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Multiple Fruits Classification Using ComputerVision

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***Abstract*—**Fruits are an abundant source of vitamins, minerals,and fiber. There are numerous varieties of fruit, including apples, lemons, guavas, gooseberries, oranges, berries, melons, tomatoes, and avocados. Fruit classification would be put to use in industrialapplication. In this paper, Our proposed method consists of four main steps: object detection, image processing, feature extraction and Classification. Collected a dataset of multiple fruits images captured in a black background. Six categories of fruits are included in the dataset such as apple, lemon, orange, guava,gooseberry, and tomato. To train and test the random forestclassifier, divide the dataset into training and testing sets. The accuracy of the proposed approach for classifying multiple fruits using computer vision techniques was 75 percent on the training set and 81 percent on the testing set, according to the results, which show its effectivity.

***Index Terms*—**Computer vision, Machine learning, Seman- tic.ai, Random forest, YOLOv3

I. Introduction

Incorporating fruit into your diet can greatly benefit your health by decreasing your chance of disease. Fruits contain valuable vitamins, minerals, and plenty of fiber. Including fruitin your diet has been linked to lower risks of heart disease, cancer, and diabetes. Industrial applications rely heavily on specific categorization of various fruit species. Through the implementation of deep learning, image processing becomes more effective with the use of a multilayer structure to sort through notable features [1]. Various applications benefit from image recognition, such as video analysis, face recognition, and image classification, amongst others. Image identifica- tion has significantly improved from Deep Learning (DL),a subdomain of Machine Learning (ML)[2]. Over the pastfew years, computer vision has utilized machine learning techniques successfully for multiple purposes, including object detection, image segmentation, and image classification. fruit classification system can also be implemented as a smart- phone application. It's especially beneficial for individualswith health concerns. The app offers guidance in determining whether a particular fruit or vegetable variety meets their nutri-tional needs [3]. Based on several reasons, fruits classification through computer vision remains a challenging task, including: Among the various kinds of fruits, there exists an overlap
in their shape, color and texture. This shared similarity canbe observed across a wide range of species. Depending onfruit maturity phase and presentation form, there is significant inconsistency within a particular class. Deep learning is the basis of the proposed work. Through deep learning, image or text classification can be automatedly performed by computers.Fruit classification in this work is executed by the convolu- tional neural network (CNN) algorithm[4]. Structured deep learning, a subset of machine learning, is part of the broader family of Artificial Intelligence (AI). Like the human brain, it processes data for useful decision making through pattern recognition. DL operates with semi-supervised, unsupervised, and supervised functions. Features can be extracted from input using multiple layers in deep learning, which automatically arranges them in the exact level that a large dataset provides. To connect one layer to the next, connecting channels are employed within deep learning[5]. Manual feature extraction can be eliminated by various deep learning

architectures, such as Deep Belief Network, Deep Neural Network, and Convo- lutional Neural Network. Among these, Convolutional Neural Network (CNN) is the most popular for image classification. CNNs operate by learning from image data. With the helpof computer vision, it will be a easy to handpick using this application, and saves a lot of time[6]. Using computer vision, we have devised a plan for the categorization of numerous types of fruit which we will present through this article. The Computer vision techniques used for feature extraction, random forest for classification and the dataset corresponding for both will all be discussed. Additionally, our paper will feature a section encompassing a literature review of relevant works in the field. The paper's third section details the process employed, outlining the dataset and machine learning and deep learning algorithms utilized. Experimental results are revealed in the fourth section, while a discussion of these outcomes is given in the fifth. Ultimately, the proposed approach issuccinctly summarized in the sixth and final section, followed by a brief outline of future work.

