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Fruit Quality Determination using Image Processing and Deep Learning

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Abstract- A considerably high amount of fruit produced is wasted due to improper management and utilization during harvesting, storing, transporting, and in the food processing industry. Fruit will get rotten easily if not stored properly due to bacteria accumulation. It is known to all that rotten or defective fruits are harmful to health. It may damage the fresh fruits which are in surface contact with the rotten fruits in the inventory. These rotten fruits should be detected and sorted as early as possible. The problem that comes across in manual checking by humans is less uniformity and accuracy as the manual examination by humans' eyes will consume time and energy. This research proposes a method involving the deep learning technique which is CNN (Convolutional Neural Networks) for feature extraction and classification of rotten fruits. It is one of the applications of image classification problems. This approach uses an RGB channel image of the fruit under examination. The image will be evaluated by the trained model as fresh if the percentage of rotten part detected is under the threshold value. The types of fruits that will be identified and classified in this paper are apple, banana and orange. Transfer learning technique is used, which minimizes training time and resources and aids to achieve higher accuracy. The dataset is divided into two parts, for (70%) training and (30%) validation. The raw image set used for training is first pre-processed and then fed into the model. The validation accuracy obtained in this paper is 98.47%. The total duration of the training stage is 210.37 minutes. Hence, the required time to classify a single fruit image is approximately 0.2 second. Our model can be adopted by industries closely related to the fruit cultivation and retailing or processing chain for automatic fruit identification and classifications in the future.

Keywords- Deep Learning, Convolution Neural Network, Rotten Fruit Detection, Image Processing, Classification, Inception v3.

I. INTRODUCTION

Fruits, being highly rich in nutrition, are one of the most widely consumed foods as a part of the recommended daily diet. A major chunk of fruit produced worldwide is used by the food processing industry. Fruits have a long way to travel from the moment it is grown by farmers till it reaches the end consumers or until it is processed in companies to produce various products. During its lifespan, it highly possesses a risk of getting rotten. Rottenness is the state of decomposition or decay of the quality of the fruit, which not only affects the taste and appearance but also alter its nutritional composition, causing the presence of mycotoxins dangerous for humans. According to a journal of medical science, about 2 million deaths happen every year in India due to consuming contaminated food and water. According to a report published by the World Health Organization (WHO), over half a million deaths occur every year globally due to unsafe food, where children under five are most affected. In India, households have an alarming 13.2 percent prevalence of hazardous food practices.

It will also help in reducing the consumption of stale fruits. Presently, rottenness identification is carried out using human scrutiny or using Ultraviolet light to highlight spots of rottenness represented as fluorescence. These manual methods for the segmentation of fruits are either slow or less accurate, require large human efforts, or may expose fruits to harmful radiation.

Automatic detection of rotten fruits can alleviate the costs of the manual and ad-hoc filtering activity. The state of the art in this topic reports the capturing of fruit images and then, use of deep learning algorithms on neural networks for processing those images. Among the various types of deep learning neural networks, CNNs are the best suited for understanding image pixels because its built-in convolutional layer reduces the high dimensionality of images without losing its information.

Since, the input comes in the form of an image of the fruit, texture: color and size are the key factors for fruit freshness detection. Fruits with defects that are decaying can be easily identified by their color. Fruit quality evaluation, which is based on color, shape, and size, should be carried out in a cost-effective and secure manner. These are sensitive materials, thus testing should be done using non-destructive methods. Additionally, it aids with operations related to planning, packing, shipping, and marketing. Manually making the distinction will be too slow and prone to mistakes. Fruits are categorized by humans according to their color, shape, and size. If the appropriate methods are used to translate these quality characteristics into an automated fruit grading and detection system, and programming language then the work will be faster and hassle free.

II. RELATED WORKS

The application of deep learning has changed several industries, including agriculture, healthcare, and others. There is a tonne of deep learning research being done.

