Jilin Daxue Xuebao (Gongxueban)/Journal of Jilin University (Engineering and Technology Edition)
ISSN：1671-5497
E-Publication Online Open Access
Vol: 41 Issue: 12-2022
DOI 10.17605/OSF.IO/2MABH

AUTOMATIC FRUIT CLASSIFICATION AND IMAGE RESIZING USING CONVOLUTIONAL NEURAL NETWORK WITH BICUBIC INTERPOLATION ALGORITHMS

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ABSTRACT

A system that classifies different types of fruits and identifies the quality of fruits will be of value in various areas, especially in the mass production of fruit products. Automatic classification of fresh and rotten fruits plays a substantial role in agriculture as well as the food industry. Traditional methods for fruit spoilage detection are manual, inaccurate, time-consuming, laborious, and subjective. So, this paper presents a new approach for automatic classification of fruit quality using deep learning, which is mainly focused on image resizing and classification of fruits ripeness. This paper uses bicubic interpolation approaches for image resizing to compute the loss. Then, the automatic fruit classification (different sizes concerned) is achieved by Convolutional Neural Network (CNN) with the VGG16 model. It even updates the parameters by concentrating channels with respect to Red, Green, and Blue (RGB) to identify as well as classify the images of ripened and rotten. The suggested approach is implemented on the python platform. The evaluation of CNN with VGG16 using SGD algorithm for accurate classification is determined by parameters like accuracy curve and loss curve of training dataset as well as validation dataset with different numerical output.

Keywords: Automatic classification, deep learning, image resizing, fruit spoilage detection, fruit quality.

1. INTRODUCTION

In the agricultural and food industries, artificial intelligence plays a vital role in improving product quality with increased efficiency [1][2]. There are several environmental effects in the agricultural fields faced by the farmers, in order to overcome that issues AI offers a greater extent to support farmers [3]. In the food processing unit, the automation methods implementation supports intelligent packing and outstanding production [4]. In exporting and importing processes, there are a lot of obstacles to quality checking, already this transportation process is a big process this quality checking becomes more time-consuming [5]. The fruit production in world fruit production and trading are reduced due to bad weather, changes in climate and increased temperature is the reason behind trade declination when related to prior years [6][7].

In addition to importing and exporting fresh fruits, thoughtful research is carried on to identify rotten fruit and its quality [8]. So, in order to sort and rank the quality of fruit experienced and effective technique is needed. The technical skills help computer vision-based structure to identify fruits that are defective and in the same way the

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healthy fruit production potential is improved [9]. Computer vision helps in monitoring practice, controlling, and harvesting different types of fruits effectively [10]. In this, experts are required for segregating fruits and to analyze the quality. When humans are involved in segregation, the task performed varies from person to person while sensing and seeing [11]. Moreover, based on the demands in the consumer market, food products with improved quality are required [12]. An automated method segregates fruits with increased precision and their response is faster, in the image of this fruit is captured and their features are given in detail which helps this system for quality identification [13].

In deep learning, computer vision systems became well known among researchers that support identifying the quality of fruit whether it is fresh or rotten. These automated methods produce exact results [14]. A segmentation method is used to detect the rotten apple and its rotten part is sliced out. In deep learning, apples RGB image is given as input for the segmentation process. The fruit’s quality is identified by determining the apple’s color [15]. Since each apple is unique, this conventional processing does not provide the best results. For visual recognition, the convolutional system performs well with available datasets and raised computation energy.

In Machine Learning, deep learning is used recently and its main feature is it has increased abstraction level and has the capability to learn patterns of images automatically. Specifically, in deep learning, CNN is utilized for image processing. In order to remove the noise from the image preprocessing is carried out. Those images are resized by using the Bi-cubic interpolation method. Then it is classified to identify whether the fruit is ripened or rotten by using CNN with VGG16. The classified image is evaluated by utilizing the SGD algorithm.

The main contribution of this paper are as follows,

- Initially, real-time fruit image datasets are generated.
- Next, noise in the images is removed in preprocessing stage and then those images are resized by using Bi-cubic interpolation approach.
- Then in classification, CNN with VGG16 is used to determine whether ripen or rotten fruit.
- Finally, to evaluate the classified image, the SGD algorithm is utilized.

