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FRUIT CLASSIFICATION QUALITY USING CONVOLUTIONAL NEURAL NETWORK AND AUGMENTED REALITY

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ABSTRACT

In Indonesia, the need for fruits is still relatively low. The contributing factor is that the quality of fruits in Indonesia is still quite low compared to imported quality fruits. Until now, Indonesia still relies on imported fruit rather than local fruit. For this reason, researchers have created a new innovation in this modern era, namely the application of fruit quality classification using Conventional neural networks and Augmented Reality. Convolutional Neural Network is one of the deep learning algorithms that can work well in image processing, such as classification and comparison. This research is to classify fruit using augmented Reality, which is combined with the conventional neural network. The CNN algorithm is good enough to classify fruit images into seven categories with an error of 10%. This shows that CNN, which is one of the deep learning algorithms, can be applied in agriculture. This application only needs to use a smartphone in the following way: scanned into real fruit, then this application will issue fruit quality information and three-dimensional images to compare fruit quality. So that farmers can easily separate which fruit is of low or high quality.

Keywords: *Convolutional Neural Network, Deep Learning, Augmented Reality, Fruit, Quality*

1. INTRODUCTION

In this modern era, technology is beneficial for human life, especially for agriculture. With the presence of technology, they are helping farmers to improve the quality of fruit harvests using the application of fruit quality classification with CNN and Augmented Reality. CNN shows good performance in imaging fields such as image classification and image recognition (Girshick et al., 2014). Therefore, various CNN models have been developed, and many studies using them have been carried out. The model is made according to the characteristics of the data and fieldwork, and transfer of learning using deep learning with the development of pre-training models built-in favorable conditions are also applied (Pan et al., 2010).

One of the advantages of deep learning like CNN is that it can extract features and analyze data automatically without the need for professional knowledge to enter data.

The feature extraction process is important to get information in the data. This process is to determine the performance of machine learning. A feature is extracted by prior human judgment, but more objective and better features can be achieved as this process progresses by incorporating deep learning. Automatically extracted features provide information that cannot be seen traditionally and the scope of research.

Fruits provide an important role as food in our daily lives. It provides essential nutrients for the health and maintenance of our bodies. With the help of Artificial Intelligence , Machine Learning , and Augmented Reality can help develop an automatic fruit classification system with dataset information for each fruit and display three-dimensional images for the final result of information from application usage. This system can help us to choose the fruit that suits us and teach us about the characteristics of a particular fruit.

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2. LITERATURE REVIEW

2.1 Appropriate Sensor

Recognition and classification of fruit as a subset of object classification is an inherently more complex task than other subsets of object classification. Fruit present crucial sensory and feature characteristics, which are also dependent upon the widespread applications of it.

The recognition and classification of fruit as part of object classification is an inherently more complex task than other parts of object classification. Fruits present important sensory characteristics and features which also depend on their wide distribution application. for it to be done

The selection of sensors for data acquisition is a major challenge for classification. Starting from black and white (B/W) cameras to non-visual sensors such as acoustic and tactile sensors have been used for fruit classification, but not all sensors are suitable for all applications. It is evident from [9, 10, 11, 17, 18, 19, 82] that acoustic and tactile sensors are less suitable for non-destructive classification and recognition. These sensors require physical contact or excitation of fruit for data acquisition. In addition, the visual sensor is very sensitive to many factors, namely the condition of illumination.

2.2 Feature Selection And Representation For Classification

Features are physical characteristics of an object that can distinguish it from other objects. The fruit has many physical characteristics, namely color, texture, shape, and size, that can be used as a feature for effective classification. The fruit has a lot of variation between and intraclass and equations. Variations between classes are major changes, namely changes in color, texture, and shape, whereas intraclass variations are generally much more subtle and difficult to distinguish, i.e., different types of mango or apple have only a slight variation in features. The ideal choice of features would allow the system to handle inter and intraclass classification.

Computer-based representation features are another dimension of this challenge. Significant studies have been reported regarding feature representation. Investigations have shown that one feature cannot be considered sufficient for the effective classification of fruits and vegetables or objects in general.

2.3 Machine Vision Approach

The machine vision approach is a set of machine learning algorithms used for image classification and recognition. Designed algorithms cancan be categorized in many ways. The usual categorizations are *Neural Network*-based and handcrafted. Selection of the right algorithm in any machine learning application is always AN important task but even more important in the case of fruit.

