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Fruit and Vegetable Classification and Freshness Detection using Machine learning

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***Abstract*— Freshness is a key factor in determining a fruit or vegetable's quality, and it directly influences the physical health and coping provocation of consumers. It ascertains the nutritional value of the specified fruit or vegetable. This paper proposes a well-organized and precise fruit and vegetable classification and freshness detection method. The proposed method employs state-of-the-art deep learning models, specifically convolutional neural networks (CNNs), to analyze images of fruits and vegetables captured through high-resolution cameras. The dataset used for training and evaluation is extensive and diverse, encompassing a wide variety of fruits and vegetables in various conditions. The freshness of a fruit or vegetable can be ascertained by looking at a variety of features, including color, texture, shape, and size. Fresh produce, for instance, is colorful and free of mold or brown spots. Traditional methods for assessing the quality of fruits and vegetables are both time-consuming and error-prone. These methods include inspection and sorting. It is possible to reduce these issues by utilizing automatic detection techniques. In light of this, we proposed an automated fruit-vegetable freshness detection approach that first recognizes whether the image is of a fruit or vegetable, after which it classifies it into one of three freshness categories: rotten, fresh, or mixed. To identify and categorize fruits and vegetables, two deep learning models are employed: You Only Look Once (YOLO) and Visual Geometry Group (VGG-16). The suggested method's qualitative analysis indicates superior performance on the fruit-vegetable dataset.**

Keywords – fruit-vegetable freshness, VGG-16, YOLO, Machine Learning, Deep Learning, CNN

I. Introduction

Fruits and vegetables play a crucial role in maintaining good health by providing essential vitamins and minerals and lowering the risk of major illnesses like hypocalcemia, rickets, obesity, and many other conditions. Fruits and vegetables nowadays are sensitive to various infections; people are becoming more conscious of the freshness and quality of the produce they eat. Thus, there is a need to ascertain the freshness of fruits and vegetables to safeguard against potential health issues. Also, there are other reasons, such as increasing market share and establishing better quality standards, that make it essential to detect how fresh a fruit or vegetable is. The manual method is slow, time-consuming, and full of errors. Therefore, it is necessary to develop an automated fruit and vegetable categorization system that will work faster and without errors.

This paper suggests a reliable and effective method to detect and classify the freshness of fruits and vegetables. Various features of the fruits and vegetables are analyzed, such as whether they should have vibrant colors, be smooth, and be free from bruises and blemishes. One of three categories—rotten, fresh, or mixed—can be applied to the freshness. We can easily obtain the shape of a fruit or vegetable from their images. Machine learning and deep learning techniques have proven to be highly useful in this area.

Fig. 1. Fresh and rotten fruits and vegetables [17]

Figure 1 illustrates a diverse array of fruits and vegetables. We can see that fresh produce has light colors and is smooth, while on the other hand, rotten fruits and vegetables have dull colors, brown spots, and bruises. The majority of current methods solely identify whether a fruit or vegetable is fresh or not. Notably, existing methods predominantly focus on binary freshness classification—identifying whether a specimen is fresh or not. In our research, there isn't a method for determining the mixed category, where produce exhibits characteristics of both fresh and decay. Determining the mixed category is advantageous since it minimizes the loss of fruits and vegetables. The proposed approach also categorizes a fruit or vegetable in the mixed category. The suggested methodology involves employing two deep learning models: the Visual Geometry Group (VGG-16) and You Only Look Once (YOLO). While YOLO excels at simultaneously detecting objects and determining their freshness, VGG-16 is a multi-class classification algorithm that is utilized for the initial identification and labeling of fruits and vegetables within the image. The dataset was downloaded from Kaggle. 10K pictures of six different fruits and vegetables—apple, orange, banana, bitter gourd, capsicum, and tomato—are included in it. Each photo is categorized according to three freshness levels. Every image has a size of 512 x 512.

II. RELATED WORK

In [1], fruit quality is evaluated based on three attributes: texture, color, and shape. Three supervised machine learning algorithms are used to categorize healthy apples and unhealthy apples. Among all classification algorithms, SVM shows better performance. Deep learning is applied to visual object recognition in [3]. In [5], different algorithms such as Support Vector Machines (SVM), KNearest Neighbor (KNN), Naïve Bayes (NB), and CNN are used to identify insect pests in crops such as soybean, rice, and wheat. The dataset used is publicly available. CNN shows better performance as compared to other algorithms. In [4], leaf stress issues are identified in 33 crop species, which include fruits, vegetables, and other plants. Deep learning techniques are used in this approach.

