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Deep Learning Approach for Fruits Classification

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***Abstract*— Fruit classification is an extension of object detection and accounts for a sizeable portion of fresh products in the food industry. Fruits were formerly classified, which takes time and necessitates continual human presence. Fruit classification is essential for many industrial applications. Supermarkets all across the world must arrange different fruits in order to appropriately organize their price tags and racks. It is challenging, particularly in these days. In order to manually locate the category of the item being purchased in the system, either the customer or the cashier must first determine what it is. Fruits are categorized and used in agriculture to recognize and group fruits based on characteristics including size, shape, color, texture, ripeness, and edibility. As a result, the farmer is able to sort and grade the fruits to ensure that they arrive at the market in the best possible shape. In this essay, we primarily concentrate on categorizing fruits. Three models—MobileNetv2, ResNet50V2, and DenseNet121—were trained for the classification, and we got the best classification accuracy of 98.97%.**

***Index Terms*— Deep learning, Neural networks, ResNet, MobileNet and DenseNet.**

I. INTRODUCTION

Fruit makes up a significant amount of fresh product in the food sector, and the classification of fruit is an extension of object detection. In previous times, the classification of fruits was done manually, which takes time and demands constant human presence. Classifying fruits is a critical task for numerous industrial applications. All around the world, supermarkets have to arrange various fruits in order to organize their racks and price tags properly. It is difficult, especially today when they confuse the human eye. In agriculture , fruits are been classified and used to identify and group fruits based on their features, such as size, shape, color, texture, maturity, and edibility. This enables the farmer to sort and grade the fruits in order to deliver them to the market in the best conditions. Fruit classification is a crucial activity in the food and agricultural industries because it can aid in automating the process of sorting fruits according to their external appearance, which is a crucial component in assessing their quality, size, ripeness, and market worth. Fruits classification can be beneficial or they can give the excellent service to the stake holders or the end users in varies fields. The classification can be benefited to the farmers that enables them to sort and classify their product based on the characteristics and qualities of each fruit. This can increase the price at which they can sell their produce and cut down on waste. They can spot any quality problems and fix them before the fruits are delivered to market with the aid of accurately graded fruits. This classification not only gives the excellent services in the matter of farmers but also helps consumers by enabling them to distinguish and choose fruits based on their quality, maturity, and sweetness. They may use this information to make wise decisions and get the most for their money. They can avoid purchasing overripe or unripe fruits by using proper grading. Fruits can be categorized based on their visual characteristics using deep learning, a effective method that has demonstrated significant potential for image recognition and classification applications. One of the most important

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machine learning techniques is the deep learning(DL), which can automatically pick up on a variety of features and patterns without the human input. The correctness of the fruit classification system depends on the standard of the gathered fruit photos, the quantity and types of features recovered, the kinds of features chosen, the best classification features chosen from the retrieved characteristics, and the kind of classifier used. Fruits are frequently categorized according to their size, color and shape. The domain of the fruit classification project starts with the deep learning. Specifically, it involves training a deep learning model to accurately classify images of varies types of fruits. The objective of this research is to develop a model that can recognize various fruit varieties based on their distinguishing visual traits, such as shape, size, color, and other attributes. Numerous uses for this include automated harvesting, fruit classification and sorting systems that are more effective, and quality control in the food business. Deep learning is a subpart of machine learning that utilizes neural networks to extract features from data and do predictions. Deep learning models can be trained on huge datasets of labeled photos in the context of image classification to discover patterns and features that relate to various object classes. The Fruits classification application could be useful for a variety of users who needs to identify or work with different types of fruits. The food industry can use this application to sort and grade fruits based on their appearance and quality, improving the efficiency of their operations and ensuring consistent product quality and quality control from the field to the supermarket, fruits quality can be tracked using technology for classification of fruits. Consumers can gain more knowledge about the fruits they are purchasing by using technology for fruits classification. By classifying and labeling different types of fruits, the food industry may help consumers make better purchase decisions.

