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Original

Modern techniques in detecting, identifying and classifying fruits according to the developed machine learning algorithm

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Abstract: Recent developments in machine vision have opened a wide range of applications, and farming is no exception. Deep learning (DL) has a wide range of applications because of its capacity to extract robust features from photos. The shape, color, and feel of many fruit species make it difficult to discover and classify fruits. When examining the effects of artificial intelligence on fruit identification and classification, the Author noted that, up until 2018, the majority of approaches relied on traditional machine learning (ML) techniques, while just a few ways took use of DL techniques for recognizing fruits and categorization. In this paper, the Author thoroughly covered the datasets that many academics utilized, the useful descriptors, the application of the model, and the difficulties of utilizing DL to identify and classify fruits. Finally, the Author compiled the outcomes of various DL techniques used in earlier research to identify and categorize fruits. This work examines the use of models based on DL for fruit categorization and recognition in recent studies. In order to make it simpler for beginning agricultural researchers to comprehend the importance of ML in the agricultural domain, the Author have developed a DL model for apple categorization using the well-known dataset "Fruit 360" starting from scratch. The recently proposed model demonstrated impressive results in accurately identifying the quality of various fruits, such as apples (with 99.50% accuracy), cucumbers (99%), grapes (100%), kakis (99.50%), oranges (99.50%), papayas (98%), peaches (98%), tomatoes (99.50%), and watermelons (98%).

Keywords: Deep learning techniques, machine learning, fruit detection and classification, Fruit 360

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1. Introduction

Image categorization is a tremendously active research subject that is crucial to many fields. Recognition of faces, analysis of videos, image categorization, and other applications of image recognition are available. The field of machine learning (ML)'s deeper learning (DL) subfield has demonstrated remarkable performance in image recognition (Pak & Kim, 2017). The multi-layer structure is used by DL to process image properties, greatly improving the effectiveness of image recognition (Hao, 2016). In a nutshell, the use of recognition of images and DL in the field of supply chain and logistics is starting to take off. Recent advances in machine vision (CV) have produced remarkable outcomes in many spheres of life. Fruit identification and classification have proven to be difficult and complex tasks. Research in fruit processing, covering the processing business, is particularly essential for several industries, including retail as well as wholesale marketplaces (Omasheva et al., 2018). These features have inspired researchers to create a variety of automated fruit processing techniques that can accurately identify fruits or gauge their quality. Agricultural businesses such as food processing, marketing, wrapping, and fruit categorization have taken on research areas with greater directions over the past few years. Due to the large number of types of the same fruit, for example, more than 7,000 different apple varieties are grown (Yadav et al., 2014). Globally, processing and selecting of special crop plants like orange, cherry, apple, mango, and lemon are time- and labor-intensive (Rüßmann et al., 2015).

Therefore, automation can reduce labor expenses and quickly boost production (Naranjo-Torres et al., 2020). In earlier studies, researchers proposed various approaches from CV for manually obtaining fruit characteristics and ML to categorize the CV features. Fruit color, form, dimensions, and texture features are used for algorithmic classification by CV algorithms (Omasheva et al., 2018). Most of them combined various classifiers with the pretreatment process or extraction of features by CV. Most developed classifiers, however, are not reliable for all fruit varieties, which leads to greater rates of bad classification. Convolutional neural network (CNN) has grown to be a very significant model for research in the fields of object identification and recognition of images. CNN was more robust to utilize because it could automatically extract properties from an input image. In contrast to traditional CV-based feature extraction techniques, CNN allows the image to be directly input into the network, eliminating the need of processing and extraction steps. The three levels that make up a traditional CNN are convolutional layers (CLs), layers of pooling (PLs), and fully linked (FC) layers. CNN received a lot of attention after receiving the ImageNet prize (Harrell et al., 1989). The many CNN models created by numerous academics with varied layer depths and widths were then addressed. Fruit identification and categorization present a challenging task because of the wide range of intraclass shapes, hues, and textures (Seng & Mirisaee, 2009). A lack of automatic fruit classification methods for various classifications has been caused by these restrictions (Seng & Mirisaee, 2009). To choose the proper fruit having the right food, a more sophisticated information system for fruit automatic recognition and categorization may be helpful.