In [7], various guava fruit diseases are detected using computer vision and deep learning. In this approach, features of a guava image have been extracted using Local Binary Patterns (LBP), and dimensionality reduction is done by using Principal Component Analysis (PCA). To differentiate between rotten and fresh fruits, supervised machine learning algorithms such as SVM and KNN are employed. SVM shows better performance as compared to other algorithms. In one of the approaches, citrus fruit diseases are detected. After utilizing color histogram and Delta E segmentation to extract regions of interest (ROIs), texture features are extracted. SVM is finally applied to the classification. Resnet-50 and Resnet-101 are two neural networks that are used in [6] to distinguish between fresh and rotten fruits. The method distinguishes between the two fruit varieties before determining the fruit type.

The evaluation of apple quality, as proposed in [8], comprises several stages, including image preprocessing, followed by the segmentation of defective portions using grabcut and fuzzy c-means clustering. Lastly, classification is done using k-NN classifiers, sparse representation classifiers, logistic regression, and SVM. In [9], a CNN model is developed for classifying three types (apples, bananas, and oranges) of fruits. The model achieves high accuracy. There are nearly 6,000 images in the dataset. There were approximately 3500 images in the training set and 2,000 images in the test set. A CNN model was created in [10] to distinguish between rotten and fresh fruits. There are six types of fruits used in the model. The model is trained using images from CMOS sensors and the Kaggle Fruit360 dataset. Various image modification techniques, such as brightness transformation, rotation, scaling, translation, and the introduction of Gaussian noise, are employed. The classification is carried out using CNN and Softmax [14], achieving a model accuracy of 97.14%. In a paper, first, the disease of the apple is identified, and then its freshness is classified based on its color, texture, and shape. K-means clustering and multiclass support vector machines are the two techniques used during this work.

A model for classifying the freshness of hog palm fruit is developed in [16]. Four models are based on convolutional neural networks: ResNet18, MobileNetV2, MobileNetV3-Small, and MobileNetV3-Large. Several criteria, including accuracy and precision, are used to assess and compare the results. Supervised machine learning models like KNearest Neighbor (KNN), Naïve Bayes (NB), logistic regression, and Support Vector Machines (SVM) are compared in [15]. Performance-wise, SVM outperforms other models. To extract the various features from an image of fruit, VGG16 and CNN are utilized. In [22], Logistic Regression and Naïve Bayes algorithms are used for calculating amount of water and nutrients to be released at a particular instant. The amount of water release is predicted with the help of logistic regression algorithm and nutrient recommendation is done using naïve bayes algorithm.

The points listed above provide a quick overview of current approaches to problems with fruit and vegetable classification and freshness detection. However, for the majority of the research, the data set included either a single fruit or a limited number of different fruit species. There are no considerations for different vegetable varieties. Fruits and vegetables are only classified by the majority of methods; their freshness is not assessed. There are very few for the classification of freshness. This study made use of an extensive database of fruits and vegetables that included a variety of fruit and vegetable varieties grown in various light conditions.

In conducting a literature review, it's important to acknowledge and address potential biases and generalization concerns to ensure the validity and reliability of the findings. One common concern is bias in study selection, where researchers may inadvertently prioritize studies that align with their hypotheses or overlook conflicting evidence. To mitigate this bias, researchers should employ systematic search strategies, including comprehensive database searches and consultation with experts, and establish clear inclusion and exclusion criteria.

Publication bias is another consideration, where studies with statistically significant or positive results are more likely to be published, potentially skewing the overall conclusions of the review. To address this, researchers should consider including unpublished studies and conducting sensitivity analyses to assess the impact of publication bias [2,5,23].

Sampling bias in primary studies is also important to recognize, as studies may disproportionately sample participants from certain demographic groups or geographic regions, limiting the generalizability of the findings. Reviewers should critically assess the representativeness of study samples and consider the implications for generalizability.

Furthermore, the generalizability of findings across different populations, settings, and contexts should be carefully evaluated. Results from studies conducted in specific populations or under controlled conditions may not necessarily apply to broader populations or real-world settings. Emphasizing consistency across diverse populations and settings while acknowledging limitations in generalizability is essential.

