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Segregation of Ripe and Raw Bananas Using Convolutional Neural Network

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Abstract

Agricultural sector is one of the main sectors in India. Productive growth and high yield production of fruits is important and required for the agricultural industry. Application of computer vision and image processing has aid agriculture to boost yield rating, disease spotting, irrigation, fruit classification and maturity grading. Computer vision and image processing approach can be used to lower the time utilization and has made it economical. A convolutional neural network (CNN) is a type of artificial neural network used in image identification and processing that is mainly planned to process pixel data. This paper utilized a convolutional neural network (CNN) to classify bananas into raw or ripe without requiring labour. Bananas were classified by their colour appearance in the CNN classification and not only this it can be also used to classify many other types of fruits and vegetables.

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Keywords: CNN; Image Processing; Fruit Classification; Ripe Banana; Raw Banana.

1. Introduction

India's 70% of the population rely on agriculture. Agriculture has an utmost beneficence towards economic expansion by providing food and raw material to non- agricultural sectors. Agriculture needs a lot of man labour. It requires a lot of time for the farmers for manual sorting and examining of fruits from harvest till its growth period. Manual sorting doesn't give adequate results all the time, so it needs an efficient smart farming techniques which can used to get better yield and growth with less human attempt. Recently, there are a lot of research work have been brought off by depending on the computer; to reduce the fining and processing time to provide precise outcomes. Digital image processing as a computer-based technique has been highly used in agriculture for segregation purposes. Image processing is a type of signal processing where the image is given as an input, photographs, or frames of the

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video and the output obtained will be image parameters or an image. The image processing techniques and algorithms are successfully applied in many fields like satellite, medical research and so on. Since agriculture, being the basic requirement of mankind, the image processing techniques is used to do crop detection and analysis, segregation based on colour, shape, texture, disease detection and classify them appropriately. Most of the subsisting agricultural technologies are making use of machine learning algorithms. Applications of machine learning are crop yield prediction and smart irrigation systems. Machine learning techniques are divided into two types: supervised and unsupervised learning. Examples of supervised machine learning algorithms are Naïve Bayes (NB), Discriminant Analysis (DA), Support Vector Machines (SVM), Convolutional Neural Network (CNN) and K-Nearest Neighbour (KNN). On the other hand, K-Means Clustering, Gaussian Mixture Models (GMMs), and Fuzzy Clustering are kind of unsupervised machine learning algorithms [2]. An image classification system uses features of an image to categorize various types of objects in an image. Despite this, the system can determine the type of image based on the characteristics and result in a reliable classification.

The classification of different kinds of fruits and vegetables is not easy due to several similarities in shape, size, and colour. Generally, fruits, vegetables, and crops are examined by experts or trained personnel before harvesting and releasing to the market. The colour and texture of the products are among the factors considered by these people when assessing quality. There are several potential human errors associated with manual checking and classification, however.

Globally, bananas are among the most widely consumed fruits and are ranked fourth in terms of food production considering how many bananas are consumed, manual sorting becomes very difficult, so in this paper, a convolutional neural network (CNN) was used to classify the bananas into raw and ripe without the necessity of labour. In this classification, bananas have been categorized according to their colour appearance. There have been many algorithms used, but CNN offers the best accuracy amongst them.

The organization of report starts with an introduction that sets the context for the research and literature review, which presents a review of the previous related research paper. Following the algorithm section is the section that gives a detailed description of the algorithm used, and after that comes the methodology section describing the phases of the machine learning pipeline. After that follows the results section and then the conclusion section, which summarizes the findings in the research paper. Finally, the reference section, which gives a list of reference sources, follows.

2. Literature review

In 2009 P. M.P., H. C.R., R. P. Krishnan, and S. S. Mohd Radzi in their research paper concluded, Input was taken as a RGB image of resolution 320x240. Using a heuristic method, each image was resized and scaled based on four different capture locations. During the process, three stages were used: pre-processing, feature extraction, and ripening classification. To classify ripening, 100 samples of ripe bananas and 116 samples of unripe bananas were taken. Data was saved in a spreadsheet file and sorted randomly, before being used as input to train the neural network [12]. Network architecture consisted of a node in the output layer, 9 input neurons, 45 hidden neurons, and one node in the output layer. When the fruit was ripe, the output was 1 and when it was unripe, it was 0 or near 0. 60% of samples were used for training and 100% for testing. Results showed that the ripeness recognition rate was 96%. Cashiers and customers can use it in the future to determine prices of fruits more efficiently than weighing, thus saving time.