In their investigation, Uang, Xi, and Titan employed a machine vision system to find flaws in the fruit's skin. A machine learning technique named Scalar Machine (SRM), which is used in classification, identification and as a recognizer, is the major feature and support utilized in color texture feature for classification. For smaller datasets, support scalar machines (SSMs) produce ideal and appropriate outputs. The sketched features have a major role in determining how accurate the machine learning classification approach is. Additionally, the characteristics that will be used in the machine learning method are chosen [5].

In their research, A. Deeksha, A. Mlucan, and C. Aurkan examined the effectiveness of several feature extraction strategies on fruit rottenness categorization. Following the feature extraction of fruit photos, the experiment employed a support scalar machine (SRM) classification approach. The photos utilized were divided into three distinct fruit groups, such as orange, banana, and apple, totaling 3000 in all. With an overall accuracy of 86.63%, CNNsF (Convolutional Neural Networks Features) outperformed all other feature extraction approaches. By calculating the success rates of various SSM features while each class is trained with a one-vs-all SSM classifier per feature, the experiment's performance is determined [6].

In a different study, K. Sajid, R. P. Minah, S. Junjun, and A. B. Pratapl examined how well Recursion Tree, Artificial Neural Network (ANN), and Naive Bayes Theorem classifiers performed in identifying the condition of oranges. There are IV classifications for the state: ripe, unripe, scaled, and rotting. In this study, the RGB scale space and gray values of orange photos are recovered using KIC. Following a comparison of several classifier types, Decision Tree has the greatest precision (83.17%). The precession and sensitivity when using the Recursion Tree classifier is 73.55% and 93.24% respectively. A total of 335 orange photos, including 122 unripe oranges, 81 ripe oranges, and 121 ripe oranges, were tested to get the results. Scaled or rotten oranges [7].

The fruits are physically gathered in the study by Ashash, M.K.D., Uma, K.A., Riya, M., Damrazari, P., and Latika, and the researchers themselves categorize those fruits as frail and faulty. Pre-processing the photos in this way prepares them for categorization by the CNN model. This model is 95.75% precise. This approach provides a theoretical foundation and knowledge for the most productive, non-destructive or constructive fruit quality identification possible. It is based on laser backtracking image analysis and CNN theory. This research demonstrates that the technique is reliable, non-destructive, and capable of quickly locating problem regions. The CNN model-based error detection method performs better than traditional techniques [14].

In our study, a very precise model for determining fruit quality has been established and built. The analysis will concentrate on the banana, apple, and orange fruit kinds. To determine if the banana, orange, and apple are fresh or rotting is the goal of the experiment. The method to be employed in this suggested study is CNNs of Inception v3. All of the photographs in the collection were found from the open-source website Kaggle [10]. The training option parameter of small batch size and the number of epochs in deep learning are examined to determine and confirm their link to the validation precision for experiments using the dataset to perform fresh fruit classification. Before updating the model measures, the batch size hyper parameter takes into account the number of samples from the training dataset that were employees to estimate the error gradient. The learning algorithm is known as mini-batch gradient descent when the batch size is set to greater than one and less than the instances in the training set. A sizable collection of fruit photos is amassed to serve as the CNN training dataset.

III. PROPOSED SOLUTION

The core of our ML model is the CNNs of Inception v3. We have used transfer learning approach, which will ease the real life implementation of our solution. In order to completely automate the task of filtering unusable fruits at large scale, the ML model can be deployed on a backend using framework such as Django which will be hosted over cloud services such as AWS or Azure. Snapshots of the fruits coming over conveyor will be captured continuously. APIs will be built using RESTFUL architecture which will be used for sending these images to the backend for detection and server will return a response in Json or XML format. Bots, based on the results from our model, will filter out the stale fruits.

III.1 Transfer Learning Technique

Transfer learning approach is being used in the proposed method in order to make the model efficient in predicting if the fruit is rotten or fresh.

A learning model created for one learning problem is utilized as the basis for another learning assignment in the machine learning technique known as transfer learning.