The rest of this research is categorized as follows: Section 2 describes the works of literature on automatic fruit classification. Section 3 explains the proposed approaches concept. The proposed system's performance is evaluated in section 4. Finally, section 5 finishes with a discussion of the outcome and future objectives.

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2. LITERATURE REVIEW

"In this part, some of the most recent research papers on automatic fruit classification were reviewed."

Yogesh., et. al., [16] have presented a paper in which the defective regions in pixels are divided and their features retrieved. In addition, a classifier that is a support vector machine is utilized to recognize the cause and defects. In the classification process, divide the fruits into two sections that are no defects and are defected. The observed defection in the sample image is divided into three parts fruit defections first stage, second stage, and last stage. In case of pre-trained networks unavailability, from scratch, the defected fruits database is created.

Takkar., et. al., [17] have made research on modern deep learning methods to increase object detection performance, accuracy, and system identification. Sometimes certain illness spread over the agricultural field and causes great loss, so, in order to take precautions, the proposed method sends a notification to the farmers. The major goal of this research is to identify the illness before spreading. In this, Super-Resolution Convolutional Neural Network (SRCNN) and Bi-cubic methods and applied to detect the healthy and unhealthy leaves in the system.

Mia., et. al., [18] have presented a computer vision's in-depth exploration that identifies rare local fruits. A variety of unique local fruits are identified based on the image extracted from the features. The captured image is preprocessed and then predicted features are extracted via image segmentation. Fruit classification is performed with the use of support vector machines.

Barbedo., et. al., [19] have investigated the trade-off between the quality of the image and the representation of the dataset. In this, the trained CNN captures images and it identifies the psyllids in images captured on a smartphone under more realistic conditions. Images that were scanned were useful whenever the training set of realistic images was insufficient to encompass all of the variability observed in the investigations, yet otherwise generally harmless.

Rong., et. al., [20] have presented a study in which two distinct convolutional neural network is applied for automatically segmenting walnut images and it also detects various sized unknown objects and human-made unknown objects. The suggested deep-learning method prevents manual feature extraction and in the original image, the conglomeration fact among foreign objects and walnuts is rectified. However, this method utilizes a platform with high-performance computation, increased camera quality, hardware for wide-band imaging, and large image datasets on the basics of the suggested method in real-life applications.

Wosner., et. al., [21] have made a study on how the modern deep network is applied properly in the agricultural background for task detection, and performance measurement, and their accuracy is compared to man-made performance. In this, seven different datasets are gathered for the measurement and testing of the three

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latest networks. Experiments have shown that small object handling and large-scale variance are critical failure spots. As a result, a multiple-resolution network utilization strategy was devised, which greatly improved detection accuracy on most datasets.

Xu., et. al., [22] have developed an automatic lettuce freshness method on the basics of improved deep residuals convolutional neural network. In order to obtain a lettuce leaves freshness classification dataset an image classification dataset is constructed. Then a novel method of the improved residual network is derived from the present ResNet-50 and this method consists of an additional convolutional layer, a fully connected layer, a pooling layer, and a random ReLU activation function. This proposed method is compared with AlexNet, ResNet50, VGG16, and GoogleNet, and the observed results illustrate that the proposed method has more significant benefits than the existing method.

Milella., et. al., [23] have developed an automated grapevine phenotyping method for estimating canopy volume, detection of the bunch, and counting. Both metrics are proved to be effective in the field and use a consumer-grade depth camera placed onboard an agricultural machine. Based on infrared stereo reconstruction, a rich 3D map of the grapevine row is constructed first, augmented with its color appearance. Then, for plant per plant volume estimation, various computational geometry approaches are employed and assessed.

Khan., et. al., [24] have made research on the classification and detection of different diseases of fruit on the basics of correlation coefficient and deep features. In this, the suggested method includes two primary steps: detecting infected regions and then extracting and classifying features. Initially, input image contrast is improved by using a hybrid approach proceeded by a proposed correlation coefficient-based segmentation approach that distinguishes diseased regions from the background. In the second stage, two deep pre-trained models are used to extract features from specified diseases. Prior to the max-pooling stage, a parallel features fusion step is included to consolidate the extracted features. The most distinctive features are chosen using a genetic algorithm before being subjected to the final step of classification using a multi-class SVM.