In this study, the Author looked at the most recent deep learning and machine language techniques for fruit detection and classification. As the Author provides an empirical examination of fruit categorization relying on the DL model utilizing the well-known Fruit 360 dataset, the Author also concentrates on addressing assessment measures. Additionally, the Author describes how transfer learning is used in the finding and classification of fruits and contrast the results with conventional CNN models or other widely used approaches that still rely on antiquated methodologies as opposed to the technology the Author discusses in the study (Omasheva et al., 2018; Seng & Mirisaee, 2009). Moreover, the most crucial points are: 1) to the greatest extent of the Author's understanding, the Author gives the first thorough analysis of the use of DL in the context of fruit recognition and categorization to date due to the uniqueness of the use of DL in the researched area, 2) the Author describes the concepts employed in recent studies and openly accessible data sets for identifying and categorizing of fruits (Seng & Mirisaee, 2009), 3) extensive research has been done in two key areas relating to fruit identification and categorization, and 4) the Author offers an overview of theory on CNNs in order to provide a better grasp of the way DL (CNN) systems are put into effect. Additionally, the Author performed a fruit categorization test utilizing the well-known data set (Feng et al., 2019).

2. Introduction of convolutional neural networks (CNNs)

CNNs are the primary DL architectures for classifying images. The Author observes that over the last three years, the application of CNN for fruit identification has greatly increased and has generated good results using either novel algorithms or pre-transformed training networks (Krizhevsky et al., 2017). CNNs are a subset of neural networks made up of neurons that employ compression in a minimum of two of their layers. CNNs have grown in prominence and are now regarded as a viable image-classification tool in several fields. Fruit recognition and categorization are being applied, particularly in farming, using CNN-based methods. The CNN's normal variant is the multilayered perceptron; each network in a multilayered sensor is typically completely interconnected, i.e., each neuron in each layer is linked to the next (Blanes et al., 1970). Contrary to CNNs, convolution processes are employed in at least one of their layers, whereas the Author can theoretically specify a convolutional neural network's operation's architecture from a single layer to the next. The basic CNN structure design for fruit recognition is illustrated in Figure 1.

The recognition process of the fruits can be in the following steps: 1) recognizing a fruit (distinguishing between a fruit and a thing, such as a leaf with a backdrop) (Harrell et al., 1989; Navas et al., 2021), 2) taxonomy of fruit organisms, including such like citrus and tangelo, and 3) identification of a variety of fruit organisms, such as the distinction between Crimson White and Granny Smith apples.

Recognizing the specifics of the issue, as it is described in this article, is the proper approach to determine which species are suitable and choice of fruits (Navas et al., 2021). Fruit categorization is a rather challenging topic because there are so many different types. Images are also blurred because of the small coverage of the lens by the lightning's scenery, the distance, and direction. Another issue is if the object is completely or partially obscured. Due to this flaw, there are no multi-class automatic fruit categorization systems in use today. Numerous studies are carried out with diverse goals and purposes to classify and recognize fruits. The enactment steps for object recognition and categorization (Bac et al., 2016), which are the same for identifying fruits and classification, are shown in Figure 2. In this study, the Author thoroughly investigated the different deep neural network models used for fruit recognition and categorization. Significant differences in appearances occur between species and varieties, and they include uneven shapes, hues, and materials.