In 2015, D. S. Prabha, J. S. Kumar in their journal concluded, Different maturity stages of the banana are classified by using the maturity classification algorithm which is developed on the image processing method based on colour and size [4]. Further in 2017, B. Kanimozhi and R. Malliga in their journal concluded, there are various classifiers in image processing to support precision, accuracy, consistency of the data compared with image samples [11]. Decision tree algorithms, artificial neural networks, KNN, Back propagation algorithm, Bayes algorithm. Support vector machine algorithms.

In 2020, Aaron Don M, Africa, Anna Rovia V. Tabala, Mharela Angela A Tan in their journal concluded, Prior to their release in the market, ripe fruits are classified and graded for quality by humans. Recent studies, however, indicate that utilizing physical characteristics like shape, colour, and texture as the only criteria for estimating quality could be prone to human error since these factors require consistency during the examination. Several studies have proposed and presented different methods to detect and classify fruits more accurately. The authors were able to enumerate some most widely used and most effective methods including deep learning, image illumination, faster-CNN, and the use of a gas chromatograph for the detection of ethylene gas.

In 2020, R. Dandavate and V. Patodkar in their journal concluded, An important aspect of this industry is the classification of fruits into edible and non-edible categories [13]. The proposed system uses Convolutional Neural Networks to classify bananas, papayas, mangos, and guavas according to raw, ripe, and overripe stages. This resulted in an accuracy of 97.74 % in 8 epochs with a validation precision of 0.9833.

By analysing previous work, the test using Convolutional Neural Network can give higher accuracy. The fundamental benefit of CNN over its predecessors is that it discovers essential traits without the need for human intervention.

3. Algorithm

The key to Deep Learning architectures for image classification are the convolutional neural networks (CNNs). The use of CNN for recognition of fruit has increased drastically over the last three years (2018 to 2021) and has generated excellent results through new models or pretrained transfer-learning networks. The convolution process extracts tiles from an input feature map, and applies filters to them to construct new features, producing an output feature map, or convolved feature map (which may have a different size and depth from the input feature map). CNNs are types of artificial neural networks that works in at least one of their layers with convolution [7]. CNNs have been seen as a competitive tool for image classification in various fields since 2012, when Krizhevsky et al. [8] won the ImageNet Competition (ILSVRC) [9]. Its architecture is inspired by the organization of the Human Visual Cortex and is analogous to the connectivity pattern of neurons in the Human Brain. Individual neurons respond to stimuli only in a specific region of the visual field called the Receptive Field. By analysing images with convolutional neural networks, traditional image processing methods can be replaced by automated methods. As an adequate tool for image classification in many different areas, CNNs have acquired great popularity. Mainly, in agriculture, fruit classification [10, 1] and fruit detection applied CNN-based approaches. Evolution of Convolutional Neural Network is traced back to multi-layer neural network that was first proposed by LeCun et al. in 1998. As CNNs follow a hierarchical model, they build a network, like a funnel, and finally they give off an output layer with all the neurons interconnected and processed. Multi-layer perceptron is a regularized form of CNN. The multi-layer perceptron usually means that all networks are completely connected, i.e., each neuron in one layer is linked to the next layer. Unlike CNNs, convolution working is used at least in one of their layers. Figure 1 shows the diagram of basic CNN architecture:

