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Fruit Quality Classification Using Deep Learning

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ABSTRACT—

Classifying fruit according to quality is crucial in a variety of industrial settings, including factories, supermarkets, and other places. Those with specific nutritional needs may also benefit from fruit quality classification if they use it to select the right fruits. Fruit classification used to be done manually, which takes time and necessitates a constant human presence. Numerous deep-learning techniques for classifying fruits have previously been proposed. Deep learning's detection and classification capabilities suggest that it could be a potent engine for producing results that can be applied to the world of today. As a result, an efficient fruit classification model was created using a convolutional neural network. The model is trained with three categories of fruits which contain good, bad, and mixed-quality fruits. The model is made in Keras. This model will help in detecting the fruit quality efficiently. It has been trained for 350 epochs and had an accuracy of more than 95%. We can input a fruit image and the model will classify the image based on the trained data set and result in the output with the fruit quality.

Keywords— Deep Learning, classification, and convolutional neural networks

Introduction

One of the greatest economic sectors, agriculture, and horticulture is crucial to India's economic development. In India, human specialists continue to carry out the customary fruit examination. A lot of time is spent in the fields or factories inspecting the crops' quality. In this project, the fruit or vegetable quality is evaluated using an affordable and secure method based on appearance, shape, and size. Fruits are sensitive materials and should only be evaluated using non-destructive methods. Fruit color is more of a visual trait, while fruit size is the most important physical characteristic. Hence, classifying fruit is essential for assessing agricultural output, ensuring that quality criteria are met, and raising market value. It also helps with operations related to planning, packaging, transportation, and marketing. The process will be unduly slow and occasionally prone to error if categorization and grading are done manually. Fruits and vegetables are sorted by color, size, and other factors by the workers. If an automated system is constructed using the appropriate programming language and these quality measures are mapped into it, the work will be accomplished more rapidly and error-free.

Fruits are an important part of a healthy and balanced diet since they provide a variety of critical nutrients that are required for the normal functioning of the human body. Fruits are high in vitamins, minerals, fibre, and other plant chemicals that aid in the prevention of chronic diseases. People who consume a diet high in fruits and vegetables have a lower risk of chronic diseases such as heart disease, stroke, diabetes, and several types of cancer, according to research. Fruits are particularly important because they are high in antioxidants, which help to protect against cellular damage and inflammation. AI and ML can be used to develop an automatic fruit classification system that can help people identify and learn more about different types of fruits. Computer vision techniques can be used to create this system, which will analyse the physical traits of fruits such size, shape, colour, and texture. By training the system on a large dataset of images of fruits, it can learn to classify different fruits accurately and quickly. Such a system can be helpful for individuals who may not be familiar with certain fruits and their nutritional benefits. It can also aid in teaching children about different types of fruits and encouraging them to make healthy food choices. Additionally, the system can be used to assist robots in identifying and harvesting fruits, which can improve efficiency and reduce waste. Overall, the application of AI and ML in fruit classification can have significant benefits in promoting healthy eating habits and optimizing fruit harvesting processes.

For the purpose of classifying fruits according to their colors, there are numerous different color systems in use. There are several ways, including fuzzy logic, neural networks, genetic algorithms, and systems based on color histograms. To check the fruit's size and color, the entire system was created using MATLAB software. Although the fruit's color plays a significant role in classification, the size also plays a role in resolving issues of this nature because some fruits' colors are comparable. To classify fruit according to kind, valuable information must be taken from the fruit's surface using its color and size. Fruit samples are examined to determine their size, shape, and color using an artificial neural network (ANN).

Fruit detection and recognition systems can have various applications in the food industry, including smart refrigerators and online shopping platforms. By using these systems, smart refrigerators can track the freshness and quantity of fruits, while providing users with information about the nutritional content of different fruits. The system can also suggest healthier options based on a user's preferences and past consumption patterns.Moreover, in supermarkets and online shopping platforms, fruit detection and recognition systems can help customers choose fruits that are in season and of high quality. The system can also provide information about the origins of fruits, their nutritional content, and recipes that can be made using them. This can be particularly useful for people who are trying to make healthier food choices.Overall, fruit detection and recognition systems have various applications in the food industry, and they can provide users with valuable information about the nutritional content and freshness of different fruits. By using these systems, people can make more informed decisions about the foods they consume, leading to better health outcomes.

