FRUIT RIPENESS DETECTION USING CONVOLUTIONAL NEURAL NETWORK

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Abstract: Fruit ripeness detection is crucial in the agriculture field to determine the time of harvest and fruit quality. Delays or errors in timing can lead to significant loss in crops, consequently affecting income rates. Manual detection of ripeness in fruits can be inefficient for large scale implementation and pose issues such as requiring lots of time and intensive labor. Hence, in this project, fruit ripeness is detected using machine learning and computer vision technologies. This system will use the CNN algorithm to identify the fruits and classify its ripeness on the basis of the dataset it is trained on. Our system will detect ripeness of 6 different types of fruits. Data augmentation techniques are used to increase the size of the dataset prior to building a trained model. This technology can be integrated with robotics to implement smart agriculture and help farmers view their crops in real time, know the number of mature fruits, plan harvesting and assist in fruit picking and sorting.

Keywords- Fruit Ripeness, Convolutional Neural Network, Machine Learning

I. INTRODUCTION

Crop yields, quality and labor practices have improved in the agricultural sector since the past years, but with the increase in human population and climate changes food demand has also increased. Technology, specifically Artificial Intelligence with Machine Learning and Computer Vision are transforming the agricultural industry. Its adoption in this field has escalated as it saves time, efforts, cost, and human resources. Crop and soil monitoring, insect and plant disease detection, livestock management, intelligent spraying and automatic weeding are some of the many applications utilizing technological advancements to improve agriculture. One more such application is maturity or ripeness detection.

Automatic identification or categorization of a fruit is a developing area that utilizes computer vision and machine learning techniques to gather convenient information about the growth and ripeness of fruits. [4]. This can be applied to the tasks of monitoring, sorting and choosing fruits for quicker production [4]. Nowadays, several research studies are furnishing various techniques for the detection and classification of fruits and vegetables. The maturity level of crops is usually estimated by external features such as color, texture, shape and size. Some of the techniques used for automatic ripeness detection are image processing, machine learning or by using sensors that detect the ripe fruits based on the emitted gas [7].

Despite several challenges such as wide variety, irregularity and inconsistencies in shape, size, color and texture of fruits, automated fruit detection systems help reduce the complexity of these tasks to an extent. Fruit Ripeness detection embedded systems can be useful in deploying drones and robots to assist in real time field implementation for harvesting as well as to segregate fruits and prevent their decay by giving priority to ripe ones first at the seller's end.

II. LITERATURE SURVEY

The implementation of fruit detection and checking fruit quality system[1] is made by Mr. Akshay Dhandrave et al. using computer vision. In this project, a fruit classification and detection system is developed, incorporating fruit grading using a conveyor assembly. The conveyor assembly, equipped with hardware, separates good and bad fruits on separate sides of the conveyor belt. The classification of fruits involves converting input images to the desired size, converting them to grayscale, and applying an SVM algorithm. For fruit quality detection, a neural network is utilized that has been built using the TensorFlow library for training and testing. Real-time fruit image detection is achieved using the OpenCV library in Python software.

The Ripe-Unripe: Machine Learning based Ripeness Classification System [4] is carried out by Brinzel Rodrigues et al. In their paper, the authors introduced a technology that automates the fruit classification process based on ripeness using Machine Learning and Computer Vision. They employed a Convolutional Neural Network (CNN) algorithm with VGG architecture to classify fruits as ripe or unripe based on color, using a dataset of banana images at different stages of maturity. After collecting and preparing the images by cropping and converting them to RGB channels, the trained model can accurately classify fruits in real-time using Object Detection techniques.

The Banana Ripeness Classification Based on Deep Learning using Convolutional Neural Network [6] developed by Raymond Erz Saragih et al, utilizes computer vision and machine learning technologies for automatic fruit ripeness classification. The Convolutional Neural Network (CNN) is applied to classify the ripeness of bananas, which is categorized into four classes: unripe/green, yellowish-green, mid-ripen, and overripe. Two pre-trained models, MobileNet V2 and NASNetMobile, are used in the study. Image preprocessing techniques, including bilateral filtering, are employed to remove image noise prior to training. Data augmentation techniques are applied to introduce variations in the training data. The experiment is conducted using Google Colab and various libraries such as OpenCV, Tensorflow, and scikit-learn.