Previous learning is sometimes referred to as the source and upcoming learning as the aim. In essence, it uses a neural network that has already been trained (for Task1) to reduce training time (positive transfer learning) for Task2. To train the network using the traditional image classification approach, we need a large amount of data. This endeavor would entail tremendous time, effort and money which at many occasions, might make it realistically infeasible. In this circumstance, we may utilize the Transfer Learning approach, which leverages pre-trained Neural Networks and uses the resulting weights on fresh data.

The early layers of ConvNet, which deal with general characteristics including edge detectors, texture detectors, and patterns, are shown in Fig. 1. The network's final layers become increasingly specialized to the specifics of the picture collection. The benefits of transfer learning are now presented. The earliest layers of the pre-trained network will be fixed or frozen, while the remaining layers will be retrained using fine-tuned backpropagation. We just transfer the weights previously learnt by a pre-trained network, such as Inception v3, and save time and effort by not starting our network's training from the first layer.

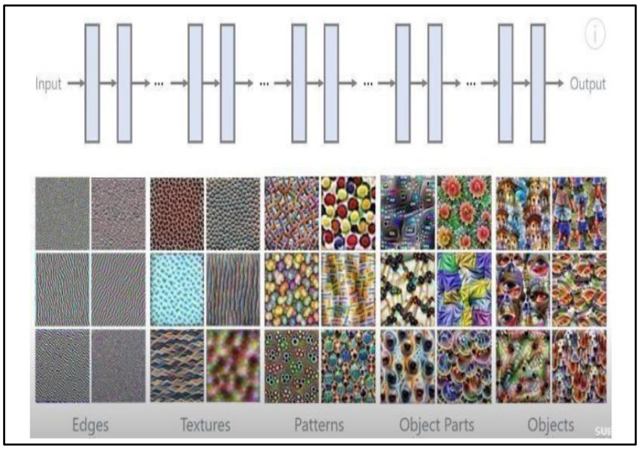

Fig. 1. Variation between Start Layers and End Layers [1]

III.2 Flowchart

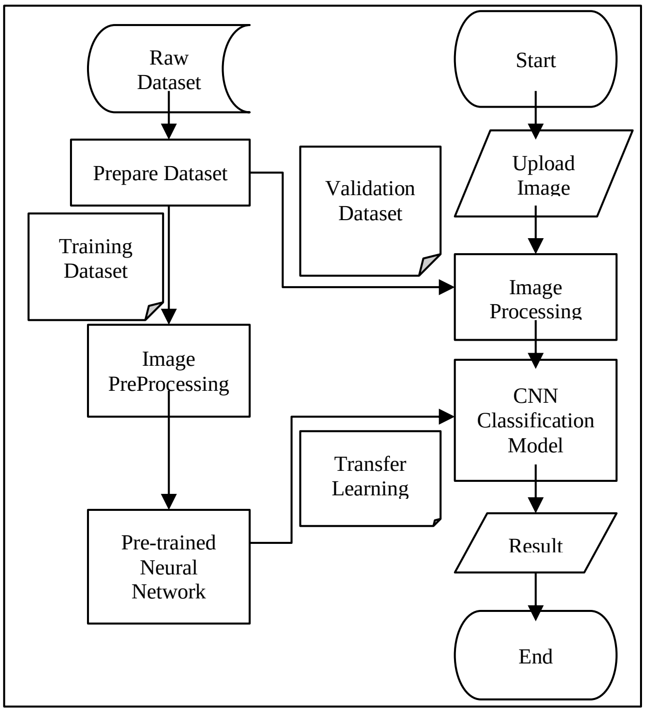

Fig. 2. Workflow of our Proposed Methodology

IV. EVALUATION

In order to validate the proposal, a web based user interface is built for user where they just need to upload image of the fruits and then at server there will be a model which will be trained on dataset and which will detect the freshness of fruits and return the result which will be displayed on the webpage. The backend where the ML model will be deployed is built using Django, which is a python based backend framework. HTML, CSS, Javascript is used in creating frontend User Interface.

A brief summary of the major product functions and what the end user may perform on the application include:

- User opens the web application in the browser.
- User will upload an image of a fruit by clicking on the upload image button.
- After uploading the image the user will click on the result button to get results.
- Then the result will be returned from the server and the user can view the result on the webpage.

