritizes the ease of maintenance and management throughout the project's lifespan. Deep learning models can be continually updated and refined by incorporating new data and enhancing the training process. This dynamic nature ensures the system's continuous evolution, enabling it to remain up to date with emerging fruit varieties and evolving quality detection requirements.
In essence, our proposed framework for fruit recognition and quality detection, empowered by deep learning, aspires to deliver an accurate, efficient, and manageable solution for fruit identification based on size, shape, and color attributes. By leveraging pre-trained models and employing an incremental development approach, the system exhibits the capacity to enhance its performance and adapt to emerging challenges within the realm of fruit identification.

4. PROPOSED METHOD

The ResNet architecture is a popular deep neural network architecture commonly used for various computer vision tasks, including image classification. The ResNet models, such as ResNet-18, ResNet-34, ResNet-50, ResNet-101, ResNet-110, ResNet-152, ResNet-164, and ResNet-1202, differ in the number of layers they contain.

In the case of ResNet-50, it is composed of 50 layers. The ResNet architecture introduces the concept of residual learning, which helps to alleviate the vanishing gradient problem and enables the training of very deep networks.

The bottleneck building block is used in the 50-layer ResNet, also known as a bottleneck residual block. It incorporates three convolutional layers: a 1x1 convolution layer to reduce the dimensionality of the input, a 3x3 convolution layer for feature extraction, and another 1x1 convolution layer to restore the dimensionality before adding the original input. This bottleneck structure reduces the number of parameters and computational complexity compared to a plain convolutional layer, making training more efficient.

By utilizing the ResNet-50 model, which has demonstrated strong performance in image classification tasks, you can leverage its pre-trained weights or train it on your specific dataset to achieve accurate fruit classification and recognition in your system.

Table 1: ResNet Model Architecture

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		[3×3, 64; 3×3, 64] ×2	[3×3, 64; 3×3, 64] ×3	[1×1, 64; 3×3, 64; 1×1, 256] ×3	[1×1, 64; 3×3, 64; 1×1, 256] ×3	[1×1, 64; 3×3, 64; 1×1, 256] ×3
conv3_x	28×28	[3×3, 128; 3×3, 128] ×2	[3×3, 128; 3×3, 128] ×4	[1×1, 128; 3×3, 128; 1×1, 512] ×4	[1×1, 128; 3×3, 128; 1×1, 512] ×4	[1×1, 128; 3×3, 128; 1×1, 512] ×8
conv4_x	14×14	[3×3, 256; 3×3, 256] ×2	[3×3, 256; 3×3, 256] ×6	[1×1, 256; 3×3, 256; 1×1, 1024] ×6	[1×1, 256; 3×3, 256; 1×1, 1024] ×23	[1×1, 256; 3×3, 256; 1×1, 1024] ×36
conv5_x	7×7	[3×3, 512; 3×3, 512] ×2	[3×3, 512; 3×3, 512] ×3	[1×1, 512; 3×3, 512; 1×1, 2048] ×3	[1×1, 512; 3×3, 512; 1×1, 2048] ×3	[1×1, 512; 3×3, 512; 1×1, 2048] ×3
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Table 2: Accuracy using different pre-trained models.

	Accuracy%	Loss%
VGG16	86	31
ResNet	85	45
Xception	98	4
Inception	-	-

We have experimented with different models and found ResNet-50 to be the most reliable and accurate for our fruit classification task. Each of the models mentioned, including Xception, VGG16, ResNet50, and Inception-v3, have their unique characteristics and architectural design choices that contribute to their performance.

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Xception represents an expansion of the Inception framework, implementing the filtering process initially on each depth map. Subsequently, it employs 1x1 convolutions across the depth to effectively reduce the input space. This approach bears resemblance to the long-standing utilization of depth separable convolutions in the design of neural networks. Notably, Xception diverges from Inception by introducing variations in the presence or absence of a non-linearity following the initial operation.

In contrast, ResNet stands as a profound neural network architecture that revolutionized the notion of residual learning. It incorporates skip connections or shortcuts, enabling the network to leap over certain layers, thus facilitating the training of exceptionally deep networks. By introducing these skip connections, ResNet effectively addresses the vanishing gradient issue, empowering the training of deeper models that exhibit enhanced performance.

VGG16 is a widely used object detection and classification algorithm. It is known for its simplicity and uniform architecture. VGG16 consists of thirteen convolutional layers, five max pooling layers, and three dense layers. The name VGG16 comes from the fact that it has sixteen weight layers, despite having a total of twenty-one layers.