However, the authors note that it is not very accurate to construct the obstacle map performing the proposed use of conditional random fields for almond segmentation. They proposed a five-class segmentation approach, which studied features using the Sparse Auto Encoder (SAE). These features were then used in the CRF framework and proved to outperform previous work. They get impressive segmentation performance but do not perform object detection. Furthermore, they note that occlusion presents a major challenge. Intuitively, such an approach is only capable of dealing with low levels of occlusion. Deep neural networks have shown high expectations when used for multiple multi-modal systems in areas outside of agricultural automation, such as in, where audio/video has been used with great success, and in where image/depth performs better than with the use of each modality alone. This work follows a similar approach and demonstrates the use of a multi-modal region-based fruit detection system. CNN is a very powerful algorithm closely related to the deep neural network, which is widely used for image classification and object detection. The powerful feature extraction capabilities and hierarchical structure of an image make CNN a very powerful algorithm for various image and object recognition tasks.

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For this application, apply augmented Reality as an object detector in three-dimensional fruit. Then, from three-dimensional augmented Reality, objects detect and read the information on objects scanned on a camera with a CNN camera, helping to perform fruit analysis and classification. In the Fruits dataset, 1260 images were taken from 7 different categories: 85% of the images were used for training, and 15% were used to test the model. The network was trained for ten epochs with a batch size of 14. The accuracy of the proposed model is 98.74%. Comparison model with the conventional model shows that the results of this model are very good and promising to be used in real world applications. The training image for each fruit is 1260, and the test image is created from the detection set using this fruit classification approach.

3. METHOD AND DATASET

3.1 Method

Convolutional Neural Network (CNN) is included in the type of Deep Neural Network because of its high network depth. Technically, a convolutional network is an architecture that can be trained and consists of several stages. The result of each stage are several arrays called feature maps. The output of each stage is a feature map of the processing results from all locations on the input. In stage consists of three layers, namely the convolution layer, activation layer and pooling layer. *CNN* can be prepared to perform image analysis tasks including object recognition, segmentation, classification, and image processing. *CNN* can know to recognize certain patterns by feeding them large amounts of food from the data.

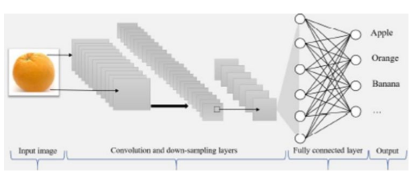

Figure 1: A Convolutional neural network (CNN)

Source: Mehenag Khatun, *Fruits Classification using Convolutional Neural Network,* July 2020

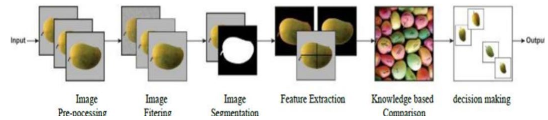

Figure 2: Flow of fruit classification process

Source : Mehenag Khatun, Fruits Classification using Convolutional Neural Network, July 2020

of orange, 180 pictures of pears, 180 pictures of pineapples and 180 pictures of strawberries were taken and from 140 test pictures 20 pictures of apples [red variation] , 20 images of banana [yellow variety], 2 images of mango [green variety], 20 images of orange, 20 images of pears, 20 pineapples pictures and 20 pictures of strawberries were taken.

Then remove noise, sharpen, smooth the image as well as resize the image. *RGB* image changed to gray image also image contrast increases to a certain degree. Such pre-processing operations are also called grading Segmentation, is used to partition an image into parts. The purpose of image segmentation is to determine and change the representation of an image, which is more meaningful and easier to analyze. Image segmentation are categorized on the basis of the two properties of discontinuity and similarity. The method based on discontinuity is called the boundary-based method. and based on a method called the region-based method. The next step in the fruit classification process after segmentation is feature extraction. The main and important visual external features for fruit is its color, size, shape, and texture. The feature description is a representation of the image or part of it, the extract of which is useful information and discard unnecessary information used for image recognition and object detection.Knowledge-Based Decision Comparison of features extracted from images takes place with predefined classification and sorting criteria or rules. The features are compared based on the extracted features, and a classification is made for the fruit. That knowledge-based comparisons and decision making have been made using a convolutional neural network algorithm.

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Figure 3 :The method

Source : Dewi Agushinta R., Ihsan Jatnika , Henny Medyawati , Hustinawaty, Augmented Reality Design of Indonesia Fruit Recognition, December 2018

The research method used to design Augmented Reality is divided into several stages, shown in Figure 3. At the planning stage, identification of problems and information related to research are done. Supporting theories are collected from various sources. Furthermore, at the analysis stage, formulate problem solving based on supporting theories that have been collected in the form of an overview of how the application program works with the help of the *CNN* method for the analysis process. At the design stage, the application program is designed according to the problem solving that has been determined.