Duong., et. al., [25] have developed a practical approach for fruit recognition based on two recently created classifiers that have proven to be simultaneously effective and efficient. In a deep neural network, two families that are EfficientNet and MixNet are used for constructing an expert system that detects fruits swiftly and accurately. These methods are installed on devices with limited processing capabilities to provide precise and fast suggestions. The performance of the proposed method was tested using a real-world fruit dataset.

3. PROPOSED METHODOLOGY

The main aim of this study is identification and classification in which different stages of fruits like ripening and rotten stages. In this research, climacterics and non-climacteric

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fruits are taken into account. Banana and papaya are two climacteric fruits utilized. Consider orange as a non-climacteric fruit. The main focus of this research is collecting images of ripened and rotten fruits for real-time datasets. The proposed methodologies workflow diagram is shown below the figure 1.

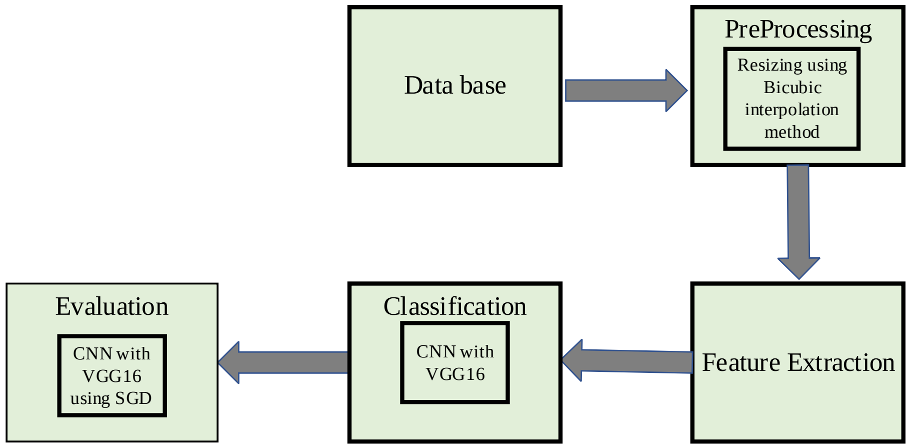

Figure 1: Workflow diagram for the proposed methodology

3.1 Dataset Collection

The main goal of this research is to capture the fruit ripened and rotten stage image to generate a real-time dataset. First, images are gathered by the researchers from web-based resources. Overall collected images are 8562 and it has two sections training and testing data. But this data collected did not achieve the specific accuracy rate, so, their requirements are not met. In preprocessing, resizing is used to resize the images to 100*100 pixel and then enlarged. While preprocessing, lot of important information's are lost, so, it is impossible to learn much in this model. As a result, this dataset was rejected, and the author acquired new fruit photos. The fruits were purchased from different vendors in the Thiruvallur area of India this time. Climacteric fruit banana, papaya and non-climacteric fruit orange are considered in this research. RGB images of ripe and rotting fruits were used in this study as data. Overall collected images are 6702 and in these 324 images are removed by preprocessing. Balance 6378 is examined for testing and training. The segregation of collected data is shown below in table1.

Table 1: Collection of ripe and rotten fruit

Name of the fruit	Collection source	Overall collection	Elimination during Preprocessing	Balance
Ripe orange	RK Fruit Shop, Spar Super Market	1115	48	1067
Rotten orange	RK Fruit Shop, Spar Super Market	1120	52	1068
Ripe papaya	Reliance Fresh, Ponnu Super Market	1115	59	1056
Rotten papaya	Reliance Fresh, Ponnu Super Market	1120	50	1070
Ripe banana	RK Fruit Shop	1115	60	1055
Rotten banana	RK Fruit Shop	1117	55	1062
		6702	324	6378

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3.1.1 Image Acquisition:

Images were obtained from retailers in the Thiruvalluvar region of Maduravoyal. RGB images are taken with a 15.2-megapixel digital still camera and a Complementary Metal Oxide Semiconductor (CMOS) image sensor. It is taken in a standard room-like setting. The author added diversity to the dataset by photographing the fruits in various locations and rotations. Images are captured at various times of the day. The fruits were categorised by the sorting and grading expert based on their physical outward appearance, such as colour, size, shape, firmness, and scent.