IV.1 Methodology

4.1.1 Basic Image Processing Steps

The capture, enhancement, and segmentation of images are some of the fundamental processes in image processing. In general, pre-processing tasks like picture rescaling, denoise, and edge smoothing are included in the image capture stage. One of the most enticing aspects of digital image processing is picture enhancement. Through a process of varying brightness and contrast, the procedure aims to enhance the details of blurred elements. The segmentation process fragments the image into its basic components [3]. So the aim is to basically make the input image more suitable for analysis. One of the thing that can be done is to wipeout the background of an image and take the foreground as the area of analysis for the next process. In our work, we perform image processing in 4 unit steps. The first step is to load the image into image processing program. Then we segment the image to extract the foreground (fruit). Now the extracted foreground is used by our model for feature extraction and classification. It has two benefits. Feature extraction will take less time. The other benefit is to make the learning process more accurate by removing background noise. The Background Substraction Method (BSM) is used to identify the background of the fruit images. Three parameters of color are hue (H), saturation (S) and value (V). Hue contains the color from red to blue from the angle of 0 to 360 degrees. Saturation controls the virtue of colors. It has value from 0 to 1 [11]. For the scope of our work we have taken three fruits, apple, orange and banana for analysis. Each fruit has two category: rotten and fresh. 3000 images in all have been used in our model. Model training dataset has 70% and 30% is for use as validation dataset. Table I describes the dataset for training and validation steps. Training dataset is meant for model learning while Validation dataset is used to determine accuracy.

Table 1. Count of Images

Category of fruit	Practice Set		Checking Set	
	Rotten	**Fresh**	**Rotten**	**Fresh**
Apples	350.0	350.0	150.0	150.0
Bananas	350.0	350.0	150.0	150.0
Oranges	350.0	350.0	150.0	150.0

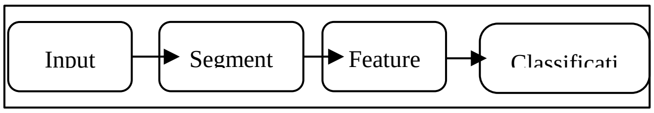

Fig. 3. General steps in Image Processing.

4.1.2 Convolutional Neural Networks (CNNs)

In the field of deep learning, CNNs is recognised as a class of deep neural networks. The primary applications for this deep learning approach include the classification, object recognition, object detection, and other types of picture analysis. CNNs' purpose is to learn and classify an image.. The images will undergo multiple convolutional layers including filters, then pooling, then fully connected layers and finally applying the softmax function to detect the input image. Fig. 4. Dictates the internal architecture of the CNNs. The first layer is convolution to extract features from an input image to get useful information for classification. Convolution learns visual characteristics from tiny input data squares, preserving the link between pixels. In other words, two inputs such as picture and a filter are utilised to accomplish a mathematical action. Sometimes the convolution layer's filter may not match the input pictures precisely. Two possibilities for padding are shown in this instance. The first approach is to add zero padding to the photos to make them fit the filter. Legitimate padding is a different choice that only uses the valid portions of photos.

The most prevalent kind of nonlinear activation function is called a ReLU (Rectified Linear Unit). This function's objective is to provide CNNs some nonlinearity. This is so that CNNs may learn non-negative linear values, which the real-world data may anticipate. In essence, this process zeroes off all of the negative pixels in a picture. The pooling layer is used as a down sampling procedure to shrink the spatial size while keeping the crucial properties when the size of the pictures is too large. Max pooling, which delivers the biggest value from the corrected feature areas, is the most used form of pooling layer.