In designing this Augmented Reality application program, we need to consider and analyze hardware and software requirements that will be used so that the program can run as expected. The process of developing this application program requires hardware and software as the media and tools used. It starts from model design until the program is finished, and when the program is implemented, it becomes real living environment. There are several hardware needed for application programs ranging from creation, storage until the program is used in actual conditions. The first is the computer used for designing, writing programs, and testing programs. Next is the database server that functions as a database storage containing fruit data and other information will be used for the program. In addition, the program requires a mobile device that has a minimal Android camera sensor. Almost all mobile devices with the Android operating system already have a camera. This tool functions as a media to install and run programs that will be used by users to get information about fruits. then in the process of making Augmented Reality, there will be an automatic dataset reading to separate the quality of the fruit in scanning photos using the camera.

3.2 Dataset

The data used in this case uses data *Fruit Images For Object Detection.* The dataset can downloaded at

https://www.kaggle.com/mbkinaci/fruit-images-for-object-detection

training and testing, all the pictures were choose from the fruits 360 dataset. The dataset contains different fruits pictures of classes. Class represents one type of fruit are apple, banana, orange, pear, mango, pineapple and strawberry. Then the classes are chosen some fruits have similar appearances and frequently bought in markets. the data set has been in order to not make the paper to extensive. All types of a fruit reside under the same class. This means all types of apples reside under the apple class and similar for each fruit. Each class have approximately 200 images. After removing the background, all the fruits were resized to 100×100 pixels of standard RGB pictures. Here has been used 1260 images (85%) to create the training set and the rest 140 images (15%) for testing the model.

4. MORPHOLOGICAL FEATURES

The most common characteristics used for fruit classification are morphological characteristics, namely shape and size. Size is a physical dimension measurement that tells about the appearance of an object. Then, area, circumference, length of major and minor axes, and aspect ratio are usually used as morphological features. Morphological features are widely used in industrial automatic sorting purposes. Area is a scalar quantity which is the actual number of pixels in the region. Perimeter is a scalar quantity and it is the distance around the boundary of a region. The principal axis length is a scalar quantity that represents the principal axis length (in pixels) of the principal axis of the ellipse which has the same normalized second center moment as the area. The length of the minor axis is also a scalar that determines the length of the minor axis (in pixels) of the minor axis of the ellipse which has the same normalized second center moment as the area.

5. TEXTURE FEATURE

Texture represents the appearance of the surface and the distribution of elements. Texture is an important feature in predicting surfaces in terms of contrast, roughness, orientation, entropy, etc. Various techniques are used to describe the texture of an image. In a model-based approach, a set of parameters derived from the variation of pixel elements is used to define an image model such as the Gaussian Markov Random Field (GMRF), the fractional Brownian motion conditional probability of a particular pixel depending on the neighboring pixel values.

6. COLOR FEATURE

The image has an RGB color model. The most common Color Model in image processing, is based on the primary colors red (R), green (G), blue (B). Basically, for color features, each image is separated into red, green and blue fields, respectively, and through these fields, the mean, median, standard deviation are calculated. The *NTSC* or *YIQ* color space consists of three luminance components, which represent grayscale information, hue and saturation, which carry information from a signal.

7. TENSORFLOW

TensorFlow is programming library for *machine learning* applications such as neural networks. TensorFlow was developed by the Google Brain group for exploration and advancement of Google products. TensorFlow can run on multiple CPUs and GPUs in workspace conditions and is used in areas such as voice recognition, personal computer vision, mechanical technology, data recovery, and characteristic languages.

8. THE SYSTEMWORK

The framework takes an image of the fruit with the camera, and the first step runs a tiny nervous system in TensorFlow to recognize whether the image is a natural product. The image is then passed to the TensorFlow neural system learning.

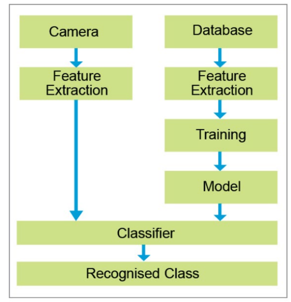

Figure 4 : Block diagram of fruit recognition system

Source:https://www.electronicsforu.com/electronics-projects/electronics-design-guides/fruit-classification-quality-detection-using-deep-convolutional-neural-network

The TensorFlow code is a that alters the union, pooling, and arrange configuration to coordinate the number of classes and classes of pixels in the picture with minor alterations to the last layer. CNN places a convolutional layer and a pooling layer in the concealed layer between the info and yield layers.