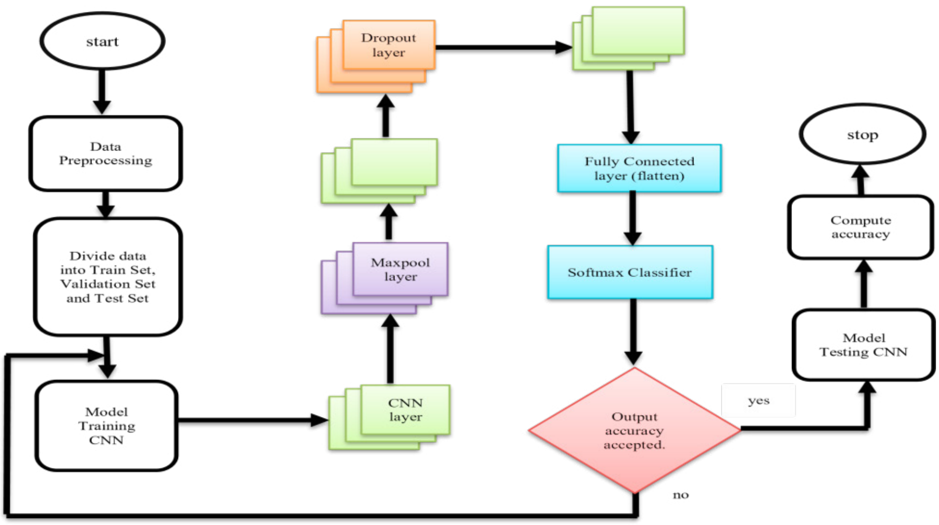

Fig. 1. Schematic diagram of basic CNN architecture for fruit detection and classification. [6]

The reason CNN is so popular is their architecture - the best thing is that there is no need for feature extraction. The next layer of features is convoluted with different filters to create more abstract and invariant features, and the process continues until the final, invariant output (let's say a face of X) is generated. Also, deep convolutional networks work well on image data since they're flexible. Also, an image classification involves observing patterns in a dataset by analysing the image features. Since the trainable parameters become extremely large when using an ANN for image classification, it would be very expensive in terms of computation. With the use of CNNs, the number of parameters can be reduced while maintaining the quality of the models. Because each pixel is considered as a feature in images, CNNs can learn from images that have high dimensionality.

4. Methodology

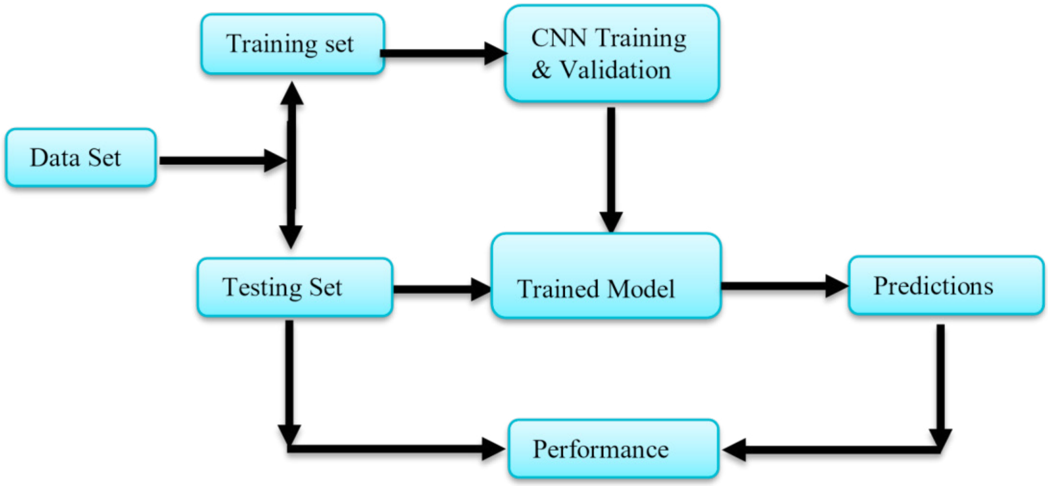

Fig. 2. Machine Learning Pipeline

Above Figure 2 depicts a typical machine learning pipeline.