Within the Inception lineage, Inception-v3 emerges as an additional convolutional neural network architecture. It integrates various enhancements, including label smoothing, factorized 7x7 convolutions, and the implementation of an auxiliary classifier to propagate label information effectively. Notably, Inception-v3 garners recognition for its commendable computational efficiency, demonstrating a reduced parameter count in comparison to VGGNet while preserving performance standards.

Each of these models has its strengths and trade-offs. By choosing ResNet-50 based on its reliability, accuracy, and loss percentage in our experiments, we have made a sound decision for the fruit classification system.

5. METHODOLOGY

The proposed system is designed to overcome problems of manual techniques. This system consists of several steps to detect the quality of fruit using CNN architectural methods using pre-trained models. There are seven steps in the proposed model for quality detection as shown below.

5.1 Segregation of Dataset

The Dataset is segregated based on the quality of fruits. It contains three distinct categories namely Good Quality, Bad Quality and Mixed Quality. The total number of images is 12069 for training the model.

5.2 Splitting the dataset

We have divided our dataset into a training set,testing set and a validation set.

In our case, out of the total 12,069 files, we have allocated 9,656 files (approximately 80% of the dataset) for training the model. This larger portion of data will be used to train the model and adjust its parameters to minimize the training loss and improve its ability to classify fruit quality accurately.

The remaining 2,413 files (approximately 20% of the dataset) have been reserved for testing. These files will be used to assess the model's performance on unseen data, allowing you to measure its accuracy, precision, recall, or any other evaluation metrics relevant to your task.

By splitting the dataset into a training set and a testing set, we can train and assess the performance of the ResNet-50 model on different subsets of data, helping us gain confidence in its ability to classify fruit quality with precision.

5.3 Load the ResNet Model

Fig 1. ResNet Model

```
resnet_model = Sequential()

pretrained_model= tf.keras.applications.ResNet50(include_top=False,
                   input_shape=(180,180,3),
                   pooling='avg',classes=3,
                   weights='imagenet')
for layer in pretrained_model.layers:
        layer.trainable=False

resnet_model.add(pretrained_model)
resnet_model.add(Flatten())
resnet_model.add(Dense(512, activation='relu'))
resnet_model.add(Dense(3, activation='softmax'))
```

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5.4 Train the Model

To set the parameters for the ResNet model, we consider the following options:

1) ResNet models offer a range of variations denoted by names like ResNet-18, ResNet-34, ResNet-50, and more, which signify the network's layer count. The selection of the appropriate number of layers depends on the desired complexity and depth needed for fruit classification tasks. ResNet-50, encompassing 50 layers, stands as a popular option that strikes a balance between performance and computational efficiency, making it a commonly favored choice.
2) When working with the ResNet model, the decision to utilize pretrained weights from the ImageNet dataset or commence training from scratch lies in our hands. Opting to initialize the model with pretrained weights can prove advantageous, particularly if our fruit classification task exhibits resemblances to the ImageNet classes. This approach can serve as a solid starting point, potentially enhancing convergence and accuracy. Nonetheless, if our fruit dataset significantly differs from ImageNet, commencing training from scratch may be a more suitable course of action.
3) Validation Set: A crucial decision to make is whether to incorporate the validation set into the training process or reserve it exclusively for model evaluation. The act of dividing the dataset into distinct training and validation subsets enables continuous monitoring of the model's performance throughout training. This practice allows for informed decisions, such as implementing early stopping based on validation metrics. It is generally advised to maintain a separate validation set to ensure impartial evaluation and mitigate the risks of overfitting.
4) Other Parameters: Aside from the aforementioned considerations, there exist numerous additional parameters that necessitate configuration, tailored to the specific demands of our fruit classification undertaking. Among these parameters are the learning rate, batch size, choice of optimizer (e.g., Adam, SGD), weight decay, dropout rate, and data augmentation techniques, to name a few. Through a process of experimentation and analysis of validation performance, these parameters can be fine-tuned to optimize the overall performance of the model.

It is crucial to acknowledge that the ideal values for these parameters may differ based on factors such as our dataset, available computational resources, and unique task requirements. Engaging in experiments that involve exploring various parameter configurations and assessing the model's performance is essential. This iterative process aids in identifying the most suitable configuration for our fruit classification task, aligning with our specific needs and circumstances.