In these two layers, the way of downgrading or testing the purpose of the image is repeated. The convolution layer applies weighted channels to a piece of image information that may be useful for grouping, creating element maps. The union layer derives the element map by testing the most significant portion of the component map received from the convolution layer.

This reduces the size of the information while preserving the attributes, further prevents information discrepancies due to area changes and improves the appearance of the nervous system by reducing the size of the information. Given these removed highlights, grouping is performed.

9. KERAS

Keras is a software library that provides a Python interface for artificial neural networks. Keras acts as an interface for the TensorFlow library

10. BASIC STEPS OF IMAGE PROCESSING

Step1: Image Acquisition: This is the first step of image processing in which camera is used for capturing fruits images in digital form and store in any digital media.

Step2: Image Pre-processing: This section removes noise, smoothen the image also perform resizing of images. RGB images are converted to the grey images also contrast of image is increased at a certain level.

Step3: Image Segmentation: Segmentation is used for partitioning an image into various parts.

Step4: Feature Extraction: This section is used for obtaining features like color, texture, and shape, which reduce resources to describe a large set of data before the classification of image.

Step5: Classification: This section analyzes the numerical property of image features and organize its data into categories. It use neural network which performs training and classification of fruits diseases

11. COMPUTER VISION

Computer vision is used to gather information from images captured from the real-time world and includes methods for image acquisition, processing, analysis, and understanding of images to gather symbolic and numerical information. Basically, the goal is to duplicate the effect of human vision by understanding, understanding and classifying images electronically. Computer vision is widely used in the post-harvest industry for quality inspection and fruit grading.

12. AUGMENTED REALITY

Augmented Reality is an interactive experience of a real-world environment in which objects residing in the real world are enhanced by computer-generated perceptual information

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13. TRANSFER LEARNING

Transfer learning is a popular method in computer vision for building accurate models in a time-saving manner. In computer vision, transfer learning is usually expressed through the use of a pre-trained model. A pre-trained model is a model that is trained on a large benchmark data set to solve a problem that is similar to the problem.

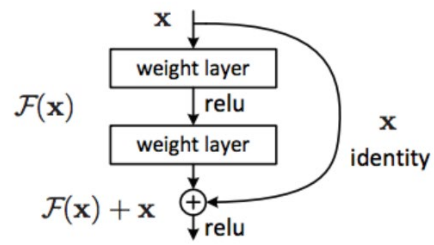

Figure 5 : Residual learning a building block

Source: https://blog.jovian.ai/fruits-classification-using-cnn-and-pytorch-bc583e6052d3

14. IMPROVING MOBILE NETV2

One way to visualize what the CNN model is learning is to look at the activation of the convolution layer, to see what information the layer holds. As can be seen, for the model, the fruit is similar. It mainly retains the shape of the fruit and its texture. This information may not be sufficient to distinguish the two fruits due to their similar shape. One of the missing features, in this case, that would be important for such differentiation is the color of the fruit. Therefore, model accuracy can be improved if additional input features (related to fruit color) are entered into the model. This work proposes three different input features and their corresponding modifications to the model.

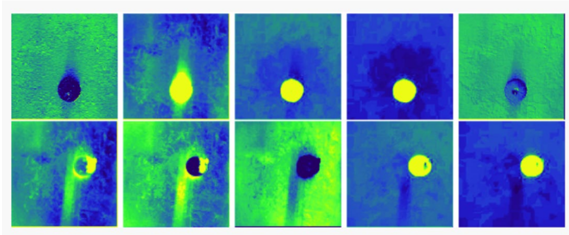

Figure 6 : Similar activations of the first convolutional layer of an orange (top image) compared to an apple (bottom image)

Source: https://link.springer.com/chapter/10.1007/978-3-030-49076-8_1

Single RGB Fruit Color. Besides the image, one additional input feature is to provide the model with a vector with RGB color values of the fruit to be classified. This color should be the one that represents, in general, the given fruit. For instance, bananas would be represented by the yellow color, thus the model receives the vector with RGB color values [1.0, 1.0, 0.0]; in the case of an orange, the vector would be [1.0, 0.64, 0.0]. This vector with three RGB values is feed into the model. RGB Histogram. An image histogram is a graph that summarizes how many pixels are at different scale levels of a given image. For this work, the histogram of each RGB channel was obtained, resulting in a vector of input values, which are then fed into the model. Figure 4 shows an example of an image RGB histogram. At this moment, one disadvantage is that most of the values would correspond to the background colors.