Zubaidah Al-Mashhadani et al, give a comprehensive study of recent development and future trends in ripeness detection in their system- Autonomous Ripeness Detection Using Image Processing for an Agricultural Robotic System [7]. Their system utilizes computer vision and image processing techniques to estimate ripeness and count tomato fruits. Additionally, the system allows for optional additional image processing to improve accuracy in uncertain weather conditions. The image processing is primarily performed in the HSV color space, with segmentation achieved through thresholding. Noise reduction and morphological processes are applied to create a masking technique that accurately detects ripe and turned tomatoes, enabling fruit counting in the process.

The Multivariate Analysis and Machine Learning for Ripeness Classification of Cape Gooseberry Fruits [5] performed by Miguel De-la-Torre et al, is an extension of a food packaging process proposed for Cape gooseberry fruit sorting, according to its ripeness level. They utilized five multivariate analysis techniques to identify feature spaces that make the classification process easier. While PCA, LDA, and ICA were used to map to a new feature space, the two selection methods (MCFS and ECFS) were employed to obtain the most relevant features for classification. Prior to feature extraction/selection and classification, the fruit underwent segmentation and manual sorting. The study compared four classifiers commonly used in ripeness classification literature: ANN, SVM, DT, and KNN.

Anupriya Mande et al, Detection of Fruit Ripeness Using Image Processing system [3] determines the level of maturity of fruit ripeness by analyzing its color in the L**a**b* color space, which gave superior outcomes compared to using edge detection. The approach of comparing two color segmented images through correlation was more effective because it considers the color information. Additionally, histogram comparison was utilized to improve image contrast and ensure that intensities were appropriately distributed on the histogram. By examining both types of comparisons, a determination was made as to whether the fruit was ripe or unripe.

Table 1 Summary of related work on fruit detection system

Literature Paper	Algorithm/ Technique
Mr. Akshay Dhandrave et al. 2021 [1]	For classification: Image resizing, converting into grayscale, SVM algorithm. For detection: Neural network using TensorFlow. OpenCV for real-time detection.
Brinzel Rodrigues et al.	CNN model using VGG architecture

2021 [4]	
Raymond Erz Saragih et al. 2021 [6]	Two pre-trained models are used: MobileNet V2 and NASNetMobile. Libraries: OpenCV, Tensorflow, and scikit-learn.
Zubaidah Al-Mashhadani et al. 2020 [7]	OpenCV and HSV colour space (Computer Vision and Image processing)
Miguel De-la-Torre et al. 2019 [5]	Techniques for information fusion and sorting : Principal component analysis, linear discriminant analysis, independent component analysis, eigenvector centrality feature selection, and multi-cluster feature Selection
Anuprita Mande et al. 2018 [3]	Conversion into LAB color space, Region of Interest (ROI) based color segmentation, Masking. For detecting maturity level: Correlation and histogram comparison techniques.

Collectively, the summary of various techniques used as per the recent literature for fruit ripeness detection is as shown in Table 1. Based on literature review, it is clear that the accuracy of these techniques ranges from 73% to 99.33%.

Table 2 Literature survey with accuracy

Literature Paper	Accuracy
Mr. Akshay Dhandrave et al. 2021 [1]	90%
Brinzel Rodrigues et al. 2021 [4]	83%
Raymond Erz Saragih et al. 2021 [6]	96.18
Zubaidah Al-Mashhadani et al. 2020 [7]	99.33%
Miguel De-la-Torre et al. 2019 [5]	Ranges from 73-95
Anuprita Mande et al. 2018 [3]	-

III. SYSTEM METHODOLOGY

A. Methodology

The proposed system aims to develop a machine learning model using CNN technique to differentiate between different fruits as ripe or unripe. Utilizing the Object Detection methodology, the fruits can be classified in real-time with the aid of the trained model.