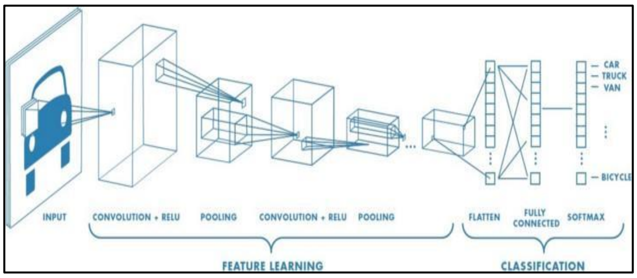

Fig. 4.Architecture of CNNs [4]

A fully connected layer, which resembles a neural network, is created by combining all the characteristics that were learnt by the preceding layer. This helps the algorithm recognise the more extensive patterns in the photos. The output is then classified using an activation function, such as the softmax function. [4].The capacity of CNNs to categorise complicated pictures grows as the number of layers does. Using Inception v3, the characteristics of photos are retrieved and categorised in this study. Inception v3 is employed since it is a 48-layer, pretrained CNN and helps shorten calculation time. The trained network can identify 1000 different object categories in photos, including keyboard, mouse, pencil, and animals [12]. Fig. 5. Describes the architecture of Inception v3. These pretrained networks have learnt a substantial number of feature representations that have been taken from the pictures.

However, the pretrained network is used as a starting point to learn a new job in order to improve the accuracy of classifying the rotting fruits. Transfer learning is used to alter the pretrained network rather than training a network from scratch. Reducing the amount of time needed to train the network is another advantage of doing this.

In MATLAB, the pretrained network is first loaded. Inception v3's 48 layers are imported into a variable. The replacement of the final connected layer comes after the network has been loaded. The fully connected (FC) layer in the pretrained network has to be replaced with a new fully connected layer that has the same number of outputs as the classes that need to be classified in order to be modified to categorise the rotting fruits. Here, the layer is determined by the quantity of outputs. The last layer of a network, or the completely linked layer, is often specified to be 6. Resizing pictures to fit the demands of the pretrained network is necessary during the network training step. The size of image that is input to Inception v3 is 299 x299.In addition, before training is carried out, a few training options must be chosen, including the learning rate factors, the quantity of training epochs, and the mini-batch size. The next section provides an explanation of the training option's specifics. Finally, while validating the network, the validation accuracy is calculated.

4.1.3. Performing Segmentation before Training

Prior to the training phase in this experiment, all of the input photos are subjected to the segmentation procedure. As seen in Fig. 6, the foreground pixels in the picture depict one of the decaying oranges with white fungus. The foreground pixels from the picture are not fully retrieved after segmentation, leaving portions of the white fungus incorrectly segmented.

The background pixels in the segmented picture have been set to zero value (black color).

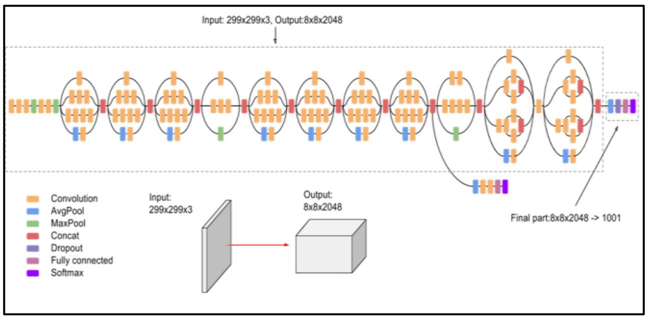

Fig. 5. Inception v3 model network structure [13]

Fig. 6.Before segmentation (left) and after segmentation (right) of a rotten orange with white fungus

The findings indicate that the validation accuracy is the same for both situations, and 98.47%, according to the data in Table II. It has been noted that segmented fruit photos and foreground detected images used to train the network have accuracy levels that are comparable. The findings also demonstrate that segmented foreground detected pictures require longer training times. It was decided to utilise the original photos without segmentation as the dataset for training as all of the original images have monotonous backgrounds in white and grey.

Next, 350 training datasets for each category are used to calculate the parameters for the training option for identifying rotting apples, oranges, and bananas. They are listed in Table III as displayed. Additional research has also been done to determine how the number of epochs and mini-batch size might affect the training time and validation accuracy while using Inception v3. The investigational mini-batch sizes are 10, 50, and 100. Additionally, between 3 and 6 epochs will be used in the experiment. The decision to utilise fewer epochs in this instance was made because if a neural network is trained using more epochs than necessary, the training model would pick up on patterns that aren't necessary.