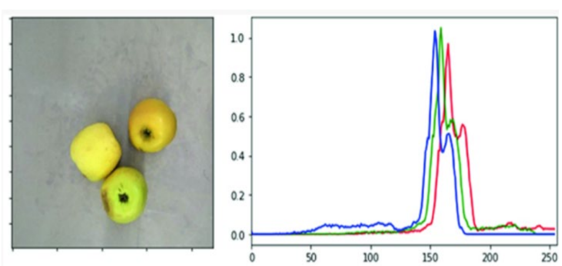

Figure 7 : Image RGB Histogram

Source:https://link.springer.com/chapter/10.1007/978-3-030-49076-8_1

In the case of RGB color and RGB histograms, a multi-input model is implemented. The model takes input images and vectors with color data, then the images are entered into CNN while color data is entered into solid layers. The results from the two networks are combined, and a final prediction is made using softmax activation.

15. COMPARISON OF CNN WITH SVM

Support Vector Machine can used for regression and classification tasks. But, it is widely used in classification objectives. However SVM algorithm has several key parameters that need to be set correctly to achieve the best classification results for any given problem. It is effective in that cases where a number of dimensions is greater than the number of samples. But this algorithm is not suitable for large data sets. Because it needs much time for training. It differentiates the two classes appropriately. However, does not perform well when the data set has more noise. Besides the support vector classifier works by placing data points, above and below the classifying hyperplane there is no probabilistic explanation for the classification. So SVM is not worked very well for data prediction. SVM is used for mangoes classifications for defective and non-defective cases. Here FCM and K-Means algorithms are also used. But for FCM, SVM classification results are not so good. Besides SVM is used only for one fruit detection. It cannot be performed for various fruits and various combinations of color features. CNN (Convolutional Neural Network) algorithm is a more powerful algorithm for classifications. CNN involves various classes for classifications compared to SVM, where classification results are also so good. Besides CNN minimizes the hyper parameters used in the algorithm. As a result it needs not much time for training. The training and testing accuracy of CNN is very high compared to the SVM method. That means it is relatively simple, quick to train, and easy to understand.

16. OPTIMIZER AND LEARNING RATE

For minimizing the error of a model optimizer plays a bigger role. Adam optimizer is used in this scenario. It replaced the classical stochastic gradient descent method, which updates network weights iteratively in training data. For its better execution, it is generally utilized by PC vision researchers.

Call for training a convolutional neural network, Learning rate plays a huge role. The classification will be more perfect if the rate of learning is lower. However optimizer will set aside more exertion to accomplish the global optima reducing the loss. Apart from that higher learning rate may not be the best for the accuracy. As a result achieve the desired goal become harder

17. EXPERIMENT RESULT

17.1 Testing And Training Data

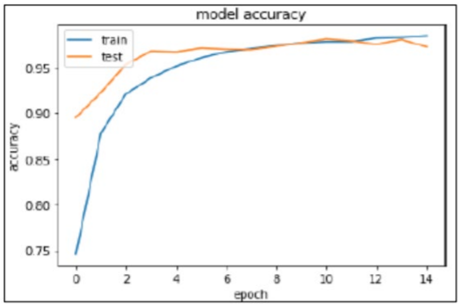

Figure 8: convolution neural network accuracy

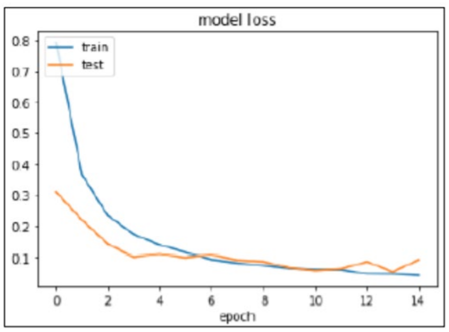

Figure 9: convolution neural network loss

This figure clearly shows that the model makes a good fit as here the testing error is lower than the training error. Running so many test cases, using dropout at a favorable label, checking early stopping at the end of an epoch give a good model for classification

The testing process in this study uses 345 images testing which consists of 23 images from 15 classes of fruit images. The testing process is carried out to test the performance of the *CNN* model that has been obtained from the learning process.