3.1.2 Cleaning:

In the cleaning process, images are sorted out class by class. Every image is viewed to detect the defects. At first, there were several obstacles because the images analyzed are all in landscape format. Initially, the images are trained and then the white region of the image is cropped to make it square.

As for as cleaning is concerned, it was done by sorting out the class of the image by class. It was then viewed to find any defects in each image. Initially, some setbacks were faced as the images that were considered were in landscape. First, it was trained as it is. Later, white regions were cropped to make it square.

The author did not employ any special preparation methods for the base dataset. This article considers 6 classes 3 fruits in ripe & 3 fruits in rotting stages. The image is 4000 × 4000 pixels in size. The 6378 total images from the RGB fruit photographs are scaled down to 2000 x 2000 square pixels. Following the completion of the data preparation, the normalization step is carried out, which entails multiplying each pixel by 255 to ensure that the entire pixel is depicted in terms of 0 and 1. The model learns more effectively thanks to this representation. In general, all neural networks that aid in learning invariant features first undergo normalization. This is the standard preprocessing method applied to all neural networks.

3.2 Pre-Processing:

The images obtained during the image acquisition phase may be inappropriate for the goal of identification and classification. We use pre-processing procedures to eliminate the noise from the acquired RGB image (true-color image), which contains noise and causes some blurring.

3.2.1. Resizing using the Bicubic interpolation method:

The original input image is scaled to 256 × 256 x 3. To simplify the original image size, an image size of 256 × 256 x 3 pixels was chosen. This input data format was created by utilizing bicubic interpolation to resize the images. Bicubic offers the ideal balance of processing speed and output quality. To estimate the pixels in the (p', q') positions, the bicubic interpolation employs a distance of 16 adjacent pixels (4x4) as sampling (S).

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The Bicubic interpolation method takes into account the 16 pixels that make up the known 4x4 surrounding pixels. Closer pixels are the best compromise between processing time and output quality since they are given a larger weight in computations. Because of this, this technique is widely used in image editing software, such as Adobe Photoshop, printer drivers, and in-camera interpolation.

$$f_{p,q} = [M_{-1}(S_b)M_0(S_b)M_1(S_b)M_2(S_b)]$$

$$\begin{bmatrix} f_{p-1,q-1} & f_{p'q-1} & f_{p+1,q-1} & f_{p+2,q-1} \\ f_{p-1,q} & f_{p,q} & f_{p+1,q} & f_{p+2,q} \\ f_{p-1,j+1} & f_{p,q+1} & f_{p+1,q+1} & f_{p+2,q+1} \\ f_{i-1,j+2} & f_{p,q+1} & f_{p+1,q+2} & f_{p+2,q+2} \end{bmatrix} \begin{bmatrix} M_{-1} & (R_a) \\ M_0 & (R_a) \\ M_1 & (R_a) \\ M_2 & (R_a) \end{bmatrix} \quad [1]$$

Where:

$$S_b = q' - q, \qquad S_a = p' - p \quad [2]$$

$f_{p,q}$ =Pixel value at position (i, j)

$$M_{-1}(s) = \frac{R^3 + 2R^2 - R}{2} \quad [3]$$

$$M_0(s) = \frac{3R^3 + 5R^2 - 2}{2} \quad [4]$$

$$M_1(s) = \frac{-3R^3 + 4R^2 + R}{2} \quad [5]$$

$$M_2(s) = \frac{R^3 - R^2}{2} \quad [6]$$

3.3 Classification

Defect identification is carried out based on surface flaws like scars, spots, etc. after feature extraction. By drawing a boundary around the defective part's contours on a filtered fruit image and filling those contours with white pixels, the defected fruit is found and its area is used as the foundation for judgment. The condition will then be implemented after that. Fruit is considered defective if the ratio exceeds the predetermined threshold value; else, fruit is considered fresh.