Related Work

[1] Fuzzy Logic Fruit Sorting and Grading:

The study describes a computer vision-based automated system for grading and sorting agricultural products. The adoption of a machine vision-based system was meant to replace manual techniques of fruit classification and sorting. Consistency in grading and sorting is difficult to maintain when using a manual examination. A method for sorting and grading agricultural items, such as fruits, has been suggested in this study work. The first step in the suggested method is to photograph the fruit with a digital camera. After being acquired, the image is analysed using image processing software before being sorted and graded using fuzzy logic techniques. Fruit is categorised based on the size and shape of the item. Using additional picture cues, such as texture and colour, can help reduce the misclassification of fruit of similar shape and size. The outcomes are really encouraging.

[2] ***Sorting and grading fruits based on colour and size:***

Size and colour Because the quality of agricultural goods is frequently correlated with their Colour and Size, fruit grading is one of the most important phases in fruit processing that directly impacts profitability. There are numerous methods for grading colours based on standards and references in the three-dimensional plane of colour space. Direct colour mapping reduces the three-dimensional colour space to a one-dimensional one. In this method, only the desired colours are chosen to be converted into a special set of colour spaces for the intended applications. Fruit area is examined using normalised second central moment for size grading.

[3] ***Flaw Detection and Classification in Citrus Fruits Using Computers:***

This study presents a technique for citrus fruit quality control. Calliper and colour are successfully used in modern citrus manufacturing businesses for automatic fruit classification using vision systems. On the other hand, human examination is used to find defects in the citrus surfaceA computer vision system that can recognise the type of imperfection and detect flaws in citrus peel is offered in this study. A review of citrus diseases was first undertaken in order to produce a database of digitalized oranges classified by the type of fault, which would be used as a training set. To segment the defective areas, the Sobel gradient is used to the image. The flaw's colour and texture attributes are then retrieved while taking into account various colour spaces, some of which are connected to high order statistics. The Sobel gradient is applied to the image to segment the defective areas. The flaw's colour and texture attributes are then retrieved while taking into account various colour spaces, some of which are connected to high order statistics.

[4] ***Fruit Detection Using an Improved Multi-Factor Algorithm:***

The capacity to efficiently locate the fruit on the tree is one of the important criteria for the fruit harvesting system. In this study, a fruit classification algorithm based on improved multiple characteristics is presented. To detect the fruit, an image processing system is trained for successful feature extraction. The algorithm's purpose is to assign weights to features of the input test image such as intensity, colour, orientation, and edge. The weights of various attributes represent the relative placements of the fruit inside a picture. The detection efficiency for distinct fruit images on trees captured at different positions can reach up to 90%. The input images are the tree section shots. The suggested method can be used to pick out certain fruits for robotic fruit harvesting.

[5] ***Fruit Recognition using Color and Texture Features:***

Intensity, colour, shape, and texture are the four fundamental qualities that characterise an object that are employed by computer vision techniques to identify a fruit. In this study, an effective combination of colour and tactile features for fruit recognition is proposed. To recognise objects, a minimal distance classifier employs statistical and co-occurrence data derived from Wavelet transformed sub-bands. The efficiency of the suggested strategy has been demonstrated by experimental findings on a database of around 2635 fruits from 15 distinct classifications.

Several food processing research fields, evaluating the safety and quality of food, keeping track of the food production process, and identifying foreign objects, have used MVS applications. Hyperspectral reflectance imaging techniques were used to assess blueberry damage or bruising in terms of food safety and quality. To differentiate between the stem and calyx, a pattern recognition algorithm was applied, find blueberries that had illnesses, and determine the direction of the berries. The suggested model not only made it possible to grade, It properly predicted how many actual days the gathered mangoes might be transported overseas using Support Vector Regression in addition to the fruits utilising Multi-Attribute Decision Making (MADM). The authors created the FIST-Rice rice data collection, which contains 30,000 samples of rice kernels, and created the Deep-Rice rice grading system, which extracts discriminative features from various rice angles. Artificial neural networks (ANN) were used by the writers and accepted the Relative Internal Distance (RID) values to categorise the morphologies of cooked prawn. The author created a banana classification system that divides bananas into healthy and unhealthy groups using methods for image processing and a neural network. and they achieved an accuracy of 97%. The dielectric characteristics of red bananas were measured in order to determine the ripening stages, and the features were then sent to a Fuzzy C means (FCM) classifier in order to determine the stages at which red bananas are. The creators of the Particle Swarm Optimised Fuzzy Model for the Ripeness Classification used a fuzzy model to determine the properties of the bananas' peak colour and normalised brown area in order to distinguish between unripe, ripe, and overripe bananas. The accuracy of this model is 93.11 percent. In the post-harvest classification of the banana utilizing tier-based machine learning, the accuracy of a random forest classifier used to identify the bananas according to their color attributes was 94.2%. In addition to classifying different banana types and their levels of ripeness from photographs, the authors applied machine learning techniques to do so. SVM classified the different varieties of bananas with a 99.1% accuracy rate and distinguished the amount of ripeness with a 96.6% accuracy rate. The grading system for banana fruit detects banana ripeness using a feature vector comprised of color and texture data, and an ANN outperforms other machine learning algorithms in this task. This system has a classification accuracy of 97.75%. In contrast to the comparable work that has been examined, In order to achieve the goals of banana grading and defective area identification, it proposes a two-layer technique. The authors created a data collection and added to it using customary data augmentation methods and a Cycle GAN-based deep learning architecture. This was done to prevent overfitting. The first layer classifier was then trained using a feature vector containing information on colour and texture. The YOLOv3 model locates the defective fruit peel regions in the photos in the ripened class, one of the output classes from the first layer.