Having a suitable dataset is a crucial element for every machine learning implementation. If the dataset is inadequate, it's impossible to train a machine to provide precise outcomes [4]. For our project the dataset consists of images of different fruits obtained from open sources on the internet. Data augmentation and image preprocessing steps are applied to obtain a larger and uniform set of data. We deploy the CNN algorithm on the training set in order to train the model. Convolution Neural Network (CNN) is an algorithm used for deep learning that impersonates the human neurons. These networks automatically obtain different characteristics from the data and use all of them to calculate the likelihood of each class when making predictions. The output is the class with the highest likelihood [4]. Hence an input image is fed into the system and the model would recognize the fruit and its ripeness.

B. System Architecture

The proposed system architecture is given in Fig. 1. The architecture is described in this section. The architecture proposed has a pipeline consisting of obtaining the dataset, data augmentation, training a convolutional neural network model, giving input image, performing machine learning and result classification of fruit into ripe and unripe.

The first step in a machine learning project is to obtain a dataset. In this case, the dataset would consist of images of fruits, both ripe and unripe. The data is obtained from the Internet and open sources like Github and Kaggle. Once the dataset is collected, data augmentation is performed which involves creating new data from the existing dataset by applying transformations such as rotations, flips etc to prevent overfitting and improve the robustness of the model.

For a real time processing system, once the image is captured or fed into the system, it can go through some preprocessing steps such as image resizing, separating fruits from their backgrounds.

Machine learning is a subset of artificial intelligence that involves training models to make predictions or decisions based on patterns in data. In this case, CNN model is used to classify fruit based on its ripeness.

C. Convolutional Neural Network

Convolutional Neural Networks (CNNs) are a type of neural network commonly used for image classification tasks. Hence we choose it as the technique to classify the fruits as ripe or unripe and build the machine learning model.

Pre-trained models can be used to implement CNN and create a trained system that classifies the identified fruits into ripe or unripe. CNN is advantageous over ANN for image classification as it can execute both feature selection and extraction.

The next step is to train a CNN model using the obtained dataset and any augmented data that has been created. During training, the model learns to recognize patterns in the data and is henceforth able to classify fruits (ripe or unripe) for each input image.

Once the model is trained, it can be used to classify new images of fruit. The input image is passed into the trained model, which produces a prediction of whether the fruit is ripe or unripe based on the output of the trained model. This is automatically done by a computer program using the model's predictions.

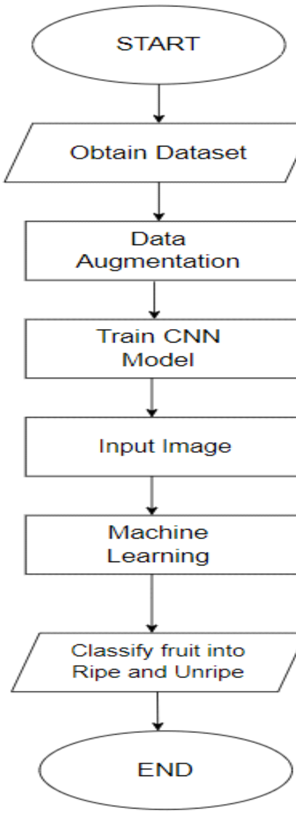

Fig. 1 Flowchart of the proposed system architecture

IV. SYSTEM IMPLEMENTATION

The implementation details of the proposed system are given in this section.

A. Software and Hardware

A central server with python and other dependencies installed are the only requirements. The system is proposed to run on any operating system and all the dependencies are open source projects. To deal with lots of data and the continuous nature of the environment, a system with 8GB RAM is required. An Intel i5 processor is used.

B. Dataset

The datasets are taken from 'Fruits 360', which is available in Kaggle and has images containing fruits and vegetables. Also, 'Lemons Quality control Dataset' and 'Frinn' Dataset were used to obtain images of ripe and unripe fruits.

Dataset properties of 'Fruit 360' :
The number of classes: 131 (fruits and vegetables).
Image size: 100x100 pixels.

Dataset Properties of 'Lemons Quality Control Dataset' :
The total number of images : 2690
Image Size : 1056 x 1056 pixels

Dataset Properties of 'Frinn' Dataset :
The type of fruits are apples, oranges, bananas, raspberries, strawberries and the state of fruits are ripe, unripe and rotten.

The dataset we created using these sources consists of images of 6 fruits, namely apple, lemon, litchi, orange, strawberry and tomato and each fruit is classified into two folders-ripe and unripe. The total number of images combined of these six fruits is 25,335.