3.3.1 VGG16 architecture as training process

The very deep convolution network, or VGG16, is straightforward and mostly used to recognize large-scale pictures. Convolution layers (f(x) and pooling layers are arranged in a certain order in a basic convolutional neural network.

$$F(x) + y = z \quad (7)$$

where f(x) is the input Image of fruits

Y is the filter or kernel or features (piece)

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The convolution layers retain the critical features in the image as it passes through them, and the pooling layers intensify and maintain these features across the network while rejecting all the data that is irrelevant to the task. The RGB image with a fixed size of 224 x 224 is created from the RGB image input source. The estimated mean RGB value from the training dataset is subtracted from each pixel to do the VGG16 preprocessing. In this study, characteristics like color, shape, and firmness—or, more specifically, the fruit's exterior—are taken into account when creating a real-time data set. The model has 16 convolutional and pooling layers. The imp feature is extracted by convolution, and it is intensified by a pooling layer. When back propagation occurs, weights are educated. A random number with a normal distribution will be used initially.

$$\text{(Learning Rate x Loss) + Previous weight} \quad .(8)$$

Loss and weights (filters) are the parameters that can be learned.

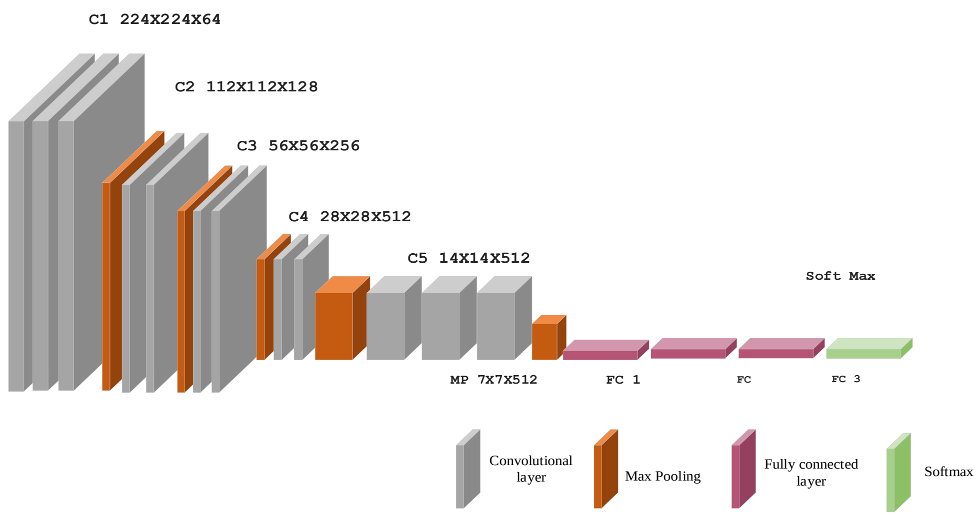

Figure 2: Architecture of VGG16

SGD & Learning Rate (0.01) are the hyperparameters taken into account (Stochastic Gradient descent). The resizer is relevant to the input image, and for our model, we change it to 224*224. Features are not taken into account because doing so will skew the model's training. Since it uses a CNN architecture, the model automatically chooses features, and it learns to modify this behavior during training. Fruits are the input image, and the 3X3 filters are applied after the input image has passed through a stack of convolution layers and a max pooling layer. Max-pooling layers come in five different numbers with a 2x2 pool size and 2x2 stride. As seen in figure 2, the output is finally routed via three dense layers that are entirely coupled.

3.3.2 SGD optimizer for training process

ConvNet's training process often uses mini-batch gradient descent, also known as SGD, to optimize multinomial logistic regression. Batch size is set to 256, or 0 to 255, and momentum is set to a maximum of 0.9. The sum of squared weight (L2) penalty

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multiplier has been established at 5x10-4 based on the weight regularisation. To enhance the performance of an overfit deep learning network in Python using Keras, each vector has a hyperparameter that must be defined. The dropout ratio used for the first and second FC layers' regularization of dropout is 0.5. While the accuracy of the validation set stops improving, the learning rate is typically set at 0.01 and then progressively decreased by a factor of 10. As a result, the learning rate has decreased by a factor of three, and it now stops after 75 iterations. As a result, it is estimated rather than having the larger parameter value and greater depth of CNN evaluated.