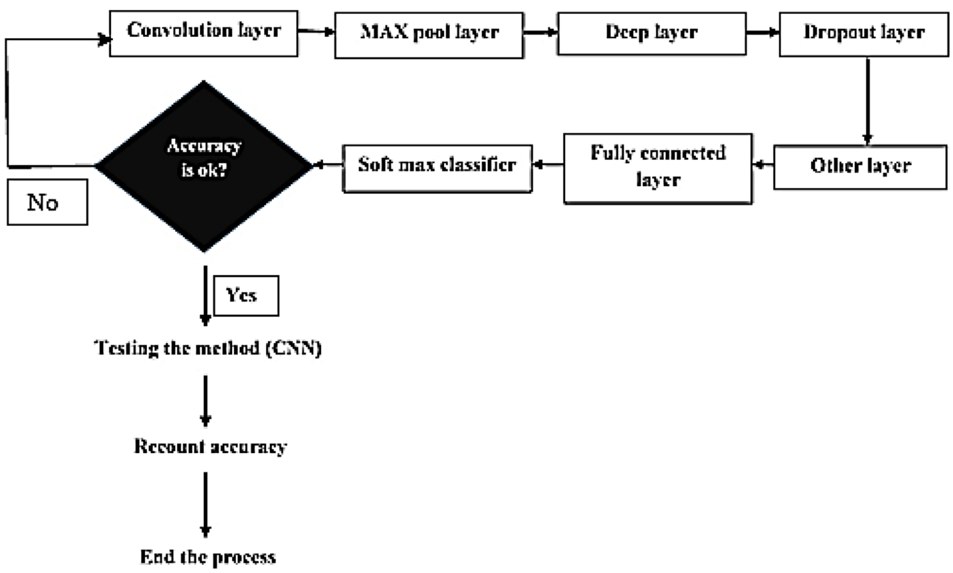


Figure 1. Basic CNN structure design for fruit recognition.

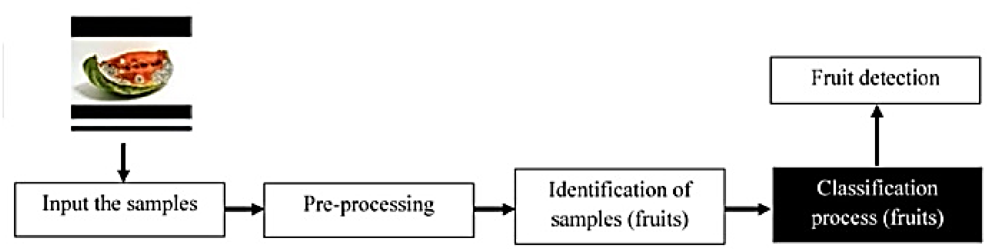


Figure 2. Simple object identification and categorization development steps.

Figure 3 shows the steps in the preprocessing phase.

A crucial stage in the realm of identification and classification is preprocessing and segmentation. Preparing is the initial and most important phase in the work of identifying fruits and categorization due to the fact that fruits differ in size, shape, color, and texture. Figure 4 illustrates how the noise from the background is eliminated from captured photos during preprocessing to obtain the fruit image. Most researchers then change the image from RGB to greyscale before changing it to binary (Ling et al., 2020). After dataset capture and before the advent of deep learning (DL), the extraction of features has been a common processing step. Before turning fruit features (such as shape, color, and volume) into vector characteristics, techniques like FCH, MI, and others are used to obtain the fruit characteristics (Lehnert et al., 2017).

Often, crucial components of a scene are divided using methods like subtraction from the background. It is possible to imagine background elimination as a technique for separating two things in an image. The feature vectors are then combined to create a final vector using the merge procedure. The Author may divide the design employed into two components, both of which are completely neural networks, since hashing is a need for object identification. The fully convolutional neural networks can be seen in operation where the regular FCN is utilized, and the R-CNN mask is employed. The most popular sort of region-based partition is this one. The setting of the segmentation image is first removed before the ROI (region of focus) is taken from the fruit data. The detection operation is then accomplished by applying the classification results of the identification network to the hash image. I provide a schematic summary of the preliminary processing and segment procedure for fruit identification and categorization because I am not overly concerned with this element (Gauchel & Saller, 2012; Lehnert et al., 2017).

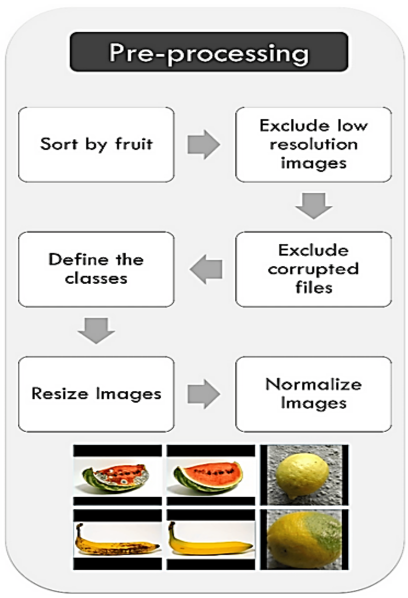


Figure 3. The steps in the preprocessing phase.