II. Related Work

The research describes a deep learning method for classifying images that makes use of a trained CNN model for feature extraction. The approach for categorizing 10,000 real-world photos of cats and dogs using the CNN with stochastic gradient descent algorithm on CIFAR-10 dataset, was presented by Panigrahi, A. Nanda [1]. Y. Naung, Z.M. Khaing, et al. proposed, a system incorporating CNN for fruit categorization and Alexnet as the algorithm was proposed. This research examines a convolutional neural network-based method for developing control systems for object recognition. The results of their test classification accuracy for the 30 classes of 971 images being close to 94%[2]. The six-layer CNN model is computationally effective and has the ability to handle massive amounts of data with speed and reliability. This paper by S. Lu, Z. Lu, S. Aok et al, suggests a method for identifying fruits based on convolutional neural networks. The experimental findings achieved a 91.44% accuracy rate[3]. With a collection of 200 fruit pictures, a system that uses K-Means, nonlinear, entirely connected layers, and pooling layers is described. Convolution neural networks-based classification strategy is proposed by R. Yamparala, P. S. R. Krishna, et al, which offers a 90% better classification result than other proposed methodologies [4]. Fruits fresh and rotten were suggested as the classification dataset together with the Transfer learning method, VGG-19, LeNet, and AlexNet as algorithms in classifying fruits proposed by Rupali Pathak and Hemanth Makwana .[5]. Using convolutional neural networks, a system that uses deep learning, data augmentation, AlexNet, VGG-16 as an algorithm and our suggested system divides the four fruits banana, papaya, mango, and guava into three stages: raw, ripe, and over-ripe which is proposed by Rucha Dandavate and Vineet Patodkar [6]. The sequential method, CBIR, and CNN are the three algorithms used in the system by Gurubhaksh Ponsa and Atul Sharma have described. This study will show how image categorization works in the setting of the CIFAR-10 dataset. They achieved 94% of accuracy for the three classes used in the CIFAR-10 dataset[7]. In the article proposed by Chandan.R.,Joshi.R, CNN models are developed to assess how well they perform on datasets for image recognition and detection. A system using Deep Learning, Overfitting Augmentation, SVM, KNN, and CNN as algorithms and CIFAR-10, MNIST as a dataset is described[8]. The system proposed by PL.Chithra, M.Henila's, along with its image processing methods, Support vector machine (SVM), KNN, suggests that after separating the fruit from its background and gathering information on its shape and colour, they applied a segmentation technique. [9]. LeNet-5, SENet, RESnet, and MNIST dataset were used in the paper proposed by Paramartha Dutta, Abu Sufian, et al. They have demonstrated improvements in CNN through this research, from LeNet-5 to the most recent SENet model. ResNet improved accuracy by combining the inception module and residual blocks with the traditional CNN model [10].

III. Methodlogy

In the proposed work, for preprocessing Neural networks technique is been used for the classification of the fruits where the features are been extracted by the model itself. Fig 1 represents image processing techniques for the classification , which contains all the steps like preprocessing, feature extraction and the classification. This methodology is been used for all the models.

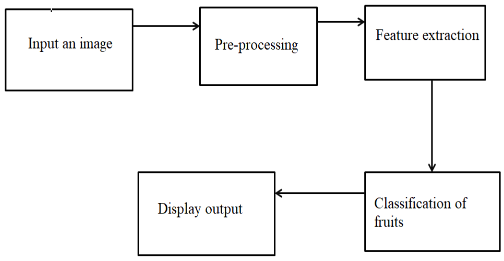

Fig 1. Fruit image classification processing

A. Dataset

The proposed model contains the dataset of 6000 images with 15 different types of fruits which is collected from the kaggle. The dataset includes Apple Barium, Mango, Avocado, Orange, Lemon, Strawberry, Raspberry, Pomegranate, Watermelon, Blueberry, Apricot, Banana, Dates , Guava and pineapple. The Dataset is also been tested with Sample Dataset which includes all the 15 classes but each class contains 10 fruits in Training dataset and 2 fruits which is being kept for testing in Test dataset. These images are being trained and tested with different CNN models like DenseNet121, ResNet50V2 and MobileNet.

B. Model Description

There are many deep learning models that are accessible at present. Neural networks are computational models made up of interconnected neurons arranged in layers and are inspired by the human brain. Data is received by the input layer and propagated through the hidden layers using weighted connections. Neurons introduce non-linarites by applying activation functions to the weighted sum of inputs. Up until the output layer begins to give predictions, this forward propagation process is continued. MobileNetV2, DenseNet121 and ResNet50V2 are considered to be the different models of CNN.