II. Literature Review

In the article[1] The proposed technique recognises veg- etables using a classifier made up of deep learning and a neural network of convolution (CNN). Images are initially read during training data, after which they are scaled and normalised as part of preprocessing. After preprocessing, a convolution neural networks model created with Keras is used. The expected vegetable class is then determined using the trained data file, after which the vegetable class is predicted using testing data.[2] Variations within and across fruit classes have always existed. The categorization method consists of two phases: training and testing. A distinct depiction of every order of categorization is produced as the result of detaching the training characteristics of the image features. Techniques from deep learning and machine learning are used to organise the photo emphasises during testing. These sorting algorithms provide more precise results for characterization.[3] One of the exciting study areas utilised to enhance the identification and retrieving of various photographs according to form and geographical factors is image categorization in region-based categories. SVM, KNN, and Nave Bayes models classifiers are combined with the watershed transforms in the segmentation as well as the classification stages of the proposed method for categorising images.[4] With the aim of accurately and quickly classifying fruits, the pictures have been segmented by employing an image threshold approach, and the KNNclassifier is used to carry out the classification. Its main em- phasis is on recognising fruit photos and presenting the name in line with the content.[5] developed a strong framework for classifying fruits using deep learning. The framework is built on two different deep learning architectures. The first is an advanced deep learning algorithm for visual geometry group-sixteen, while the second is a suggested light model with 6 neural network convolution layers.[6] Recognising and classifying 6 different fruit categories. 6 distinct fruits may be classified automatically using convolutional neural networks, which analyse the raw pictures directly. Using the VGG16 model algorithm, images of several varieties of fruit can be identified and have been trained CNN Model VGG16, fine-tuned.[7] The researchers have developed a deep neural network it can distinguish fruits from photographs. This is a part of a bigger attempt to build a classifier that can identify more types of items from photos. The term "deep learning" refers to a class of machine learning methods that make use of many layers with non linear processing units.[8] The goal of the technique is to identify several species of unripe mangoes depending on their morphology. Neelam, Chelan, Mallika, and Banganpalli are four popular South Indian mango cultivars that were chosen due to their shared morphological traits. Techniques for augmentation include flipping, rotating, adjusting hue, contrast, and saturation. The major, minor, minor axis, solidity, and diameter are among the differentiating qualities that are extracted.[9] By properly segmenting thepicture and enabling yield prediction, they showed how to compute citrus fruit yields from tree photographs using k-
means partitioning for fruit recognition. The photographs feature a variety of lighting

conditions, such as night, direct sunshine, and shadows.[10] The simplest Pure Convolutional Neural Network was suggested. The PCNN contains seven convolutional layers, and the recently developed Global Av- erage Pooling (GAP) layer, which has had great success, was utilised to prevent overfitting and average the complete collection of feature maps. They focus on categorization, or more precisely, the act of tagging an image with a certainclass label when it contains more than one examples of an object category.[11] Built a deep learning model from scratch for classifying fruits. Many researchers have employed data sets, real-world descriptors, model implementation, and the difficulties of deep learning to classify and identify fruits. The study includes an overview of the findings from various deep learning approaches as well as an examination of recently pub- lished publications that employed models based on deep learn-ing for fruit categorization and identification.[12] Developed the attention-based highly connected convolutional networks with convolution auto encoder (CAE-ADN), a hybrid deep learning-based framework for classifying fruit images that pre-trains the images using a convolution auto encoder and extracts the features of the images using an attention-based DenseNet. In the initial component of the framework, a series of pictures are used to pre-train the greedy layer-wised CAE using an unsupervised technique. The second part of the framework implements the supervised ADN with the ground truth. The framework's last component predicts the fruit category.[13] The four fruits a banana, papaya, mango, and guava are sepa- rated into three phases using Convolutional Neural Networks: raw, ripe, and over-ripe.[14] A convolutional neural network (CNN) to create a classification model to categorise photosof oranges. Using deep learning CNN, the five categories of oranges include good oranges-grade-1, good oranges-grade- 2, immature orange, rotten orange, and damaged orange.[15] They introduced a unique method employing Radial Basis Probabilistic Neural Networks (RBPNN) to categorise colour and textural faults on fruit surfaces. A grey level co-occurrence matrix is used to extract the texture and grey characteristicsof the defect region, and the applied RBPNN solution is then used to classify the defect areas.[16] They used computer vision and support vector machines (SVM) for categorization. The process of finishing the task involves various steps. First, the supplied image is downsized. The next step is to do pre- processing using a Gaussian filter to enhance the image qualityby reducing noise. Feature space is created by dividing the colour, texture, and form aspects. Principal component analysis (PCA) is used to minimise the dimensions of the feature space in order to avoid the dimensionality curse.[17] Identifies items in a picture quickly and produces an excellent segmentation mask for each one. The method known as Mask R-CNN expands Faster R-CNN by simultaneously adding a branch for object mask prediction and the branch for bounding box identification that is currently in place.[18] Multiple fruits are categorised using a deep learning approach that uses Rapid R-CNN. On the TensorFlow system, the MobileNet model
was used to classify mango and pitaya.[19] Utilising deep convolutional neural networks (CNN) and aligned RGB and NIR pictures acquired by RGB-D (Red Green Blue-Depth) sensors, a unique method for fruit recognition. It attempts to create a fruit detecting system that is more accurate, speedy, and trustworthy. Two different fusion strategies were utilised to extract features. The words ”image-fusion” and ”feature- fusion” relate to the fusing of the RGB and NIR pictures on the input layer and the feature maps of two VGG16 networks, respectively.[20] Using visual saliency to efficiently draw the areas of the items and a convolutional neural network (CNN) model to extract the image data, a method for identifying fruitsand vegetables was suggested.