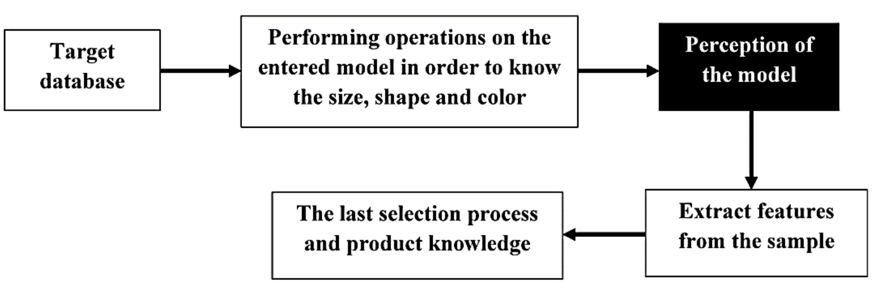


Figure 4. Preprocessing and segmentation steps for fruit detection and classification.

3. Optimization of the fruit classification model

Fruit algorithms for classification must take real-time performance into account because they are frequently utilized in systems with high real-time demands. Image categorization requires a lot of processing time for neural network models that are complicated.

A sample data set can be used as the weight of the model for setting up the training data set, considering the distributional properties of the data sets used to train the model. The Softmax layer's nodes are lowered by ten times when the model has been pretested and has achieved a specified level of accuracy, and the dataset is then utilized for weight training. Given that the model's processing of data may be impacted by various noises, an automatic noise mitigation encoder is included to the model to eliminate noise interference, and the current information set is increased using the data optimization method to improve the model's capacity for generalization.

The relevant fruit classification framework was built and optimized using the model because the image classification method needs to fulfill a specific real-time performance. Among these, the approach combining automatic encoder and convolutional neural network can be utilized to minimize noise. Data optimization can be used to improve it because there may be a problem with the over-classification of photos. In the event of a small amount of data, this classification technique performs somewhat more generally than previous algorithms. In order to ensure that the model has a strong generalization ability, the algorithm also includes an automatic noise mitigation encoder, which can efficiently decrease the impact of data noise on model performance. The model's time for training may lengthen because the new approach is based on a neural network (Cervantes et al., 2017). Figure 5 displays the enhanced fruit categorization algorithm.

The encoder modular network is utilized for classification in this study to address the issue of automatic denoising of complicated image structure. The noise reduction automatic encoder and the sparse automatic encoder are organically merged based on the current CNN model, and the input original image data is normalized to the thin autoencoder. The information pertaining to the image features is then extracted using a convolution-optimized neural networks model.

It is crucial to process the image with tools like grayscale and denoising, to choose a specific number of training inputs and test sets to the data set, and then to use the training set as the input component of the model after unsupervised learning processing when using the designed convolutional neural networks and neural network framework for fruit classification. The input object is then encoded and decoded using the concealed layer of the noise reduction autoencoder, and the processing outcomes are output to the sparse autoencoder for the subsequent layer for normalization. The sparse hidden layer trains the data one layer at a time, and then outputs the results of that training to the Softmax classifier. The gradient descent approach can be used to shore up the classifier model's parameter training in order to increase classification accuracy and enhance the performance of the image classification deep learning model. The efficiency of a fruit classification approach is next evaluated in light of the classification outcomes produced by the model once the network model has been confirmed using the image test set.

The standard neural network's restriction to just a few features in fruit categorization can be overcome by the upgraded convolutional neural network model. By normalizing sparse autoencoder, the over-modeling phenomena in data processing can be averted, and by using the concealed layer of the sparse autoencoder to train the data layer by layer, more abstract representational characteristics may be obtained. As a result of using an optimized model, the categorization result may be more accurate. Training and testing phases make up the bulk of the upgraded deep learning network model. The testing phase is primarily used to evaluate and assess the model in light of the experimental classification findings. The training phase is mostly used to construct an efficient visual classification model (see Figure 6).