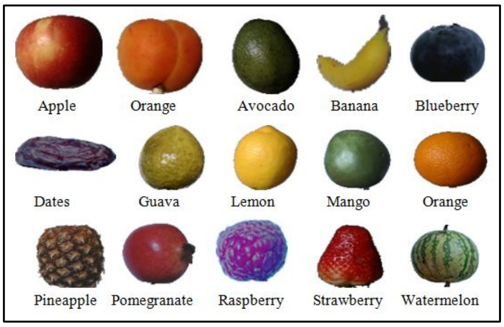

Fig 2. Dataset

1. *Mobilenetv2*

In Fig. 3, the architecture of MobileNetV2 consists of a contracting path on the left and a classifier head on the right. By repeatedly applying two 3x3 convolutions each followed by a rectified linear unit (ReLU), and a 2x2 max pooling operation with stride 2 for down sampling, the contracting route adheres to the standard design of a neural network. Repeating these three processing steps repeatedly creates a collection of completely linked layers, called Blocks. The feature map matrix is flattened into vector form at the conclusion of the MobileNetV2 stage and fed into the classifier stage, which is a fully connected layer that resembles a neural network.

2. Resnet50v2

In the fig4, Deep convolutional neural network architecture of ResNet50V2, also known as Residual Network with 50 layers and version 2, is widely employed for image classification tasks. It is a modified version of the original ResNet model that addresses the problem of disappearing gradients and makes various changes to boost performance. To create the final classification output, ResNet50V2 uses batch normalization, average pooling, and

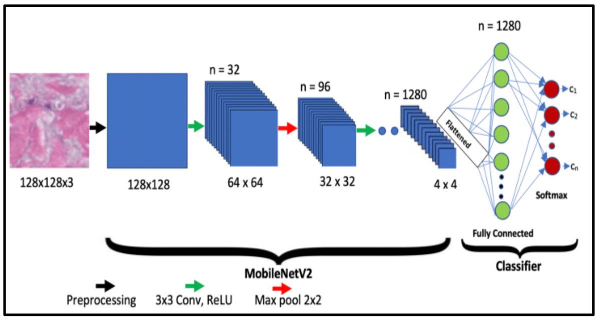

Fig. 3. MobileNetV2 Architecture

fully connected layers in combination. ResNet50V2 achieves state-of-the-art performance on a variety of image recognition benchmarks thanks to its deep structure and residual connections, indicating its usefulness in capturing nuanced features and aiding effective training.

3. Densenet121

In fig5, the DenseNet121 model begins with a series of convolutional layers that extract low-level features from the input fruit images. Multiple highly interconnected convolutional layers make up the design, allowing for direct connections between all layers and facilitating the effective transmission of information and gradients throughout the network. These features are then passed through dense blocks, which are composed of multiple convolutional layers, where each layer receives inputs from all preceding layers. Global average pooling, fully linked layers, and a softmax activation function make up the architecture's final section, which generates class probabilities for fruit categorization.

IV. Implementation

In this paper, the images from the Fruits-360 dataset were taken with the 15 classes of fruits of 6000 images, we trained and tested the images to obtain the result of which class the fruits belongs to and get classified according to their class. After the models got created, the model was tested and find its accuracy based on the size, shape, color and epochs.

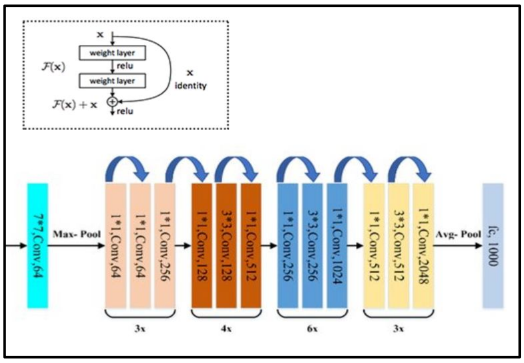

Fig 4. Reset50V2 Architecture

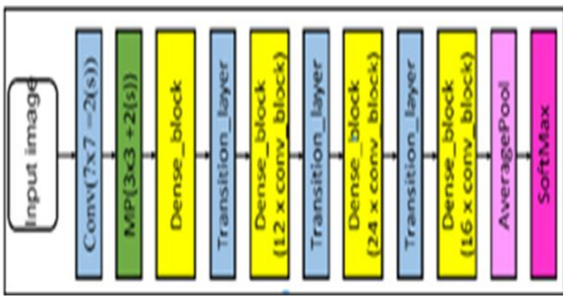

Fig 5. DenseNet121 Architecture

In fig 6, displays the project's frontend display page, which includes a visually pleasing panel for choosing an image from the dataset. The title of the project is prominently displayed on this page, drawing attention to its importance to the project's construction as a whole. Fig. 7, exhibits the selected image but also provides relevant details about it. In particular, the display contains information about the image's class, which stands for the category or label connected to the chosen image. The accuracy for each image is also displayed, indicating the model's level of confidence that the categorization or forecast it made was accurate.