III. Dataset

There are 609 photos of six distinct types of fruits in the col- lection: apple, gooseberry, guava, orange, tomato, and lemon. The images were captured in a controlled environment, with a black background, to reduce the effect of any external factors. The images have been taken using four different devices to capture them, and each fruit has been clicked with different resolutions. For each fruit, there are six samples. The dataset's diverse collection of images captured using various devices and resolutions makes it a valuable resource for training and testing machine learning models for fruit classification tasks.

TABLE I: DataSet

Samples	Apple	Gooseberry	Guava	Lemon	Orange	Tomato
fruit 1	19	20	22	30	18	20
fruit 2	14	20	19	16	19	20
fruit 3	15	20	20	9	20	20
fruit 4	15	20	20	8	10	20
fruit 5	5	20	16	6	20	20
fruit 6	6	19	19	5	19	20
Total	74	119	116	74	106	120

Fig. 1: Dataset Samples

IV. Proposed Methodology

Our proposed methodology consists of four main steps: object detection, image processing, feature extraction, and classification.

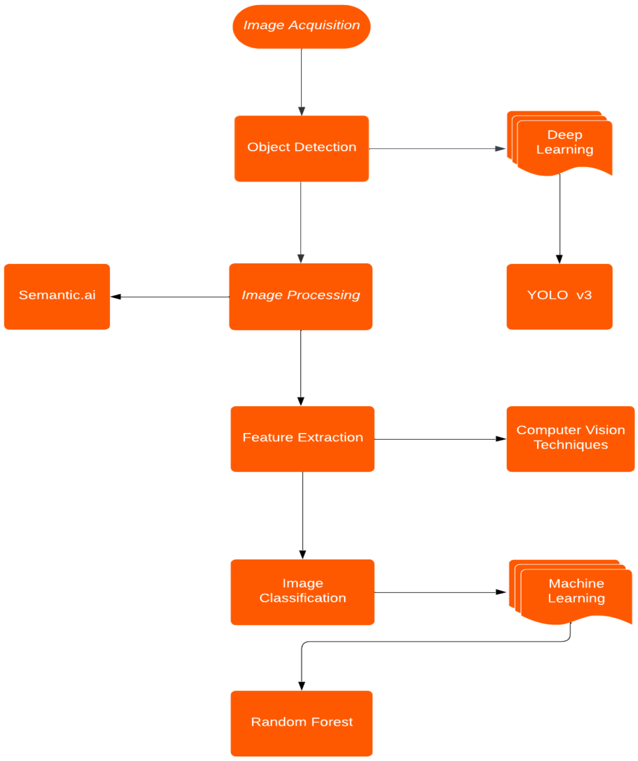

Fig. 2: Workflow diagram

A. *Object Detection*

The first step of our methodology is to detect the fruits in the image using YOLOv3, a popular deep learning-based object detection algorithm. The motivation behind this step is to accurately locate the fruits in the image and separate them from the background. YOLOv3 is a fast and accurate algorithm that can detect multiple objects in an image. To identify the fruits in the image, we utilise the pre-learned weights of YOLOv3 trained on the dataset.