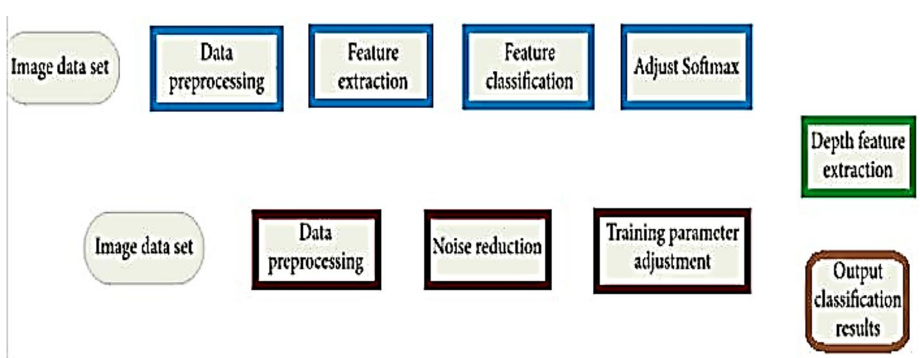


Figure 5. Enhanced classification of fruits algorithm's flowchart.

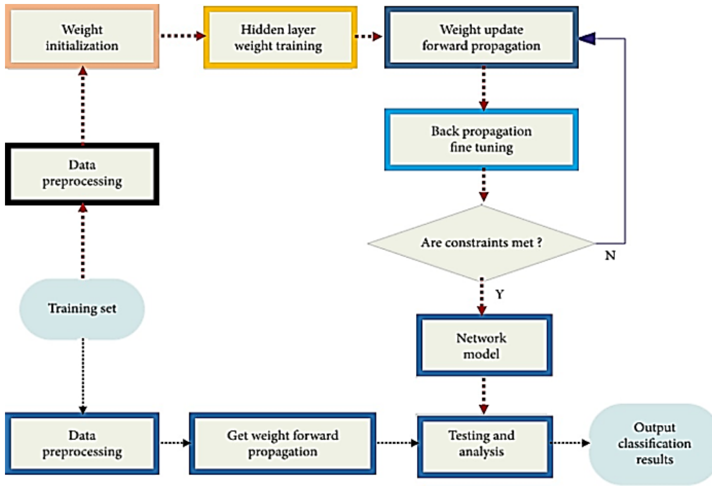


Figure 6. Deep learning network model's process as it has been modified for the suggested model.

4. Applying deep learning networks to fruit identification

Fruit identification systems have been used in a number of real-world scenarios at the checkout counter, where they may very well use scanner tags rather than human ones. It can also be used as a blind person's aid. In grocery stores, where the cashier is required to identify each kind of product whose cost it determines, the identification of various fruit species is a frequent task. The best course of action in this situation is to offer a fruit recognition system that automates price labeling and measurement. Although multiple investigators addressed the issue of fruit identification, as seen in Eizicovits et al. (2016), the challenge of creating a quick and accurate fruit detection system continues, as noted in. This is due to the wide variation in the appearance of fruits in situations in the field, comprising their color, type, scale, appearance, and reflection qualities. Lately, the categorization and recognition of objects have seen significant advancements thanks to deep artificial neural networks. The cutting-edge PASCAL detection technology has two phases (Zhao et al., 2016). Selective searching and edge boxes, among other methods for identifying desired areas of an image, are implemented in the pipeline's first stage before being fed into a more advanced neural categorization network.

Although the pipeline's great recording success, real-time application cannot be accomplished as a consequence of the pipeline's high computing cost. The system can concurrently predict and identify object borders at each place by combining a shallow convolution net for categorization with the object proposition network, which is commonly referred to as region proposition network (RPN) (Eizicovits et al., 2016). The two networks' parameters are similar, resulting in significantly higher ratings and an optimization for robotic applications. The Author will explore in detail the various DL models utilized in solving fruit detection challenges, as stated in Table 1.

Table 1. The fruit detecting algorithms used in machine learning

Year	DL method	Dataset	Partition	Accuracy	Partition
2016	Faster R-CNN	TL + Field Farm	82% Train, 18% Test	Faster R-CNN	0.83 F1
2017	VGG-16	Orchard	2268 Train, 482 Test	VGG-16	95%
2018	CNN	Kiwifruit	70% Train, 30% Test	CNN	89.29%
2019	Faster R-CNN + Iv2	Cherries	60% Train, 20% Val, 20% Test	Faster R-CNN + Iv2	85%
2019	M-RCNN + Retina Net + FPN	Straw-berry dataset	2000 Train, 100 Test	M-CNN + RetinaNet + FPN	95.78%
2020	IM-R-CNN	Apple	368 Train, 120 Test	IM-R-CNN	97.31% PR