IV.2 Results

The main objective of this project was to create the web based version for classification of Fruit pic whether it was affected by caterpillar or rottenness or healthy accurately. It will provide a time saving and easy to use platform for farmers and consumers and in industry also which will help them to increase their yields, and efficiency. This project was intended to understand the working of CNN on images of plants and how good it results can generate on working fresh and rotten images. This project provides inexperienced consumers of fruits to get results by simply just uploading images of their fruit and get results whether they are affected by pests or rottenness or not. There is a very simple interface and the model trained yields accurate results and has fast response time. This is very useful for farmers, consumers and in industries. The project idea mainly came up due to India being a largest consumer and producer of fruits and also we have an online research institute which helped us gather important insights and through which an application which can help such a cause was developed. As the number of training iterations rises, the value of loss decreases. This indicates that when additional training is added to the model, the model's ability to classify photos improves. The loss in this instance is just about 0.1, which is a negligible amount.

The prediction outcome on 4 randomly selected photos from the validation set is shown in Fig. 9. The categorization findings for these four photos are predicted accurately with a high probability. With 94.2% accuracy, the model correctly identified the first picture as a rotting apple. Only 5.8% of people can identify other fruit groups from this photograph. According to Table IV, the validation accuracy achieved when the mini-batch size is set to 10 is the greatest among all other scenarios, coming in at 98.47%. The experiment's findings and the hypothesis show a good level of agreement. In comparison to the training times for mini-batch sizes of 50 and 100, the training time for 10 is substantially longer.. This is due to the fact that changing the model's weights, which are changed after each iteration, takes time. There have been 252 iterations for case 1, meaning the model's weights have been modified 252 times. With varying numbers of iterations, Table V examines the link between the number of epochs and the validation accuracy. It demonstrates that utilizing 6 epochs for validation increases accuracy from 3 epochs to 98.47%. According to a theoretical research, using more epochs yields improved accuracy since it means the learning algorithm has had more opportunities to run over the whole training dataset.However, when there are many epochs, the training period is longer because it takes more time during iterations to update the internal model parameters through forward and backward passes of all training datasets. The findings show that the training time was 23.7 minutes for 3 epochs and 44.7 minutes for 6 epochs.

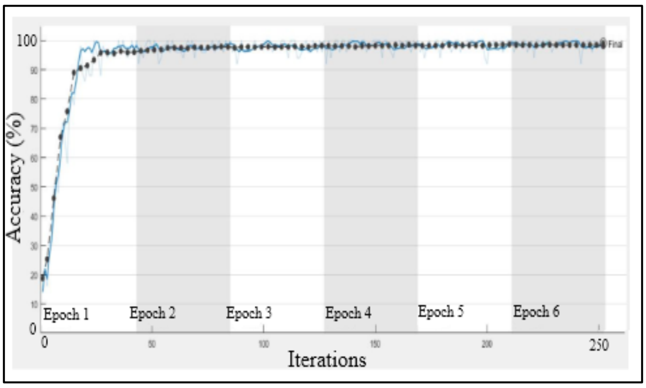

Fig. 7. (Accuracy vs Iterations) curve.

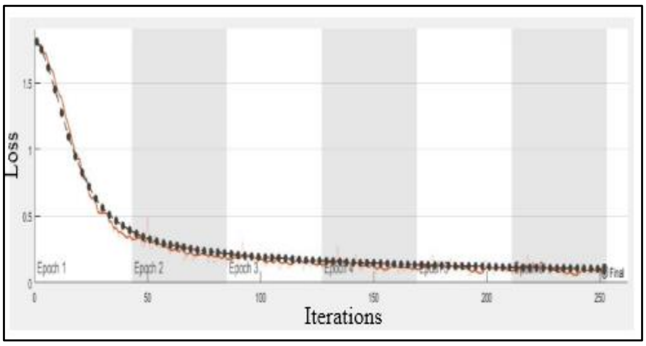

Fig. 8. (Loss vs Iterations) curve.