- The cvlib Python module provides the YOLOv3 ob- ject detection technique. Convolutional neural networks (CNNs) are used by the YOLOv3 method, a deep learning-based object detection technique, to identify objects in photos.
- The cv2 library is used to read and manipulate images, and the matplotlib library is used to display the images.
- The draw bbox() function is used to draw the bounding boxes around the detected objects. This function takes the input image, the bounding boxes, the labels, and the counts as arguments, and returns the output image with the bounding boxes drawn on it.
- The cv2.cvtColor() function is used to convert the color space of the images between BGR and RGB.
- we can adjust the confidence threshold for object detec- tion by passing the confidence parameter to the cv.detect common objects() function.

B. *Image Processing*

The second step of our methodology is to process the image by the motivation behind using Segment.ai to create a binary image is to remove any noise and improve the contrast between the fruits and the background. This is important because the quality of the binary image directly affects the accuracy of feature extraction and classification. By using Segment.ai's semantic segmentation algorithm, we can automatically label each pixel in the image with a class label that correspondsto the object or background. This allows us to focus on the shape and size of the fruits, which is crucial for distinguishing between different types of fruits. The preprocessing and post- processing techniques used in Segment.ai ensure that the bi- nary image is of high quality and suitable for feature extraction and classification.

- Semantic Segmentation: Segment.ai uses a semantic seg- mentation model to create a binary image. Semantic segmentation is a computer vision technique that involveslabeling each pixel in an image with a class label that corresponds to the object or background.

- Deep Learning Model: The semantic segmentation model used by Segment.ai is typically a deep learning model, such as a Fully Convolutional Network (FCN), that has been trained on a large dataset of annotated images. The model learns to classify each pixel based on its context and spatial information.
- Preprocessing: Before inputting the image into the se- mantic segmentation model, Segment.ai may apply pre- processing techniques such as resizing, normalization, or data augmentation to improve the model’s performance.
- Post-processing: After the model outputs the seman- tic segmentation mask, Segment.ai may apply post- processing techniques such as filtering, morphological operations, or connected component analysis to improve the quality of the binary image.
- User Interface: Segment.ai provides a user-friendly in- terface that allows users to upload images, select the desired output format, and adjust various settings such as segmentation threshold, background removal, or objectmerging.

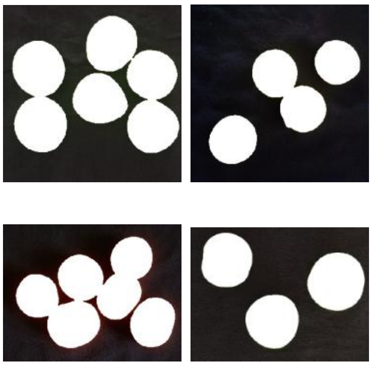

Fig. 3: binary Image

C. Feature Extraction

The third step of our methodology is to extract the features of the fruits in the image. The motivation behind this step isto provide a set of discriminative features that can be used to distinguish between different types of fruits. We extract a set of features, including volume, area, perimeter, eccentricity,major axis, and minor axis. These features are calculated using the binary image obtained in the previous step. We use the OpenCV library to calculate the features.

- Reading binary images: Reads binary images of fruits from a specified list of image paths using the OpenCV ’imread()’ function.
- Contour extraction: Uses the OpenCV ’findContours()’ function to extract the contours from the binary images. While the ’CHAIN APPROX SIMPLE’ flag compresses vertical, horizontal, and diagonal segments and retains their end points, the ’RETR EXTERNAL’ flag only returns the external contours.
- Perimeter calculation: The OpenCV ’arcLength()’ func- tion to calculate the perimeter of the contour.
- Region properties extraction: The ’regionprops()’ func- tion from the scikit-image library to extract the region properties of the binary image. The function returns a list of objects that contain various properties such as area, centroid, orientation, etc.
- Feature extraction: It extracts the following features from each image: Volume: Calculated as the contour area using the OpenCV contourArea() function. Area: Calculated from the region properties. Eccentricity: Calculated from the region properties. Major axis: Calculated from the region properties. Minor axis: Calculated from the regionproperties.
- Creating feature dictionary: Creates a dictionary of ex- tracted features for each image.
- Appending features to feature list: Appends the dictionaryof extracted features for each image to a list of features.
- Converting to dataframe: It converts the list of dictionar- ies to a pandas dataframe.