The Faster R-CNN architecture was chosen as an extractor of features to find the sorts of fruits within the box or anyplace by employing the Faster R-CNN framework in a special and modified fashion for the goal of fruit identification. The images supplied were separated during preprocessing, and the function extractor that was utilized in two modules then produced the convolutional neural network map (Lapin et al., 2014). The initial module, additionally referred to as a regional proposition network (RPN), places an anchor box at each position on a map of features using a sliding neural net. Then, the suggested regions—defined as the location of the box's boundaries and its likelihood of falling within a class or the entry's background—were defined using fully connected, similar layers. The second units generated the ROI while also cropped the feature map to use the suggested area. The ROI is then transmitted from an entirely linked layer onto a layer that pools data for probability calculation and reshaping bounding box coordinates.

5. Application of machine learning networks to fruit identification

In many different fields, the image categorization system is crucial. Images are being recognized increasingly quickly, and deep learning is assisting more and more industries. Fruit categorization is a challenging issue due to the wide range of varieties. The two main problems with categorization are typically: 1) classifying fruit into separate categories (for instance, separating apples and pears), and 2) classifying similar fruit kinds (such as apples, to distinguish between Red Delicious, nectar crisp, golden tasty, Gala, and other variations). However, due to variances in form, color, age, and other factors, it is still challenging to accomplish correct categorization, even with the initial kind of problem. The accuracy of the categorization DL models is an additional problem (Lu et al., 2018).

5.1. Datasets

Sets of information are samples of practical data in photographs, and the process of digitally collecting such photos is referred to as gathering data. Excellent data are necessary to produce a decent classifier. When there aren't enough tagged samples, identification is the most challenging task. In the span of the Author's investigation, the Author discovered that most researchers, particularly those who focus on recognizing objects, mostly engage in the real-time recognition of fruits in farms. Each investigator used different datasets. The Author am going to briefly go through a few of the datasets used by scientists to categorize fruits. Although the Author used a number of datasets, I will concentrate more on the one that I made publicly available on the internet. Table 2 lists the datasets which were accessible (Cervantes et al., 2017; Li et al., 2010).

Table 2. Dataset specification.

Name	Number of classes	Total number	Train set	Val set	Test set
Oran ge Fruit	5	1000	600	20 0	200
Fruit 26	26	124, 212	85, 260	—	3895 2
Field Farm	7	122	100	—	22
Cherr y	2	14,3 80	—	—	—

Fruit 360 is the most well-known and often used database for classifying fruits. This dataset was used by a number of academics in their study (Arivazhagan et al., 2010; Cervantes et al., 2017). The Fruit 360 dataset, which comprises 82,000 photos representing 120 kinds of fruits, is broken up into three separate sets: a set for training with 60,600 image information sets, a test set with 20,000 image information sets, and a set of validations with 106 image sets. The information was obtained by turning a low speed engine (3 rpm) and recorded for 20 seconds each, because of the variation and the inconsistent illumination, the backgrounds in all the images were changed to white. A white background of perfect 100 percent squares was present in each photograph.

5.2. Comparable evaluation indicators

A confusion matrix is a table used to evaluate the performance of a classification model in ML. It provides a summary of the predictions by comparing them to the actual true labels of the data. The matrix is particularly useful for tasks with multiple classes or categories, allowing the Author to understand how well the model is classifying instances into each class.

A confusion matrix is a square matrix representing the counts of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions made by a classification model for each class in the dataset. Each row of the matrix corresponds to the actual class, and each column corresponds to the predicted class.

The confusion matrix provides valuable insights into the performance of a classification model, helping to assess its accuracy, precision, recall, and F1 score for each class. From the matrix, various evaluation metrics can be derived, such as the overall accuracy of the model, sensitivity (recall), specificity, and the precision-recall trade-off. Figure 7 shows the architecture of the confusion matrix.

It is extremely useful for measuring recall, precision and accuracy.

TP (true positive): It refers that the Author predicted positive, and it is true.

TN (true negative): It refers that the Author predicted negative, and it is true.

FP (false positive): It is a type one error and refers that I predicted positive, and it is false.