4.1. Training set and Testing set

The dataset in this model has been divided further into two parts Training set and Testing set. A training dataset is used to generate a model using a machine learning technique during the training phase. The dataset must be resized, assigned paths, and categorized labelled before it is ready for training. Support vector machines, or SVMs, random forests, and neural networks are some of the most well-known models for these. The test dataset is frequently the result of separating the initial dataset. The performed prediction in the testing phase if often compared to the performed training process for further evaluation. There are several similarities between the train and test datasets. The training takes up 60%; the testing takes up 20%; and the validation takes up 20%. The dataset is further divided into Ripe Banana Dataset and Raw Banana Dataset.

4.2. Trained Model

A training model is a dataset used to train a machine learning algorithm. It is made up of sample output data as well as the equivalent sets of input data that have an impact on the outcome. The training model is used to process the input data via the algorithm to compare the processed output to the sample output. The model is modified based on the results of this association. The purpose of training verification is to ensure that the model's process is generalizable. The trained model is then tested to see if it can predict datasets using input variables in the test phase. For training data, there are 200 raw banana & 138 ripe banana. CNN model also needs Validation data to validate the training Model. 60 raw banana & 60 ripe banana images were provided to validate model during training.

4.3. Performance Evaluation

The evaluation of performance is an important part of the machine learning process. It is, however, a difficult task. As a result, it must be carried out with caution if machine learning can be applied to fields with confidence. The model's performance is that it has a 90% accuracy rate.

This paper uses accuracy as the performance evaluation method. The accuracy of the model can essentially be described as a measure of how well it performs across all classes. Especially useful when all classes have equal importance. It is calculated by dividing the number of correct predictions by the number of total predictions. The formula to calculate accuracy is given below:

$$\text{Accuracy}=\frac{\text{True(positive)}+\text{True(negative)}}{\text{True(positive)}+\text{True(negative)}+\text{False(positive)}+\text{False(negative)}}$$

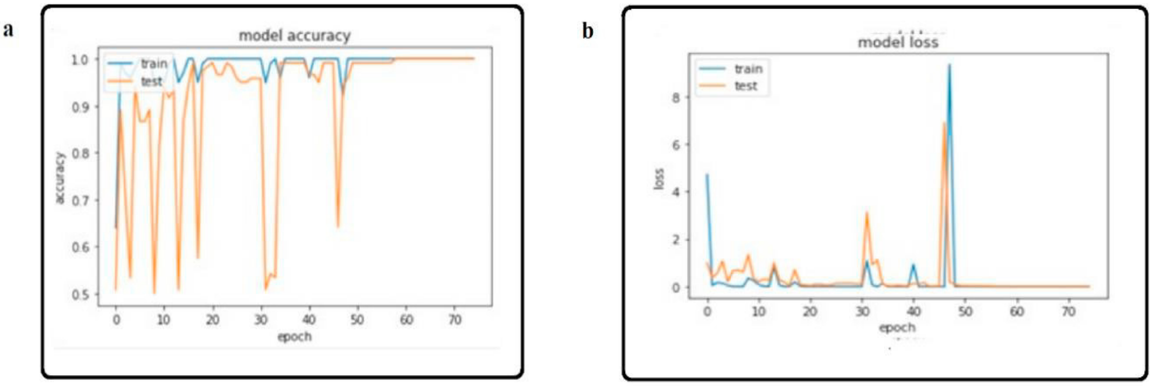

Fig. 3. (a) Model Accuracy; (b) Model Loss.

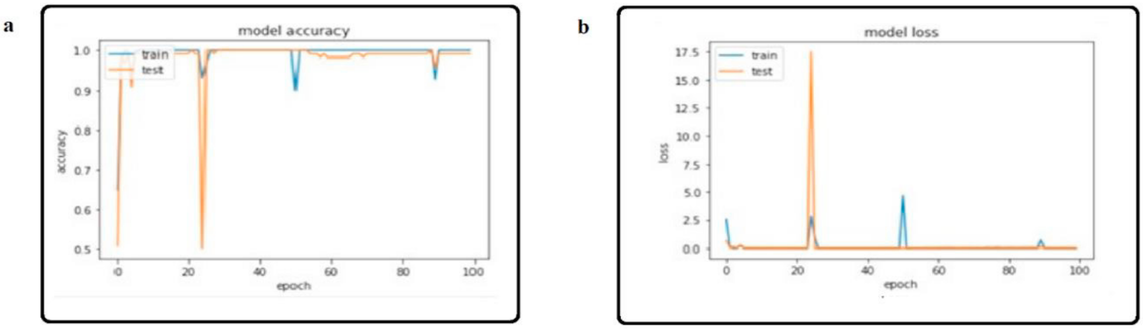

Fig. 4. (a) Model Accuracy; (b) Model Loss.