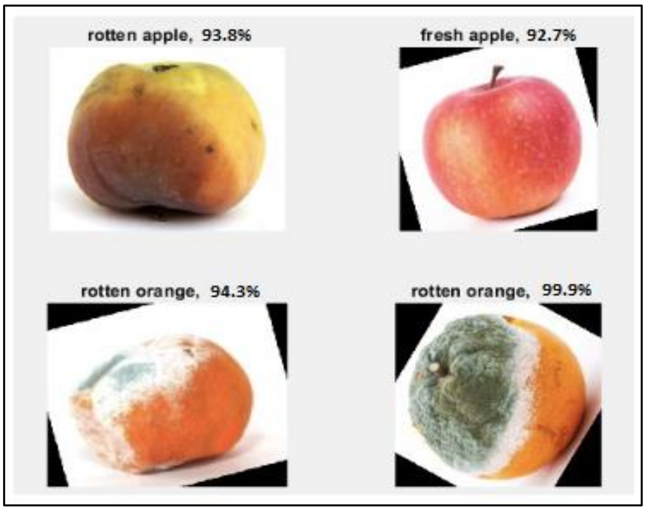

Fig. 9. Multiple variable pics from valid set with their prediction answer

Table 2. Measurement of precision before vs after segmentation

Input Images	Small-batch Sizes	Count of Echos	Precision	Practice Time (minutes)
With Segmentation	10	6	98.47%	50.40
Without Segmentation	10	6	98.47%	44.72

Table 3. Modules of practice option

Small-batch Sizes	Count of Epochs	Immediate Practice Measure	Correction Mode
50	6	0.0001	3

Table 4. Check of result in verification correct precession for 2 methods

Sr. No.	Small - batch Sizes	Count of Epoch	Number of Loops	Precession	Practice Time
1	10	6	252	98.47%	44.72
2	50	6	48	96.88%	12.59
3	100	6	24	94.68%	9.51

Table 5. Check of result in valid precision for 2 different number of epoch

Sr. No.	Mini-batch Size	Number of Epochs	Number of Iteration	Validation Accuracy	Training Time
1	10	3	126	95.93%	23.68
2	10	6	252	96.88%	44.72

The problem addressed is based on the horticulture and consumer along with the industrial domain. It helps in classification and detection of whether the fruit is affected by rottenness or illness or it is healthy. Ethylene gas is responsible for fruit ripeness and rottenness after a particular time it consumes too much of ethylene gas and becomes rotten. We have built a web based version for pest detection and classification in different fruits. The Fruits image dataset was used for training CNN models for various parameters and we have selected the best model based on the accuracy.

We have divided the data on training and validation set and used that for training our model. We have built the web version for the farmers who are inexperienced and this will help them and save their crops from getting affected by pests and hence reducing quality damage. We can use the same application in the consumer end and in the industrial end to check the amount of rottenness. We have used the trained model in our backend which will receive an image from the frontend which will be processed and then that will be passed to the model which will give the result and then that will be passed to the frontend which will be displayed to the User.

We use an equal amount of images in all three categories so that we can easily train our model. We use 350 images of apple, orange, and a banana each to categorize fresh and 150 images of rotten categories of all three categories. Which makes it a total count of 3000 images. So here all the results of precession are mentioned as shown in the table.