FN (false negative): It is a type two error and refers that I predicted negative, and it is false.

$$Accuracy = 100\% \times \frac{TP}{TP+FP} \quad (1)$$

$$Recall = 100\% \times \frac{TP}{TP+FN} \quad (2)$$

$$F1 - Score = 100\% \times \frac{2 \times Accuracy \times Recall}{Accuracy+Recall} \quad (3)$$

6. Results and discussion

Figures 8 shows the training and validation behaviors against the periods of the proposed machine learning-based model with the fruit dataset from Kaggle 360. The Author used Fast-CNN as a final classification model because this technique gives the Author greater accuracy than the other methods used (Arivazhagan et al., 2010).

Figure 9 shows comparison of the most well-known and used methods of fruit classification according to modern algorithms and compare them with the proposed method in the Author's work, so that each comparison of each method focuses on the rate of loss, accuracy in work, and the results of the method, as well as the training rate used and required in order to achieve the desired results for every style and method.

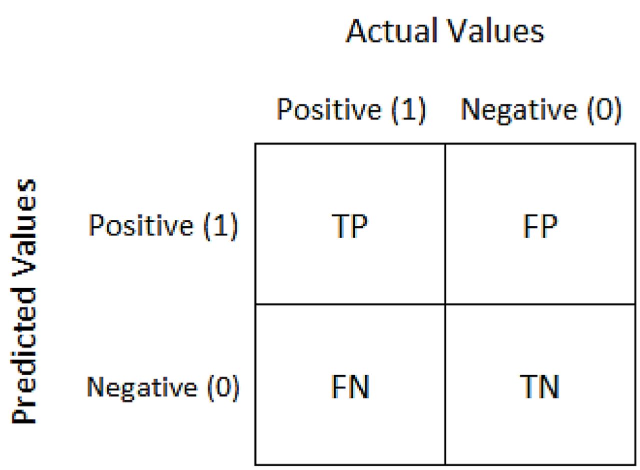


Figure 7. Confusion matrix architecture.

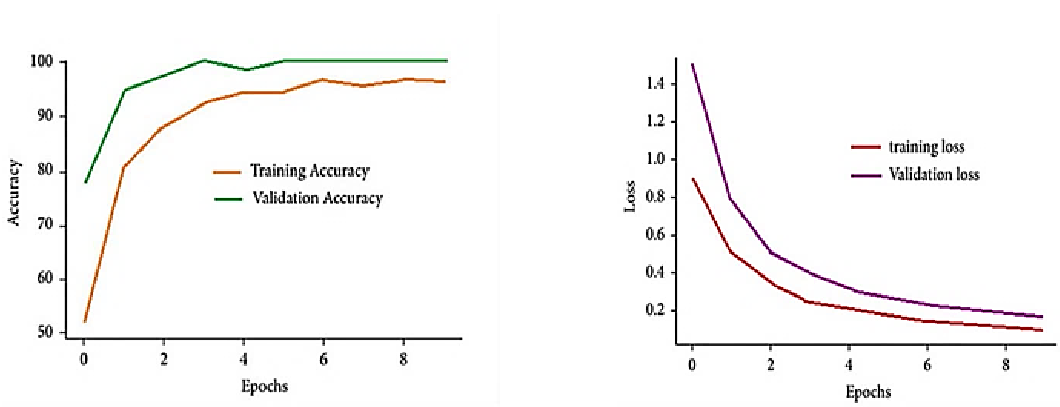
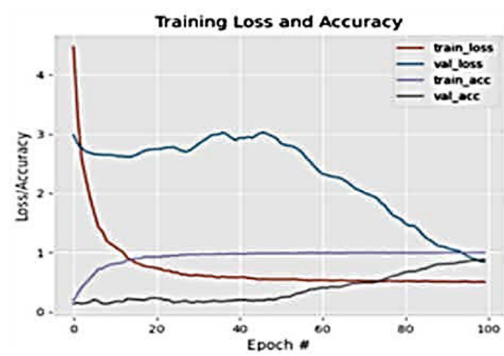
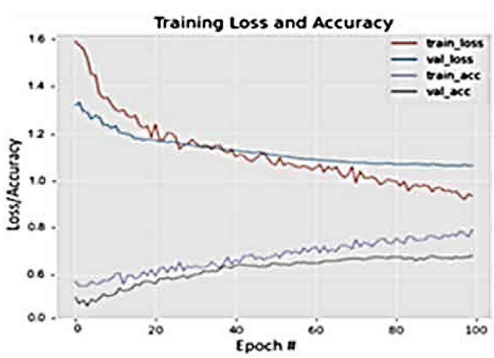


Figure 8. Training, validation accuracy and loss vs. epoch graphs of the machine learning network for the Fruit 360 data set.