Data Augmentation techniques like cropping, padding, horizontal flipping, zooming, rescaling, and more are used through Keras to increase the size of the dataset to allow the model to learn the patterns in the data.

We implemented a convolutional neural network (CNN) with four convolutional layers and three fully connected layers. The input shape of our data is (100, 100, 3) for width, height, and color channels. The output of the last convolutional layer is then flattened and passed through two fully connected layers with 64 and 16 neurons, respectively. Both of these layers use the ReLU activation function and have a dropout layer with a rate of 0.05, similar to the convolutional layers. Finally, we have a fully connected output layer with neurons equal to the number of classes in our dataset and the softmax activation function for multiclass classification. The model description is represented in Fig.2

The neural networks present in the model take the preprocessed data, that is the image of the fruit as its input, extract the various features from the data, and predict the highest probability of the type of fruit.

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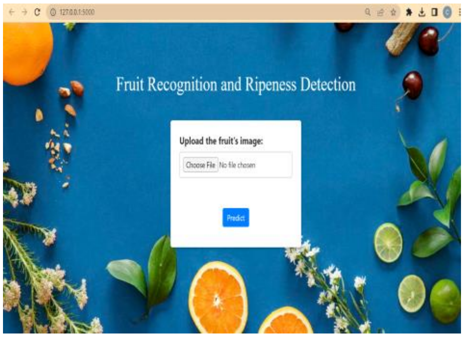
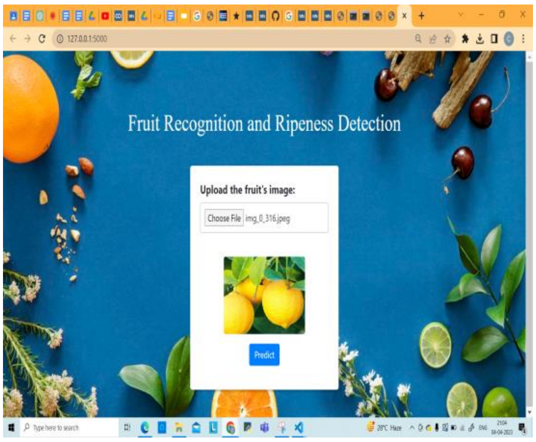
```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 96, 96, 16)        1216

 max_pooling2d (MaxPooling2D  (None, 48, 48, 16)       0
 )

 dropout (Dropout)           (None, 48, 48, 16)        0

 conv2d_1 (Conv2D)           (None, 44, 44, 32)        12832

 max_pooling2d_1 (MaxPooling  (None, 22, 22, 32)       0
 2D)

 dropout_1 (Dropout)         (None, 22, 22, 32)        0

 conv2d_2 (Conv2D)           (None, 18, 18, 64)        51264

 max_pooling2d_2 (MaxPooling  (None, 9, 9, 64)         0
 2D)

 dropout_2 (Dropout)         (None, 9, 9, 64)          0

 conv2d_3 (Conv2D)           (None, 5, 5, 128)         204928

 max_pooling2d_3 (MaxPooling  (None, 2, 2, 128)        0
 2D)

 dropout_3 (Dropout)         (None, 2, 2, 128)         0

 flatten (Flatten)           (None, 512)               0

 dense (Dense)               (None, 64)                32832

 dropout_4 (Dropout)         (None, 64)                0

 dense_1 (Dense)             (None, 16)                1040

 dropout_5 (Dropout)         (None, 16)                0

 dense_2 (Dense)             (None, 12)                204

=================================================================
Total params: 304,316
Trainable params: 304,316
Non-trainable params: 0
_________________________________________________________________
```

Fig. 2 Model Description

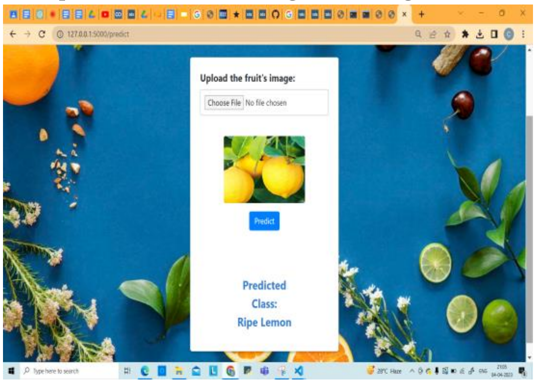
V. RESULTS AND ANALYSIS

We created a flask web app using HTML and CSS and two buttons, one for choosing the fruit image and another one for prediction of its ripeness. Fig 3 shows the frontend of our proposed system where the image of the fruit is selected from the system and uploaded, as given in Fig 4.