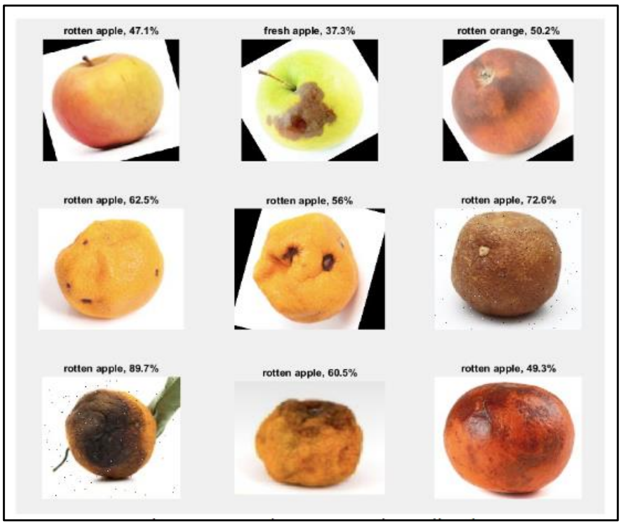

Fig. 10. Images that are wrongly predicted

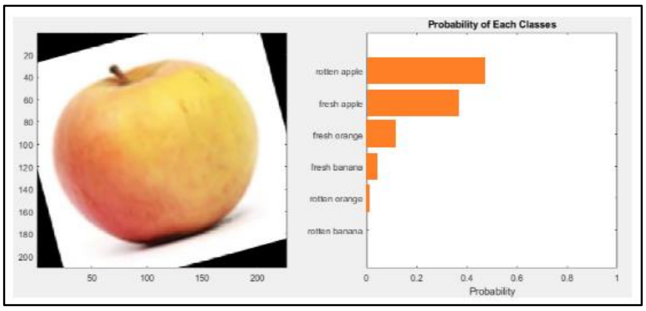

Fig. 11. Classification index

V. DISCUSSION

When a fresh set of input photos is intended to be added to the training dataset in order to improve accuracy, it is not required to repeat the training method using the previous original dataset. Instead, just load the model that was previously learnt and retrain it using the new batch of picture data. With more research, a new fruit category, such as strawberries, might be introduced for the categorization of this model. Install the pretrained network first, which already has features loaded from six categories of the original fruit photographs. After modifying the last layer to reflect the existence of seven output types, train the network using the dataset's images of strawberries. This illustrates how flexible the transfer learning approach is. The training procedure using the prior original dataset does not need to be repeated when a fresh batch of input photos is desired to be added to the training dataset to increase accuracy. Simply load the previously trained model and retrain it with the fresh batch of picture data. In further research, a new fruit category, like strawberries, can also be added for categorization using this model. First, load the pretrained network, which contains the properties of the six original fruit picture categories already loaded. The network should next be trained using the dataset containing photos of strawberries after changing the last layer to indicate there are seven output types. This demonstrates how adaptable the transfer learning approach is.

As required by the picture dataset, we were able to obtain an accuracy of 92.4%. It is crucial to ensure that the backdrop of photos has a uniform color when using the suggested model in this research for training. Our system must first eliminate any distracting and undesired noises in order to obtain a clear image of the fruit that has to be analyzed. Otherwise, it will behave as an undesirable characteristic that the model learns throughout the training phase. The categorization outcome may be impacted by this. Fruit photos with varied patterns are necessary for the model to learn the characteristics of fruit images in order to be able to classify a broad variety of patterns of a certain fruit. Based. Based on the result of classification, the majority of the wrongly predicted images are under the category of rotten orange and apple.

VI. FINAL REMARKS

Our system has detected the process of fruit detection which is very efficient in working .We used the CNN algorithm for the better detention of fruit photos that are used by the team graphic creator that converts the Photo to dark image . We used the inception model v3 for the better proposing. The trained model was then used to perform classification on the rotten and fresh .We have checked more than 3000.0 fruits photos for our precision of the device. After cross verifying the precision from the experiment, the input dataset applied for both practice and cross verification stage does not require segmentation. The practice option parameter is determined as 6 numbers of epochs and 35 small-batch sizes. With these settings, the required duration for the training stage is 215.37 minutes. Twelve categories of classification were included in this paper including rotten and fresh fruits for apples, bananas and oranges respectively. The validation precision obtained is 95.47%. We have found only 12 fruits out of a hundred which were good enough but our device accuracy got stuck here.

We anticipate working with the data and attempting to improve the precision of our image processing model, which detects rotting fruits. The likelihood of making a mistaken categorization can be decreased by the increasing number of fresh and rotting apple photos. As rotting apple and rotten orange classification challenges were raised. By distinguishing between the models, we must separate the models in order to improve the model's accuracy.

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