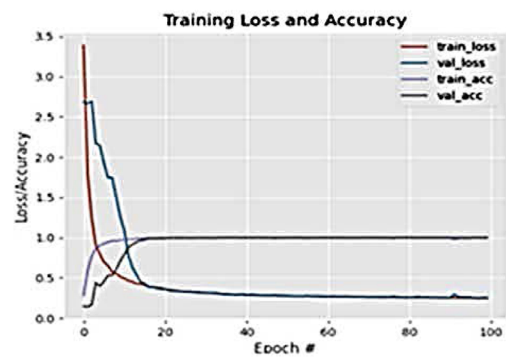
VGG-16



CNN



RCNN



Our Method

The average precision of every model developed using the fruit sample is shown in Figure 10. The result indicates that the lowest accuracy (64%) belongs to VGG-16 (Kuang et al., 2015). Even though CNN had recently added layers, its results (85%) outperformed VGG-16. RCNN's performance, which had an accuracy of 88%, was marginally superior to CNN's. This occurred as a result of just training the entire models for the remaining iterations after the first 20 rounds in which the newly inserted layers were included. Because the suggested model uses custom polygons in addition to existing preparation methods, the model's precision was 99%. The predicted rate was boosted by these preparation methods (Arivazhagan et al., 2010; Kuang et al., 2015).

7. Conclusions

In this paper, the Author looked at and analyzed a variety of deep learning techniques for fruit identification and categorization that have been put out by other researchers. While analyzing several mechanical methods for fruit recognition and categorization, the Author discovered that earlier review studies had primarily concentrated on the use of machine learning methods in the area. Models based on deep learning have a robust efficiency on many image issues related to classification, although little focus has been given to them. The Author have reviewed research on fruit identification and categorization using machine learning algorithms to close this gap. A thorough analysis that took into account the descriptions of attributes, recognition and categorization algorithms, as well as various datasets for fruits identification and sorting, was also given. Additionally, outstanding difficulties regarding data collections, representation of features, and algorithms for classification were discovered after careful study of the approaches examined. In addition, the Author also ran tests with CNN simulations to show how DL models are used in agriculture. In order to assist newcomers working in this sector, the Author expects that this poll will teach the fundamental ideas and uses of DL algorithms in the area of fruit recognition and categorization. The recent proposed model demonstrated impressive results in accurately identifying the quality of various fruits, such as apples (with 99.50% accuracy), cucumbers (99%), grapes (100%), kakis (99.50%), oranges (99.50%), papayas (98%), peaches (98%), tomatoes (99.50%), and watermelons (98%).

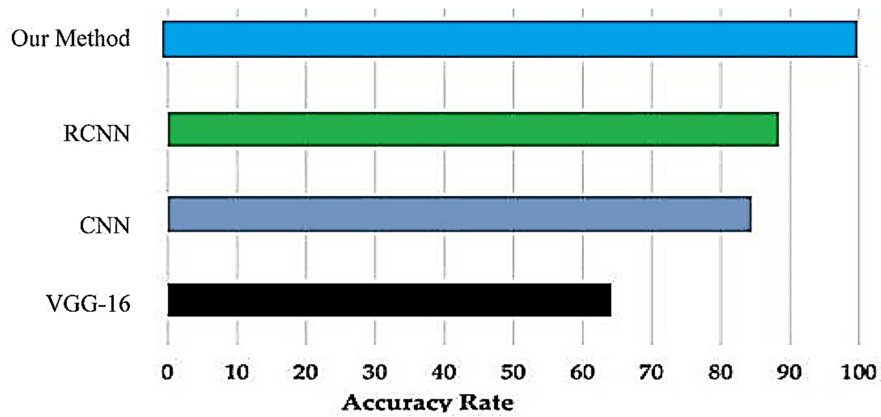


Figure 10. Degree of accuracy for every model.

Conflict of interest

The author has no conflict of interest to declare.

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