Due to pre-initialization by certain layers and implicit regularization carried out by reduced convolution filter sizes, the network also needed specific epochs to converge. The network weights are important as a result. SGD optimizer is added to the training configuration with random initialization to avoid these problems. The first five convolutional layers with three FC layers are advanced using the VGG16 with CNN architecture. While a result, the pre-initialized layer's learning rate is not lowered, but it might allow for modification as learning progresses. The normal distribution weight progressed in the sample set of the random initialization of layer with mean equal to 0, variance equal to 0, and bias originally progressed to 0.

4. RESULT AND DISCUSSION

This experimental study made use of a high-performance server with an Intel core i7 DMI2 CPU, 12GB RAM, 100GB free space, and a Quadro K600 GPU. For training the image dataset, Ubuntu 18.04.3 LST was used as the operating system. This study includes 6378 photos with a resolution of 2000 × 2000 pixels. The dataset was divided between 75% training data and 25% testing data. Based on this study, training image datasets are required, with 65% of training image data and 10% of validating image data for both ripe and rotten orange, papaya, and banana fruits, as displayed in Table 2.

In this CNN, a bicubic interpolation algorithm is used as a resizer. In the training stage it achieves 100% accuracy and in the testing stage 96.56 for 50 epochs is achieved. It has also been discovered that using a small dataset on VGG16 with the given specifications results in a high accuracy rate in classification.

Table 2: Real-time fruit dataset training and testing images

Dataset for real-time fruits	Fruit state	Number of images	Training images		Testing images
			Training	Validating	
Orange images	Ripped	1067	693	107	267
	Rotten	1068	694	107	267
Papaya images	Ripped	1056	686	106	264
	Rotten	1070	695	107	268
Banana images	Ripped	1055	686	105	264
	Rotten	1062	691	106	265
Total		6378	4145	638	1595

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This study primarily involved VGG16 instead of recognizing hyperparameters with a large number, and the VGG16 aim to have convolution layers of 3 x 3 filter with three stalks with max-pooling all and frequently utilize the same padding for 2 x 2 convolution layer for two stalks, filter with max-pooling. Throughout the architecture, this arrangement is sequenced with a convolution layer followed by one max pool layer for each stalk. Lastly, for output, it has three dense layers followed by a SoftMax.

The suggested CNN with VGG16 model is used to describe the categorization of ripped and rotten, and the training and validation accuracy, along with model loss, are shown in figures 3 and 4, respectively.

Figure 3 depicts the model accuracy, whereas the training accuracy is consistent after 38 epochs and keeps a constant accuracy of 98.5%. In this validation case, after 38 epochs, the stable rate of accuracy is 96.56. The learning rate improves with more iterations as the epochs increase, and there is a consistent rate of accuracy maintained until 38 epochs. This illustrates the learning rate changing from 0.01 to 0.1 over the course of 40 epochs.