After testing, the next step is calculating accuracy. Accuracy calculations are carried out to assess the percentage of success of the *CNN* model in classify images. Accuracy can also be a benchmark in comparison and development of *CNN* models made in the future.

17.2 Confusion Matrix

Using our data augmentation method, the confusion matrix over the test set was listed The sensitivity, specificity, precision, and accuracy over the test set was presented in The overall accuracy of all classes is defined as the number of correctly identified fruit images divided by the number of the whole fruit images. The result of our overall accuracy is 94.94%. Note that overall accuracy is equal to the average sensitivity at the condition of equal or similar class numbers, which in our case as shown in Figure.

Class	Sensitivity	Specificity	Precision	Accuracy	Class Number
Anjou pear	91.3%	99.3%	88.7%	98.8%	103
Blackberry	100.0%	99.4%	90.3%	99.4%	102
Black grape	90.1%	99.5%	91.0%	98.9%	101
Blueberry	98.9%	100.0%	100.0%	99.9%	93
Bosc pear	96.9%	100.0%	100.0%	99.8%	96
Cantaloupe	91.6%	100.0%	100.0%	99.6%	95
Golden pineapple	95.5%	99.0%	86.1%	98.8%	110
Granny Smith apple	84.6%	99.4%	89.8%	98.6%	104
Green grape	97.9%	99.8%	95.9%	99.7%	95
Green plantain	98.1%	99.9%	98.1%	99.8%	106
Hass avocado	98.2%	99.2%	88.8%	99.1%	113
Passion fruit	88.1%	99.8%	96.1%	99.3%	84
red grape	94.8%	99.9%	98.9%	99.7%	97
Rome apple	98.9%	100.0%	100.0%	99.9%	88
strawberry	100.0%	99.7%	95.4%	99.7%	104
tangerine	99.0%	99.9%	98.0%	99.8%	101
watermelon	90.4%	99.9%	99.0%	99.3%	114
yellow banana	94.7%	100.0%	100.0%	99.7%	94
Average	94.94%	99.71%	95.34%	99.43%	100

Figure 10: Performance of each class

Source: Yudong Zhang, Zhengchao Dong , Xianqing Chen , Wenjuan Jia , Sidan Du , Khan Muhammad, Shuihua Wang, Image-based fruit category classification by 13-layer deep convolutional neural network and data augmentation,Henan: February 2019

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}	C_{18}
C_1	94	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0
C_2	0	102	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C_3	0	10	91	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C_4	0	1	0	92	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C_5	0	0	0	0	93	0	3	0	0	0	0	0	0	0	0	0	0	0
C_6	0	0	0	0	0	87	7	0	0	0	0	1	0	0	0	0	0	0
C_7	0	0	0	0	0	0	105	0	0	0	3	0	0	0	0	2	0	0
C_8	9	0	0	0	0	0	1	88	4	2	0	0	0	0	0	0	0	0
C_9	2	0	0	0	0	0	0	0	93	0	0	0	0	0	0	0	0	0
C_{10}	1	0	0	0	0	0	0	1	0	104	0	0	0	0	0	0	0	0
C_{11}	0	0	0	0	0	0	1	0	0	0	111	0	0	0	0	0	1	0
C_{12}	0	0	9	0	0	0	0	0	0	0	0	74	0	0	1	0	0	0
C_{13}	0	0	0	0	0	0	0	0	0	0	0	2	92	0	3	0	0	0
C_{14}	0	0	0	0	0	0	0	0	0	0	0	0	1	87	0	0	0	0
C_{15}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	104	0	0	0
C_{16}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	100	0	0
C_{17}	0	0	0	0	0	0	0	0	0	0	11	0	0	0	0	0	103	0
C_{18}	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	89

Figure 11: Confusion matrix over test set

Source: Yudong Zhang, Zhengchao Dong , Xianqing Chen , Wenjuan Jia , Sidan Du , Khan Muhammad, Shuihua Wang, Image-based fruit category classification by 13-layer deep convolutional neural network and data augmentation,Henan: February 2019

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The fruit with worst performance is eighth class (Granny Smith apple). From the confusion matrix in Figure 7 Granny Smith apples were misclassified as Anjou pear, 1 Granny Smith apple was misclassified as golden pineapple, four Granny Smith apples were misclassified as green grapes, and 2 Granny Smith apples were misclassified as green plantains.