Quality assessment of included studies is crucial to evaluate methodological rigor and risk of bias. Reviewers should use validated tools or frameworks appropriate for the study designs employed and transparently report the quality assessment process.

Overall, transparent reporting of the literature review methods and findings is essential to facilitate reproducibility and enable readers to assess the reliability of the review findings. By addressing potential biases and generalization concerns, researchers can enhance the credibility and robustness of their literature reviews, ultimately contributing to evidence-based decision-making and advancing knowledge in the field.

III. Proposed Approach

Existing systems classify fruits and vegetables as fresh or not. The proposed approach also defines the mixed freshness group. The proposed method first identifies the input image as a fruit or vegetable, assigns its label, and then classifies whether that fruit or vegetable is fresh, mixed, or rotten. VGG-16 and YOLO are two types of deep learning used, and then their results are analyzed and evaluated. VGG-16 is a classification system that can classify fruits and vegetables and classify them as fresh. YOLO is a product search tool that can sort fruits and vegetables and classify their freshness, as well as find products in photos. The process is shown in **Figure 2**.

IV. Methodology

A. Dataset

Approximately 10K images of different fruits and vegetables are available in the dataset. Mainly, fruit category contain apples, oranges, bananas and grapes, and vegetable category contain tomatoes, onions, chilli and capsicum. Each fruit or vegetable in each image is either fresh, rotten, or mixed. The size of each image is 512 × 512. The dataset is publicly available. Images of fruits and vegetables were taken using mobile phone cameras. The images are clicked with different backgrounds and varying light intensities. They may contain multiple fruits in an image.The dataset comprises a wide array of fruits and vegetables sourced from various geographic locations, including both common and exotic varieties. Each image within the dataset is meticulously annotated with metadata encompassing attributes such as fruit or vegetable type, ripeness stage, organic certification status, and other relevant characteristics like size, shape, and blemishes. Furthermore, the dataset encompasses fruits and vegetables across different seasons and climatic conditions, capturing the variability inherent in natural produce. To enhance the dataset's diversity, samples from different sources, cultivation methods (e.g., conventional, organic), and storage conditions (e.g., refrigerated, ambient) are included. Additionally, the dataset accounts for variations in image quality, lighting conditions, and backgrounds to simulate real-world scenarios. By incorporating such diverse and representative data, the research aims to develop robust deep learning models capable of accurately discerning the freshness and organicity of a wide spectrum of fruits and vegetables, thereby contributing to improved food quality assessment practices.

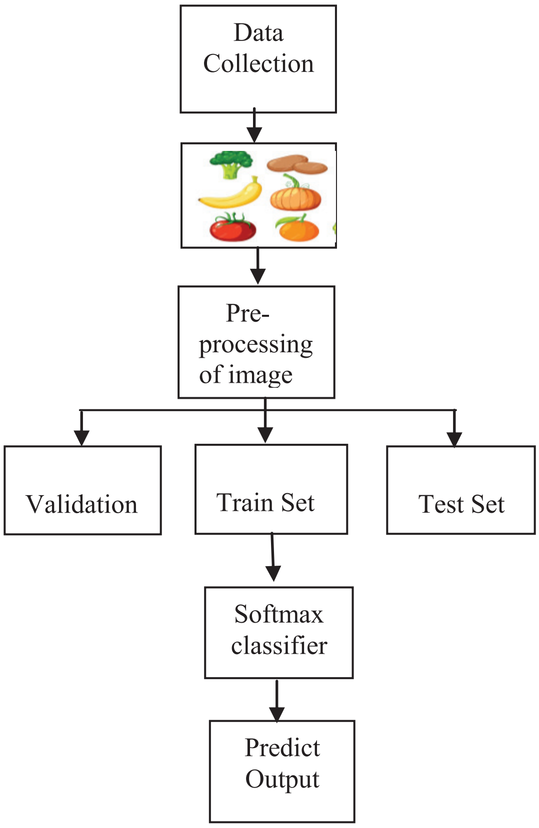

Fig. 2. Flow of Proposed method

B. Data preprocessing

Data preprocessing is a method for transforming unprocessed data into an easily understandable dataset. Preparing the data for analysis entails cleaning, processing, and integrating it. To fit the model, pre-processing of the data is done. Images are cropped and resized. The ImageDataGenerator library from Keras is used for augmentation. During this procedure, some image-enhancing techniques are also carried out, including segmentation, noise reduction, contrast enhancement, color correction, and feature extraction.