As soon as the image is uploaded and the predict button is clicked, it gives output by detecting the fruit and gives information on the ripeness of the fruit as given in Fig 5.



VI. CONCLUSION

There are several existing fruit ripeness detection mechanisms that classify a fruit as ripe or not on the basis of their color feature by applying image processing and image segmentation techniques or using various machine learning mechanisms to extract features from images and learn to predict from them. This project uses deep learning mechanisms, convolutional neural networks to classify the fruit and give results similar but efficient than human abilities. As an additional prior step, the type of fruit is identified as well. The system can be further modified to classify the fruits in real-time using Object Detection techniques. This system can be implemented in the agriculture sector for easier segmentation of fruits, estimating harvest times with greater accuracy and can be a helping hand to farmers or other individuals working in this area. We have achieved an accuracy of 81% in our system for detecting the ripeness.

VII. REFERENCES

[1] Mr. Akshay Dhandrave, Dr. V.T. Gaikwad "Implementation of Fruit Detection System and Checking Fruit Quality using Computer Vision," IRJET, vol. 8, no. 6, pp. 4116-4120, June 2021.

[2] Aaron Don M. Africa, Anna Rovia V. Tabalan, Mharela Angela A. Tan, "Ripe Fruit Detection and Classification using Machine Learning," International Journal of Emerging Trends in Engineering Research, vol. 8, no. 5, pp. 1845-1849, May 2020.

[3] Anuprita Mande, Gayatri Gurav, Kanchan Ajgaonkar, Pooja Ombase, Vaishali Bagul "Detection of Fruit Ripeness Using Image Processing" in Advances in Computing and Data Sciences,Ed(s). Mayank Singh, P. K. Gupta, Prof. Dr. Vipin Tyagi, Jan Flusser, Dr. Tuncer Ören, Springer, Singapore, 2018, pp. 545–555, doi: https://doi.org/10.1007/978-981-13-1813-9_54

[4] Brinzel Rodrigues, Revant Kansara, Shruti Singh, Dhruwa Save, Shreya Parihar "Ripe-Unripe: Machine Learning based Ripeness Classification" presented at the the 5th International Conference on Intelligent Computing and Control Systems (ICICCS 2021), Madurai, India, 2021, doi: 10.1109/ICICCS51141.2021.9432349

[5] Miguel De-la-Torre, Omar Zatarain,Himer Avila-George, Mirna Muñoz, Jimy Oblitas, Russel Lozada, Jezreel Mejía and Wilson Castro "Multivariate Analysis and Machine Learning for Ripeness Classification of Cape Gooseberry Fruits," presented at the 8th International Conference on Software Process Improvement, León, Guanajuato, México, 23–25 October 2019.

[6] Raymond Erz Saragih, Andi W. R. Emanuel "Banana Ripeness Classification Based on Deep Learning using Convolutional Neural Network," presented at the 3rd East Indonesia Conference on Computer and Information Technology (EIConCIT), IEEE, Surabaya, Indonesia, 2021, doi:10.1109/EIConCIT50028.2021.9431928

[7] Zubaidah Al-Mashhadani; Balasubramaniyan Chandrasekaran, "Autonomous Ripeness Detection Using Image Processing for an Agricultural Robotic System," IEEE, pp. 0743 - 0748, 2020, doi:10.1109/UEMCON51285.2020.9298168

[8] Frin Dataset for Fruits : https://github.com/ece324-2020/FRINN

[9] Fruit 360 Dataset : https://www.kaggle.com/datasets/moltean/fruits Version - 2020.05.18.0

[10] Lemons Quality Control Dataset: https://www.kaggle.com/datasets/maciejadamiak/lemons-quality-control-dataset,DoI-10.5281/zenodo.3965568