Methodology Used

The methodology section provides a thorough explanation of the suggested system. The machine learning field of deep learning includes convolutional neural networks. As the human brain is too complicated, Deep Learning algorithms process information on a much smaller scale than the human brain does (our brain has around 86 billion neurons). The proposed methodology takes image of a fruit as input and then it extracts the features of the image to classify the quality of fruit such as good, bad, and mixed variety fruits. The process of classifying the fruit is explained in detail as follows:

In the proposed system the model is implemented with CNN algorithm where we have constructed the five hidden layers to process the image data along with the input and output layers. The model is trained with different types of images to get the accurate results. The features of the inputed image is extracted and then it comapared with the trained model which results the output.

The proposed fruit quality classification system includes data preprocessing, data augmentation, model implementation, and post processing.

Data Preprocessing:

Data pre-processing is an essential step in any machine learning project, including fruit quality classification using Convolutional Neural Networks (CNNs). The following are the steps followed in data pre-processing of this project:

a) Data collection: Collecting a dataset of images of fruits from different angles and lighting conditions.

b) Data cleaning: Cleaning the dataset by removing any duplicate or irrelevant images, as well as any images with poor quality or low resolution.

c) Data labeling: Labeling each image with the corresponding fruit type. Quality classification is based on factors such as colors, size, and ripeness.

d) Data augmentation: Augmenting the dataset by applying various transformations to the images, such as rotation, scaling, and flipping, to increase the diversity of the dataset and improve model's robustness to variations in the input.

e) Data normalization: Normalizing the pixel values of the images to a common scale (eg., 0 to 1) to make it easier for the CNN to learn from them.

f) Data splitting: Splitting the dataset into training, validation, and tests the set to evaluate the model's performance on unseen data and prevent overfitting.

g) Data batching: Creating batches of images and their corresponding lables to feed to the CNN during training.

Data Augmentation:

Data augmentation is a technique used in machine learning

to increase the size and diversity of a training dataset by creating new variations of existing data. In this project of fruit quality classification using CNN, data augmentation can be used to generate additional training images that are similar to the original images but with different variations, such as different rotations, flips, translations, and zoom levels. Here are the steps how data augmentation works in our project:

a) Define the augmentation operations: Define the set of augmentation operations to apply to the original images. Common operations include rotation, scaling, flipping, cropping, and noise addition.

b) Apply the augmentation operations: Apply the defined augmentation operations to each image in the training dataset, generating new variations of the original images.

c) Update the label for each augmented image: Update the label for each augmented image to reflect the same fruit and quality score as the original image.

d) Merge the augmented images with the original dataset: Merge the augmented images with the original dataset to create a larger and ,more diverse training dataset.

By applying data augmentation, the CNN model can learn to recognize different variations of the same fruit and quality, making it more robust and accurate. Data augmentation helps to prevent overfitting by increasing the size of the dataset and reducing the likelihood of the CNN model memorizing the training data rather than learning to generalize to new images.

Model Implementation

The following are the steps followed in implementing the model for fruit quality classification The data collected and preprocessed in previous steps are used to train and implement the model.

Model design: Designing a CNN architecture that is suitable for fruit quality classification. This typically involves choosing the number and size of the convolutional and pooling layers, the activation function, the number and size of the fully connected layers, and the output layer.

b) Model training: Training the CNN model on the training set using backpropagation and stochastic gradient descent to minimize the classification error. The training process involves setting the hyperparameters, such as the learning rate and the number of epochs, and monitoring the validation error to avoid overfitting.

c) Model evaluation: Analyse the trained CNN model's performance on the test set to determine its F1 score, accuracy, precision, and recall. This entails producing the classification report and confusion matrix, as well as visualising the feature maps and classification outcomes.