C. Algorithm Used

1) VGG-16

VGG-16 is a type of convolutional neural network model. VGG-16 consists of an input layer, an output layer, and various hidden layers. It is an object detection and classification algorithm that classifies fruits and vegetables.

The architecture of VGG-16 is shown in **Figure 3**. After pre-processing the data, we use ImageDataGenerator, which labels all the data automatically. Then the data is passed to the VGG-16 network. The Softmax activation function is used to classify multiple classes (fresh, mixed, and rotten). The Softmax layer output is in the range of 0 and 1.

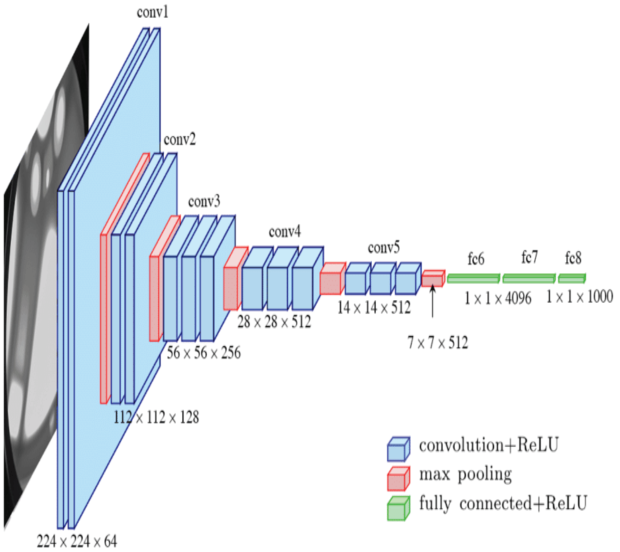

Fig. 3. VGG-16 CNN Architecture [18]

$$s\left(x_i\right) = \frac{e^{x_i}}{\sum_{j=1}^{n} e^{x_j}}$$

Where n = 3 (fresh, mixed, or rotten) and x is the vector.

Decrease function Since there are three classes, categorical cross entropy, or CE, is employed.

$$CE = -\sum_{i}^{C} y_i log(\hat{y}_i)$$

Given that y_i is the output of the softmax function and C = 3.

2) YOLOv5

YOLOv5 is an object detection algorithm whose foundation is regression. It combines bounding box prediction and object classification into a single network. It is available in four models: s, m, l, and x, and each one shows different performance and accuracy. It is easy to install and use, and it has high speed and accuracy. **Figure 4** displays the architecture of YOLOv5. We supply one annotation text file per image for training, with a bounding box included in each file for every object in the image.

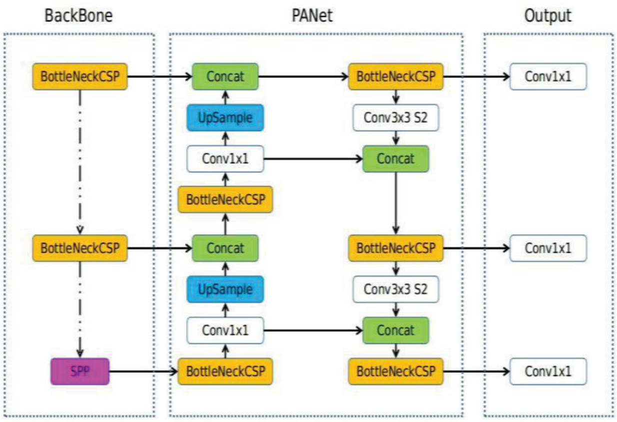

Fig. 4. YOLO-v5 architecture

The model contains two layers: the backbone layer works as a feature extractor, and the head layer predicts the output. It uses the ReLu activation function, and the output layer uses the linear activation function. To find the objects in an image, YOLOv5 cuts that image into squares and then finds out if there is any object in that square or not. YOLO is one of the best algorithms due to its high speed and accuracy. If an image contains multiple grid box objects for prediction, it uses IOU to discard all these grid boxes. The value of IOU lies between 0 and 1.