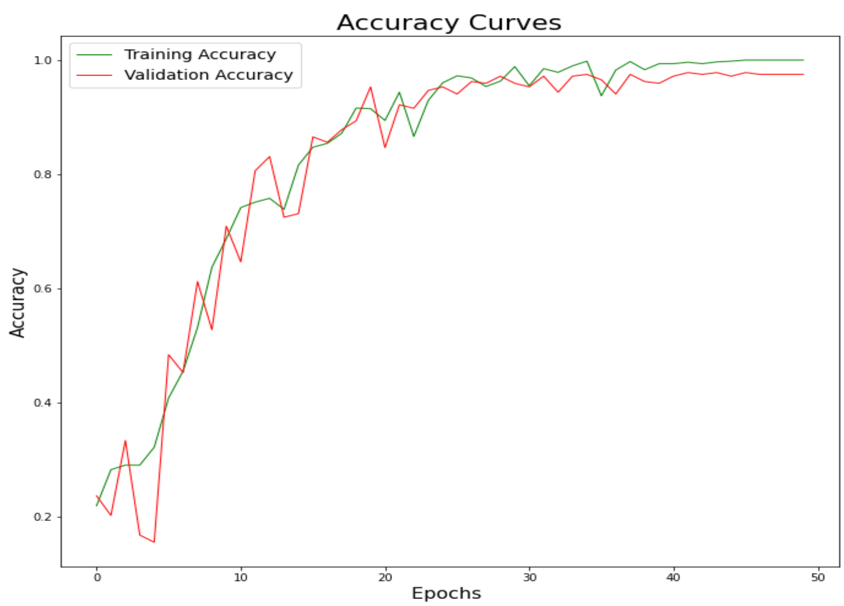

Figure 3: Model for Accuracy Curve

Figure 4 depicts the model loss in both training and validation, with the loss being greater in training because the model is not initially trained better. When the period is expanded, the losses decrease from 1.75 to 0.19, indicating that transfer learning is taking place to minimize the loss. In the validation case of the loss curve, the initial epoch loss is very less when compared to training loss but it raises after 20 epochs. There is a greater difference after 40 epochs, where the loss increases somewhat

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until 50 epochs. Thus, the model is adequately trained using ripe and rotten fruits and it classifies the model with higher accuracy of 96.56%. (Table 3)

Table 3: Model Specification

Extracting features automatically	Total params: 134,285,126 Trainable params: 134,285,126 Non-trainable params: 0
Input image size	(224, 224, 3)
Resizer	Bi-cubic interpolation
Kernel size	3 X 3
Optimizer	Stochastic gradient descent
Current Learning rate	0.01 (Standard Learning rate: 0.001)
accuracy of the Training stage	100%
accuracy of the Validation stage	96.56 % 50 epochs

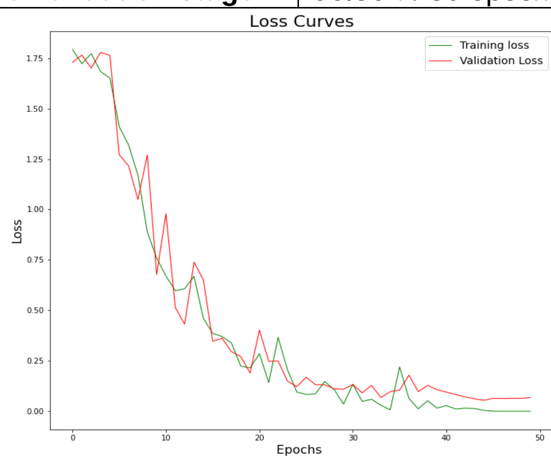

Figure 4: Model for Loss curve

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Figure 5: Real-time fruit images for both ripe and rotten fruit

In figure 5 the real-time fruit images are shown in which the ripe and rotten status of orange, banana, and papaya fruit images are displayed. These images are trained and tested in classification. This was implemented on the python platform and they achieve high accuracy and very less loss rate.

5. CONCLUSION

In deep learning, automatic fruit quality detection is based on resizing images and classifying ripened fruits. The real-time dataset has been developed and distributed to the scientific community. The innovative model developed is utilized to classify six types of fruits as ripe or rotting. To achieve a high learning rate, the classifier training parameters are evolved using the VGG16 convolutional architecture. The method produces a 96.56 accuracy rate o for 50 epochs using a Stochastic gradient descent optimizer, the learning rate of 0.01 versus the standard learning rate of 0.001, and a Bi-cubic interpolation technique as resizer. It has also been discovered that a small dataset on VGG16 with the following specifications can reach a high accuracy rate in classification. As a result, the suggested CNN with VGG16 has higher accuracy in distinguishing ripe and rotten fruits.

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Jilin Daxue Xuebao (Gongxueban)/Journal of Jilin University (Engineering and Technology Edition)
ISSN：1671-5497
E-Publication Online Open Access
Vol: 41 Issue: 12-2022
DOI 10.17605/OSF.IO/2MABH

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