The combination of OpenCV and scikit-image functions to extract contour and region properties of binary images, It extracts the contour of the largest connected component inthe binary image and calculates its area using the OpenCV cv2.contourArea function. Therefore, if there are three objects in the image, it will provide the all features for the largest object. The extracted features are stored in a pandas dataframe for further analysis.

TABLE II: Feature Extraction

Fruit	Volume	Area	perimeter	Eccentricity	Major axis	Minor axis
Apple fruit 1	192143	27224	1772.4852	0.327083	191.6080	181.0688
Apple fruit 2	313107	62198	2384.1076	0.8585	408.5826	209.5113
Apple fruit 3	180047	31693	1718.8284	0.60057	272.4268	217.8245
Apple fruit 4	180929	53367	1721.6568	0.39603	326.0926	299.4304
Apple fruit 5	314824	83345	2278	0.5342	456.0221	385.4898
Apple fruit 6	108416	29947	1416	0.8729	328.7526	160.3822
Gooseberry fruit 1	176926	16010	1747.6812	0.1684	143.8314	141.7755
Gooseberry fruit 2	102184	13341	1388	0.9087	224.9435	93.8777
Gooseberry fruit 3	105819	12731	1402.8284	0.7428	225.5556	225.5556
Gooseberry fruit 4	108824	14559	1422	0.7271	237.2001	162.8218
Gooseberry fruit 5	109800	15765	1426	0.7214	214.1311	148.2830
Gooseberry fruit 6	105948	16809	1408	0.5270	184.9586	157.1793
Guava fruit 1	130950	19692	1510	0.4233	166.4290	150.7828
Guava fruit 2	409367	64016	2698.8284	0.8975	481.5568	212.3420
Guava fruit 3	326652	66540	2314	0.73936	506.5828	341.0874
Guava fruit 4	129658	22015	1502	0.7818	279.2064	174.0736
Guava fruit 5	401884	93136	2662	0.5521	446.2830	372.0768
Guava fruit 6	404976	95076	2660	0.5737	467.1790	382.6202
Lemon fruit 1	433788	29703	2842	0.4050	203.4909	186.0545
Lemon fruit	29582	3351	2400.0	0.8963	339.920	150.676

2	9	1	559		7	1
Lemon fruit 3	0.5	40779	7.4142	0.9303	417.9533	153.2753
Lemon fruit 4	0	21863	4	0.6926	248.9615	179.5615
Lemon fruit 5	0	55898	4	0.7157	468.4705	327.1703
Lemon fruit 6	0	33431	2	0.5608	272.4591	225.5686
Orange fruit 1	425997	32923	2844	0.1610	206.1313	203.4403
Orange fruit 2	103292	10271	1386	0.8918	179.6637	81.2690
Orange fruit 3	243741	45159	2116	0.2943	326.5720	312.1027
Orange fruit 4	429710	78221	2826	0.6930	464.3675	334.7544
Orange fruit 5	421800	84402	2788	0.5723	464.5869	380.9565
Orange fruit 6	112320	22601	1428	0.5142	222.8615	191.1337
Tomato fruit 1	0.5	8018	3.4142	0.6534	116.2099	87.9669
Tomato fruit 2	0	15447	0	0.9033	226.5584	97.1796
Tomato fruit 3	0	22604	2	0.7022	242.9893	172.9845
Tomato fruit 4	0	34774	6	0.2908	284.8932	272.5776
Tomato fruit 5	0	45708	0	0.7534	393.6946	258.8462
Tomato fruit 6	6	89197	22.1421	0.7049	516.9726	366.6518

D. Classification

We use the Random Forest Classifier method from the Scikit-learn module for classification jobs. By building nu- merous decision trees and combining their predictions, this approach makes use of ensemble learning to improve accuracyand reduce overfitting. Each tree is trained using a unique random subset of the data and features in order to ensurevariety.