Fig 6 GUI for Fruits Classification

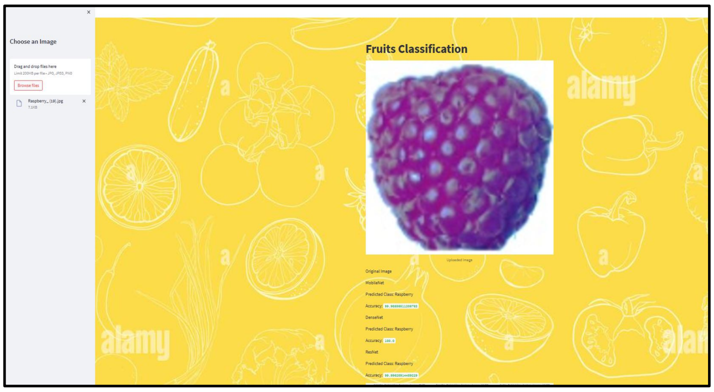

Fig 7 Result obtained for test query

V. RESULTS

In fig 8, a thorough display of graphs corresponding to a certain fruit chosen as it is shown. These graphs show data ranges and variations based on the degrees of accuracy produced from the used models. Notably, for a single fruit, the graphs for all three different models are displayed simultaneously. The accuracy levels associated with the models are indicated, offering helpful insights into the confidence and precision of the predictions, and each graph in the figure displays the predicted ranges specific to the chosen fruit.

A. MobileNetV2

The table I, shows the accuracy when tested for MobileNetV2 gives the Maximum accuracy of 99.81%, which is considered to be the highest one when compared to all the results in MobileNet model. Dataset of 70 – 30 ratio works well with this model which results giving the highest of all the accuracies.

TABLE I. ACCURACY RATES OBTAINED FOR MOBILENETV2

Train Data	Test Data	Epoch 1 (%)	Epoch 2 (%)	Epoch 5 (%)	Epoch 10 (%)
80	20	98.33	98.33	98.33	98.33
70	30	98.36	99.16	99.81	98.63
60	40	99.19	99.19	99.19	99.19
50	50	99.66	99.66	99.66	99.66

B. ResNet50V2

TABLE II. ACCURACY RATES OBTAINED FOR RESNET50V2

Train Data	Test Data	Epoch1 (%)	Epoch 2 (%)	Epoch5 (%)	Epoch 10 (%)
80	20	99.13	99.33	99.40	99.20
70	30	99.36	98.16	99.81	99.60
60	40	98.59	99.80	99.19	99.89
50	50	99.66	98.76	99.67	98.66

TABLE III. ACCURACY RATES OBTAINED FOR DENSENET121

Train Data	Test Data	Epoch 1 (%)	Epoch 2 (%)	Epoch 5 (%)	Epoch 10 (%)
80	20	99.13	99.33	99.40	99.20
70	30	99.36	98.16	99.81	99.60
60	40	98.59	99.90	99.19	99.69
50	50	99.66	98.76	99.67	98.66

The table II, shows the result when tested with ResNet50V2 model falls for the highest accuracy of 99.89% which is considered to be the best accuracy. This strategy works well with the 60-40 dataset classification which results in highest outcome accuracy.

C. DenseNet121

The table III, when dataset tested with DenseNet121 model falls for the highest accuracy of 99.90% which is considered to be the best accuracy. This strategy works well with the 60-40 dataset classification which results in highest outcome accuracy. This model is considered with 100% of accuracy which is best in all the three tested models.

D. Results with 10 epochs on all models

TABLE IV. ACCURACY RATES OBTAINED FOR 3 MODELS

Train Data	Test Data	Epoch	MobileNetV2 (%)	ResNet50V2 (%)	DenseNet121 (%)
80	20	10	98.33	99.40	99.97
70	30	10	98.63	98.81	99.89
60	40	10	99.19	99.39	99.89
50	50	10	99.66	99.67	98.97

In table IV, the Dataset when tested with the epochs of 10 with all the models including all the specified training and testing data, DenseNet is considered to be the best working model. DenseNet121 gives upto the accuracy of 100% which is considered to be the most specific and well suited to test the Dataset.

VI. CONCLUSION

After using these models, we obtained the accuracy of 99.97% of average of all the models. We trained and tested images and used all the three models namely MobileNetV2, ResNet50V2 and DenseNet121 for the image classification. After testing for epochs of 1, 2,5 and 10 for all the four models we obtained the accuracy of 99.97%.

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