V. Results and Discussion

The tough fruit and vegetable dataset, which includes three fresh and six unique fruit and vegetable categories for each class, is using the suggested method. The fruit-vegetable dataset is divided into a test set in a 70:30 ratio for training and assessing the method.

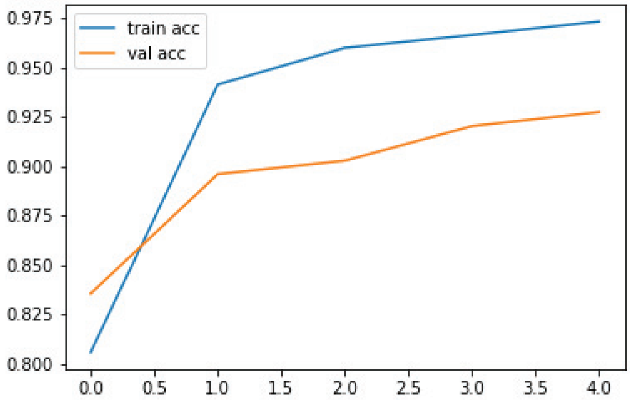

Fig. 5. Training and validation accuracy versus epochs

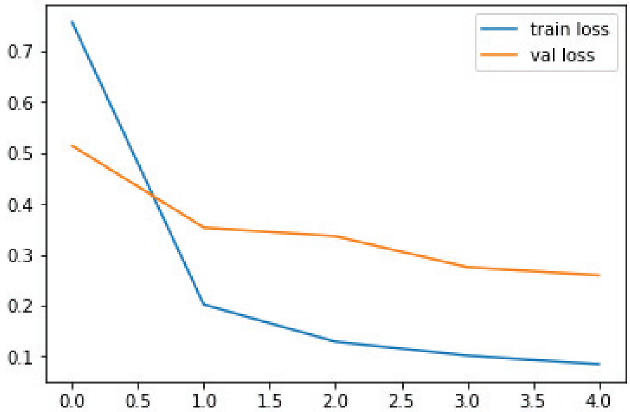

Fig. 6. Training and validation loss versus epochs

The VGG-16 model's training and validation accuracy versus epochs is presented in **Figure 5**. On the fruit and vegetable dataset, **Figure 6** presents the training and validation loss versus epochs of the VGG16 model. There are 30 batches and 50 epochs in the model's training.

The training and validation graph of the YOLOv5 model on the fruit and vegetable dataset is presented against epochs in **Figure 7**. The model's performance is based on data from training and validation. There are 8 batches and 200 epochs in the model's training. The second column represents object loss, and the third column represents classification loss, while in the bottom row it represents validation data. The last two columns represent recall and precision.

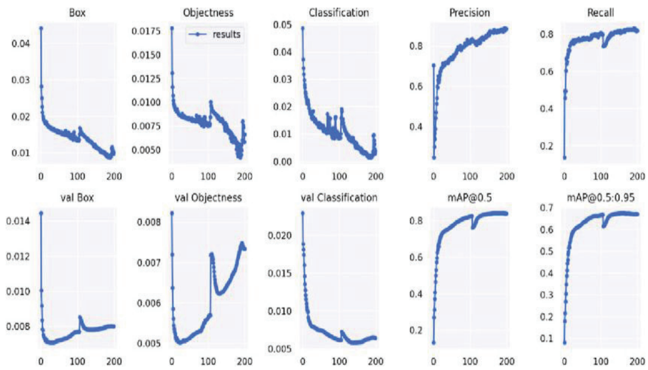

Fig. 7. YOLOv5 Training and validation graph

VI. CONCLUSION

This paper focuses on deep convolutional neural network models to propose a system that is beneficial for everyday life. The system classifies the given input image as a fruit or vegetable and then detects its freshness. The model also detects the mixed category. VGG-16 and YOLOv5 are the two deep learning models that are used. The models are trained and tested, and then their results are evaluated and compared. We use these models because they are easy to install and use and have high accuracy. We also intend to increase the dataset, which will contain more varieties of fruits and vegetables.

In the future, we hope to investigate more precise and efficient models and expand the range of fruits and vegetables. We can add many other models and compare their accuracy to find the best one. Additionally, we want to create an intuitive mobile application that will classify fruits and vegetables, display the results on screen, and suggest whether it is healthy to eat that fruit or vegetable or not. This application will be helpful for consumers, retailers or agricultural producers.

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