- A plotting library called Matplotlib can be used to make interactive, animated, and static visualizations.
- A Python data visualisation package called Seaborn makes use of Matplotlib. It offers a sophisticated drawing interface that makes it possible to create informative and captivating statistics visuals. Data mining and machine learning are performed using Python's scikit-learn pack- age.It offers a selection of Python-based supervised and unsupervised learning algorithms.
- Python's scikit-learn library is used for data mining and machine learning. It offers a selection of Python-based supervised and unsupervised learning algorithms.
- The library pandas-profiling is used to create reports frompandas DataFrame.
- Labels with a value in the range of 0 and n classes-1 are encoded using the.LabelEncoder.
- Activate the dataset: The read csv() function loads the dataset into a Pandas DataFrame.

- Data exploration: Examining data The sample() function displays a portion of the dataset, and the columns attribute displays the names of the columns.
- Model creation and training: Constructing and training models The fit() function is used to train the model on the training set after 300 decision trees are used to create a Random Forest Classifier.
- The number of trees in the forest are specified by the n estimators parameter; more trees may increase accuracy but may also increase computational cost.
- Use the train-test split technique to split the dataset into training and testing sets. This makes it possible to assess the model's performance using previously unexplored data. With a smaller value, more data will be used for training, and vice versa, and the test size parameter specifies the percentage of the dataset to use for testing.
- Using tools like "dropna," "LabelEncoder," and "Stan- dardScaler," data preprocessing techniques like removing rows with missing values and standardizing the dataset are used. By eliminating noise, lessening the effect of outliers, and preparing the data for the algorithm, these techniques can help the model perform better.
- Using a DataFrame, the classifier's feature importances are stored and sorted in descending order to visualize feature importance. For each feature, line plots are made to show their relative importance.
- The accuracy score is determined using the accuracy score method from Scikit-learn, and the Random Forest Classifier is trained and tested using training and testing sets.

V. Experimental Result

The experimental results obtained from our study are pre- sented in this section. We conducted a series of experiments using a dataset of 609 images of different fruits, including apple, gooseberry, guava, orange, tomato, and lemon. Each

Fig. 4: Object Detection

feature (Volume, Area, Perimeter, Eccentricity, Major axis, and Minor axis) over the dataset is represented by a line plot, which shows the trends and patterns of each feature over time. The index of the data points is represented by the x-axis, and the corresponding feature values are represented by the y-axis. Consecutive data points feature values are connected by a line in the plot. We can spot trends, patterns, or changes in the feature values by tracking the path of the line. It will give insights into how the different fruit features vary across the dataset by looking at the line plots. Based on these features, it may be easier to comprehend the traits and distinctions between the various fruits. This will help in understanding the characteristics of the fruit samples and their potential impact on the classification process.It will present the data visually and act as a tool for exploratory data analysis. They aid in comprehending the trends and patterns in the dataset and can direct further analysis and decision-making.