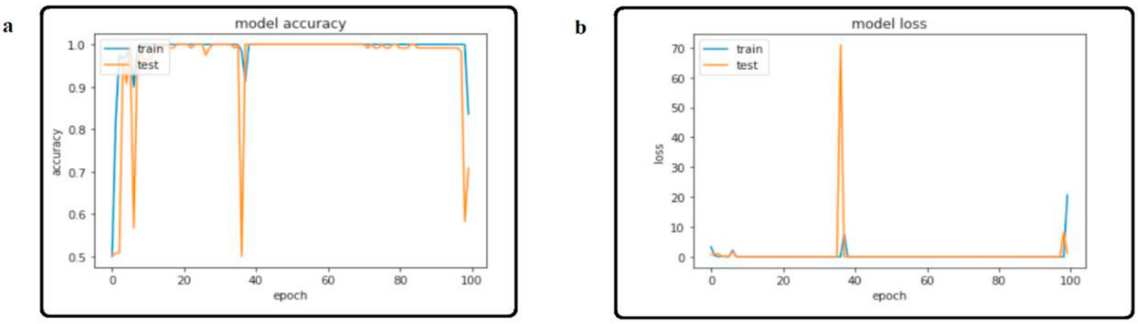

Fig. 5. (a) Model Accuracy; (b) Model Loss.

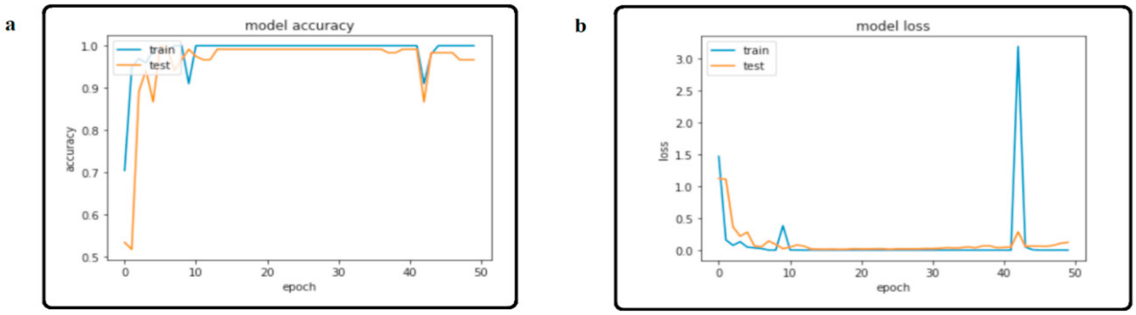

Fig. 6. (a) Model Accuracy; (b) Model Loss.

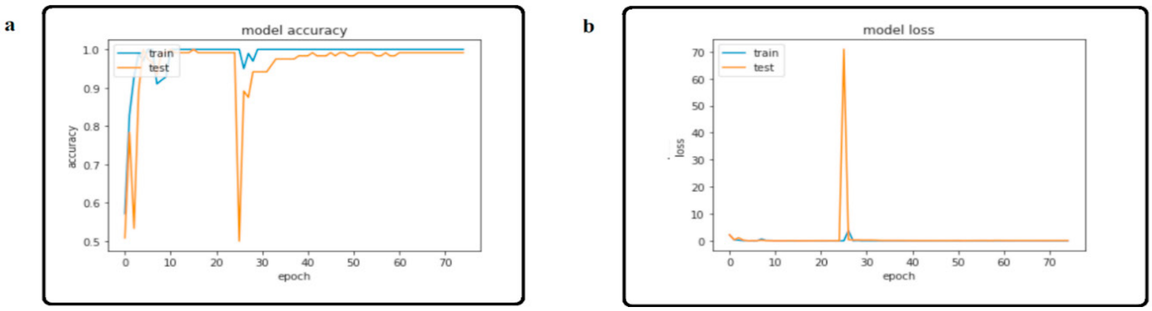

Fig. 7. (a) Model Accuracy; (b) Model Loss.