5.5 Train the Model Evaluation

Evaluating the model's performance on a test set is crucial to assess its generalization capability. By achieving the desired results on our test set, we can have confidence in the model's ability to accurately classify fruit quality, including identifying bad quality fruits.

It's important to continue evaluating the model on a diverse range of test samples to ensure its robustness and reliability. Additionally, you may consider other evaluation metrics such as accuracy, precision, recall, or F1 score to gain a comprehensive understanding of the model's performance.

When we input an image of a bad quality apple and the model produces accurate results, it suggests that our ResNet-50 model has learned the relevant features and patterns associated with various qualities of fruits. This demonstrates the effectiveness of the model in distinguishing between different quality categories of fruits.

6. RESULTS

Training a ResNet-50 model to identify fruit and classify its quality is a valuable application of deep learning. Evaluating the performance of the model is an essential step to assess its effectiveness. We have got the desired results as shown in the following fig. ,which shows our model works efficiently and predicts the accurate results for the desired input.

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Fig 2. Prediction of results of an input image

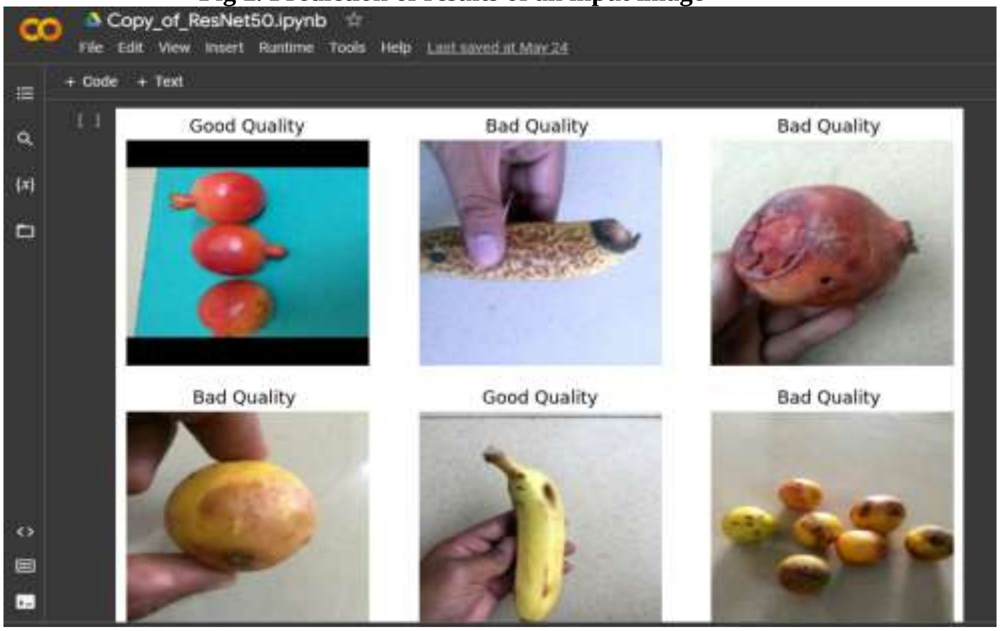

Table 3 : Samples of images of fruits of each class

	Good Quality	Bad Quality	Mixed Quality
Apple			
Banana			

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Guava			
Lemon			
Orange			
Pomegranate			

7. CONCLUSION AND FUTURE SCOPE

The use of the ResNet50 model for fruit quality detection in our project seems to have yielded promising results. ResNet50 is a powerful pre-trained CNN model known for its deep architecture and efficient performance. Its ability to handle hundreds or thousands of convolutional layers makes it suitable for complex image processing tasks.

By leveraging the ResNet50 model, we were able to achieve better accuracy and loss percentages, indicating that the model effectively learned the features and patterns necessary for fruit quality detection. This demonstrates the capability of deep learning and CNNs in particular, to address complex tasks in the field of image classification.

The successful identification of fruit quality using the proposed method suggests the potential applicability of this technique in various domains such as juice manufacturing facilities, fruit and vegetable farms, and packing industries. The ability to automatically detect and categorize fruit quality can streamline processes, improve efficiency, and enhance quality control.

It is worth noting that future research could compare the performance of CNN-based quality detection methods with other mechanical and automated methods to evaluate their strengths and weaknesses. This comparative analysis can help determine the most suitable approach for specific applications and identify areas for further improvement in fruit quality detection.

Overall, the utilization of the ResNet50 model and the successful implementation of the proposed method highlight the potential of CNNs in fruit quality detection and open up possibilities for advancements in automated quality assessment in the fruit industry.

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