Importing the necessary libraries: TensorFlow, Keras, NumPy, Matplotlib, etc. The library tensorflow is used to convert the image to matrix and then to a single binary number to classify the data. The model is made in keras. The When there are two or more output labels in a multi-class classification model, categorical-crossentropy is used as a loss function. One-hot category encoding value in the form of 0s and 1 are allocated to the output label. The output label is converted into categorical encoding using the keras.utils to categorical method, if it is present in integer form.

Preparing the data: This involves loading the training and testing data, preprocessing the data (such as normalization, data augmentation, and reshaping), and splitting the data into training and validation sets.

Post Processing

Post- processing in this project using CNN typically involves applying some additional steps after the CNN model has made its predictions. The purpose of post-processing is to refine and improve the quality of classification results. The following are the post-processing techniques that are used

a) Filtering: Filtering is a process that removes noise and outliers from the classification results. For example, if the CNN model predicts that an image contains a fruit with a low quality score, but the surrounding images contain high-quality fruits, the filtering process can reject the low-quality classification and replace it with a more accurate one.

b) Smoothing: Smoothing is a process that reduces the sharpness of the classification results. For example, if the CNN model predicts that an image contains a fruit with a high quality score, but the surrounding images contain fruits with lower scores, the smoothing process can adjust the classification score to be more in line with the neighboring scores.

c) Calibration: Calibration is a process that adjusts the classification scores to match the real-world probabilities of each class. For example, if the CNN model is biased towards certain classes, such as ripe fruits, the calibration process can adjust the classification scores to reflect the true distribution of fruit quality in the dataset.

The following flowchart defines the working of fruit quality classification i.e., how the fruit is classified based on the features of the fruit:

- Firstly the fruit image is given as input and then the features of image gets extracted by converting the image into a matrix.
- In the second step the image data processing will happens i.e., the features of the image extracted and it is converted to single byte data.
- Then the image features is compared with the trained data set to identify the category.
- Finally the fruit is classified into the expected category by the model trained.

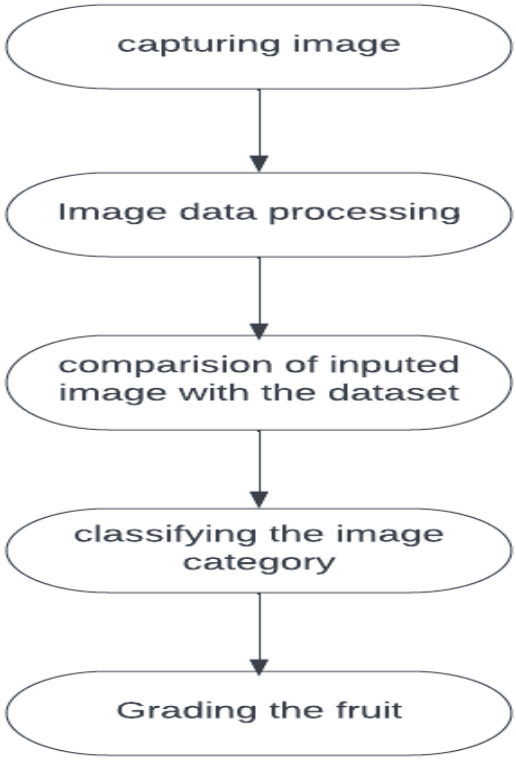

Figure1: Flow of fruit quality classification

Conclusion and Future Scope

Convolutional neural networks, a powerful technique for classification, are the foundation of the "Fruit Quality Classification" project, a deep learning model that allows us to categorize fruit by extracting its properties. First, use any smartphone camera or a normal digital camera to take a picture of the fruit. The sampled image effectively extracts the features. The parameters look, shape, and size are used to base the extracted features. The quality is examined using the CNN method. Using fruit attributes gathered with the use of CNN, the quality is assessed. The suggested method successfully determines the fruit's quality. The three selected fruits, which differ in look, shape, and size, produced good results. These systems can be used in fruit and juice production facilities. Future CNN-based quality detection techniques should be compared to existing mechanical and automated techniques.

The dataset is now saved on a local workstation, which is inadequate for larger datasets. So, even if we have more datasets, we can manage the system by using cloud services. Also, we can incorporate the raspberry into our project as it is where the raspberry pi is located by getting an image of the fruit from the raspberry pi's attached camera. Currently, we have trained the model to identify three fruit qualities: apple, pomegranate, and banana. By training the model, we can expand its application to numerous additional fruits.

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