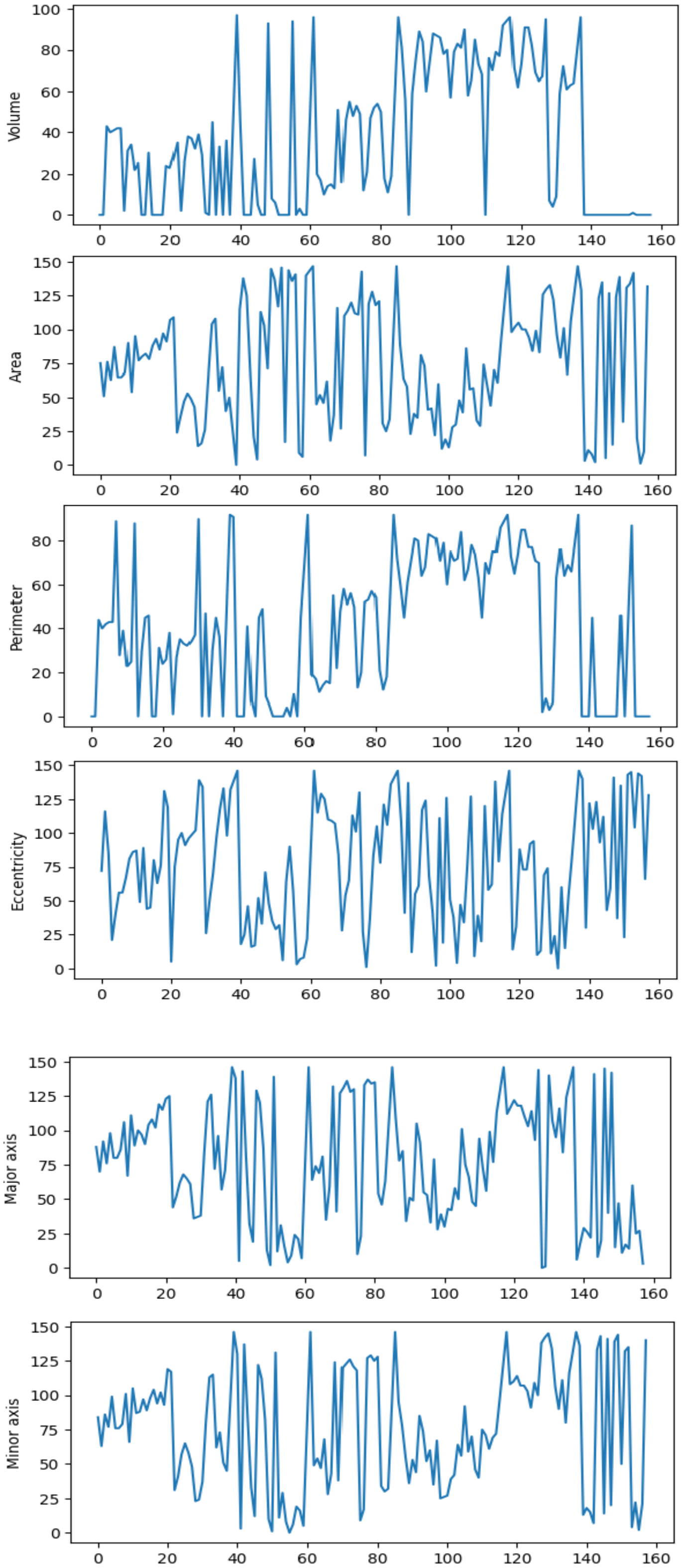

Fig. 5: Line Plot Graph

VI. Discussion

We collected a dataset of 609 images of six different fruits
- apple, gooseberry, guava, orange, tomato, and lemon. Each fruit was captured in six different samples. All images were captured on a black background to minimize external factors that could affect the analysis.We used feature extraction and Random Forest classification techniques to analyze the dataset. After preprocessing the data by standardizing the features and encoding non-numerical data, we trained the Random Forest model using the training sets and achieved an accuracy score of 81 percentage on the test set. Overall, our study demonstrates the potential of using feature extraction and Random Forest classification techniques for fruit classification, which could have in the industrial applications.

VII. Conclusion

In conclusion, this study presents a method for fruit recog- nition and classification using computer vision techniques. Wecollected a dataset of 609 images of six different types of fruits captured in a controlled environment with a black background. For each fruit, there were six samples, with variations in res- olution and captured using four different devices. The results show that the proposed approach can achieve high accuracy of 75 percentage on the training set and 81 percentage onthe testing set, which demonstrates the effectiveness of the proposed approach. The study shows that machine learning algorithms can be used to accurately classify fruits based on their visual characteristics. The approach can potentially be used in various applications such as fruit sorting and grading in the food industry. Future research can explore the use of deep learning models and larger datasets to improve the accuracy of fruit classification.

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