17.3 Pooling Technique Comparison

Pooling layer aims to reduce the dimensions of the feature map (downsampling) and overcome overfitting. Dropout layer is a regularization technique in a neural network where some neurons will be selected randomly and not applied during the training process. Flatten layer is used to transform the feature map in a multidimensional array into a vector form that will be used as an input for the fully connected layer. The difference between traditional neural network and CNN is the convolution layers. The input of the convolution layer is an image which is used for the classification process, and the output is the feature map.

Pooling	Overall Accuracy
Max-pooling	94.94%
Average-pooling	94.83%

Figure 12 : Pooling Technique Comparison

Source: Yudong Zhang, Zhengchao Dong , Xianqing Chen , Wenjuan Jia , Sidan Du , Khan Muhammad, Shuihua Wang, Image-based fruit category classification by 13-layer deep convolutional neural network and data augmentation,Henan: February 2019

The comparison results between max-pooling and average-pooling approaches in showed max-pooling gives 0.11% better accuracy than average-pooling. Previous studies have shown that average pooling considered all elements in the region, hence, it will down-weight the strong activations. Nevertheless, the improvement of max-pooling in this study is slight

17.4 Optimal Structure CNN

Number of Combined Layers	Overall Accuracy
2	90.17%
3	94.06%
4 (Proposed)	94.94%
5	92.33%
6	92.00%
7	92.89%

Figure 13 : CNN structure with different number of convolution layers

Source: Yudong Zhang, Zhengchao Dong , Xianqing Chen , Wenjuan Jia , Sidan Du , Khan Muhammad, Shuihua Wang, Image-based fruit category classification by 13-layer deep convolutional neural network and data augmentation,Henan: February 2019

The convolution layer and pooling layer are the most important among all layers. Our CNN contains four combined layers (convolution layer and pooling layer). observed that CNN with 2, 3, 4, 5, 6, and 7 combined layers yielded an overall accuracy of 90.17%, 94.06%, 94.94%, 92.33%, 92.00%, and 92.89%, respectively. Hence, we select 4 combined layers in our proposed structure

17.5 Numerical Experiment

Binary files containing protocol buffers for storing information such as image height, width, depth, and even raw images. Using these files, we can create queues for entering data into the neural network. By calling the batch shuffle method, you can provide random input to the network. The way of this method is to provide an example tensor for images and labels, and it returns a batch size tensor of the form x

image dimensions and batch size x label. This greatly helps lower the chances of using the same batch multiple times for training, which in turn improves network quality.

On each image from the batch we applied some preprocessing in order to augment the data set. The preprocessing consists of randomly altering the hue and saturation, and applying random vertical and horizontal flips. For the hue and saturation, we use the TensorFlow methods: random hue and random saturation. To further improve the accuracy of the network we converted each image from the batch to grayscale and concatenated it to the image.

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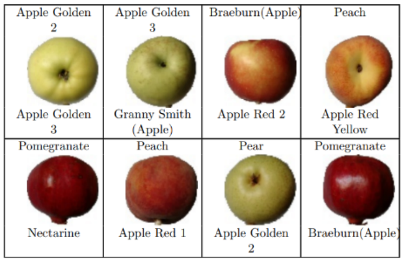

Figure 14: Some of the images that were classified incorrectly. On the top, we have the correct class of the fruit, and on the bottom we have the class that was given by the network.

Source: Horea Muresan, Mihai Oltean, Fruit recognition from images using deep learning,Ausi,2018.

Every 50 steps we calculated the accuracy using cross-validation. This showed steady improvement of the network until reaching 100% accuracy on cross-validation. For the testing phase, we used the testing set and the calculated accuracy was 96.3%.

17.6 Result On Imperfect Images

Collected 173 fruit images with realistic complicated background, 136 fruit images with decay, 145 fruit images with camera not well focused, 161 fruit images with partially occluded by other stuffs.

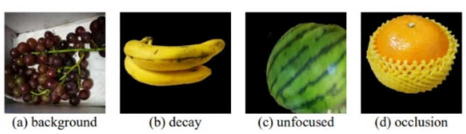

Figure 15 : Imperfect samples of fruit images

Faulty Type	Overall Accuracy
Background	89.60%
Decay	94.12%
Unfocused	91.03%
Occlusion	92.55%

Figure 16 : Performance of our method over faulty image

Source: Yudong Zhang, Zhengchao Dong , Xianqing Chen , Wenjuan Jia , Sidan Du , Khan Muhammad, Shuihua Wang, Image-based fruit category classification by 13-layer deep convolutional neural network and data augmentation,Henan: February 2019

observe that the overall accuracy over background fruit images is 89.60%, over decay images is 94.12%, over unfocused images is 91.03%, and over occlusion image is 92.55%. found that the overall accuracy over decay images is nearly the same as over our clean dataset. For the fruit image with complicated background, the performance deteriorates. In the future, we shall include those imperfect images to our dataset, so our trained CNN classifier can be generalized to identify them.