Fig 3 (a) & Fig 3 (b) configuration: Batch 10 Epoch 75 with Step 10.
Fig 4 (a) & Fig 4 (b) configuration: Batch 30 Epoch 100 with Step 10.
Fig 5 (a) & Fig 5 (b) configuration: Batch 30 Epoch 100 with Step 5.
Fig 6 (a) & Fig 6 (b) configuration: Batch 10 Epoch 50 with Step 10.
Fig 7 (a) & Fig 7 (b) configuration: Batch 10 Epoch 75 with Step 5.

5. Result

Fig. 8. (a) Raw Banana; (b) Ripe Banana.

Fig 8 (a) & (b) shows the final output of the system. Fig 8 (a) shows prediction from trained model as output 0 i.e., Raw Banana & Fig 8 (a) shows output 1 i.e., Ripe Banana.

Below table displays multiple runs for batch size, epoch, and number of steps per epoch to determine the best combination. After training the model with multiple combination of batch size, epoch, and number of steps per epoch the testing was performed with 120 images with raw & ripe bananas. Below is the result of that 120 test images.

Table 1. Result.

Sr no.	Batch	Epoch	Step	Total Test	Error	Success%	Failure%
1	10	75	10	120	9	92.50	07.50
2	10	50	30	120	1	99.17	00.83
3	2	100	20	120	13	89.17	10.83
4	20	100	10	120	27	77.50	22.50
5	10	100	20	120	2	98.34	01.66
6	5	100	10	120	4	96.67	03.33
7	5	100	20	120	10	91.67	08.33
8	10	100	10	120	2	98.34	01.66
9	30	100	10	120	2	98.34	01.66
10	30	100	5	120	32	73.34	26.66

Fig. 9. Graphical representation of result

Table 1 shows the following information that with higher steps per epoch i.e., 30 has higher success rate with 99% success rate. With low steps per epoch there are high failure rates, 5 steps had 26% Failure with detection.

From Sr no. 3 & 7 has similar no of epoch & steps per epoch, lower batch size has higher error rate then higher one. Increasing more batch size in Sr no. 8 & 9 result was same for both the run. Batch with 10 is best fit for the combination. Our model was optimized after numerous trials to classify artificially ripened bananas.

On observing above data, CNN with higher Epoch and Steps gives better results. Test run with 100 Epoch with 20 steps has 98.34% Success i.e., 118 out of 120 in detecting right type of banana.

6. Conclusion

The present study concluded that productivity growth and improved yield are so crucial to the agricultural industry, which is in great need, so smart farming is used to replace manual sorting to reduce a lot of time and energy. Convolutional Neural Network (CNN) algorithm is used in image analysis tasks like Image identification, Object detection and segregation. A new approach to classifying ripe and raw bananas is presented in this research. This technique reduces the effort of humans and can give 90% to 98% accurate results. For neural networks to produce sophisticated and accurate outputs, a vast amount of data is required; however, our results indicate that despite having limited datasets, our accuracy rate is 90%. Lower batch sizes have greater error rates than bigger ones, even if Sr. Nos. 3 and 7 have identical numbers of epochs and steps each epoch. The results of increasing the batch size in Sr. numbers 8 and 9 were same for both runs. The combo works best with batches of 10. After multiple tests, our model was refined to classify artificially ripened bananas. This indicator outperforms state-of-the-art techniques for bananas with or without severe defects and its improvements are significant (as shown in Table 1).

Using Convolutional neural networks, the test can provide higher accuracy after analysing previous work. Thus, this will enable more research possibility such as detection of degree of ripeness or predicts the number of days when the fruit will be ripe enough to consume it. The same work can be analysed with different colour format like RGB, CMYK, HIS, YCBCR, etc.

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