17.7 Accuracy Calculation Process

The accuracy in this study is variables that represent the performance used to assess the success benchmarks of the CNN model for model classifying fruit images. Accuracy calculations are carried out to assess the percentage of success of the CNN model in classify images. Accuracy can also be a benchmark in comparison and development of CNN models model made in the future.

17.8 Illustration Of Data Augmentation

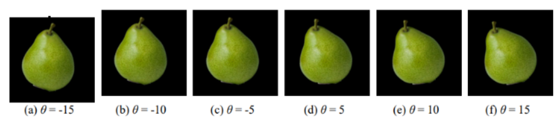

Figure 17: present the generated images by image rotation, gamma correction, noise injection, scale transform, an affine transform, respectively.

Source: Yudong Zhang, Zhengchao Dong , Xianqing Chen , Wenjuan Jia , Sidan Du , Khan Muhammad, Shuihua Wang, Image-based fruit category classification by 13-layer deep convolutional neural network and data augmentation,Henan: February 2019

one fruit image can generate 34 new simulated images. In this way, the training dataset expands times as large as the original. This enlarged training set can help the deep learning learn more stable features than the original training set.

17.9 Evaluating Model

The model is one thing to note that normalization in such types of images works poorly. The accuracy is very low because it is more difficult to distinguish the color of each fruit in some instances.

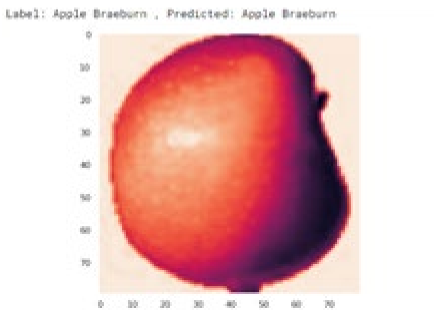

Figure 18: Evaluation Model

Source : https://blog.jovian.ai/fruits-classification-using-cnn-and-pytorch-bc583e6052d3

17.10 Outcomes Of The System

In the proposed system, a model is introduced to recognize fruits from images. During this type of work, machine learning approaches have been developed to establish the model. In this study, a fruit dataset of 4 classes was introduced for introduction. To perform the model task, Convolutional Neural Networks (CNNs) were used, which were developed to carry out a machine learning approach. This model is able to get an accuracy of 99.89%, which proves that the performance of this model to recognize fruit from images is more advanced. The high accuracy of the model shows that CNN is very suitable for this kind of fruit recognition and also found a good algorithm for CNN which has been successfully implemented for fruit recognition. The optimized hyper CNN parameters show that CNN significantly improves fruit recognition accuracy compared to the conventional method using a support vector engine (SVM) with augmented reality features with three-dimensional images.

17.11 Knowledge-Based Comparison And Decision Making

Comparison of features extracted from images takes place with predefined classification and sorting criteria or rules. The features are compared based on the extracted features, and a classification is made for the fruit. Knowledge-based comparisons and decision making have been made using a convolutional neural network algorithm

18. CONCLUSION

A new method for classifying fruits using a convolutional neural network algorithm has been carried out. The results include the acquisition using 7 test samples taken the actual number of 180 and 20 images used for training and testing. Then testing has been carried out. This application is made based on a smartphone with a combination of three-dimensional images and can.

With an image scan that will bring up a three-dimensional image as information on the comparison of fruit quality and fruit quality

Different fruit varieties having different backgrounds were taken for training and testing. The proposed

The algorithm provides an accuracy rate of 98%. This paper explores fruit classification based on the CNN algorithm. Accuracy and loss curves were generated using various combinations of hidden layers for five cases using a 360 data set. This paper discusses various methods and algorithms used for fruit recognition and classification based on computer vision augmented Reality.

Approach. Better cnn performance to achieve better fruit classification. They were taken using a smartphone camera. The CNN model will classify the fruit images that it does not recognize into the fruit class that is considered the most similar among the fruit classes.

19. FUTURE WORK

Hopefully, in the future, the work can be extended with larger datasets having more fruit categories. Have plans to implement several other CNN-based models to compare and further develop three-dimensional-based applications with augmented Reality.

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